

The Ohio Criminal Sentencing Commission (Commission) unanimously voted to approve the report and recommendations of the Ad Hoc Committee on Bail and Pretrial Services on June 15, 2017.¹ Based in part on this report and the recommendations in a subsequent Task Force,² the Supreme Court proposed changes to Rule 46 of the Rules of Criminal Procedure that took effect July 1, 2020.³ Changes to this rule did not require the use of a pretrial risk assessment tool in Ohio courts, yet it did not prevent judges from adopting and implementing such a tool locally. Concerns about bias in pretrial risk assessment tools prevented support for requiring their use statewide. This concern also motivated a well-known national pretrial organization, the Pretrial Justice Institute, to remove their support for the widespread adoption of such tools. Their statement can be found [here](#).

In Ohio and across the country, practitioners are considering increased use of pretrial services and/or (re)considering the role of risk assessment in bail decisions. For those still in favor of pretrial risk assessment tools, it is more important than ever to understand the chosen tool and how it can be validated in the local population. Consistent with the recommendations of the Commission's report to create a list of validated risk assessments, we have compiled a snapshot of information about existing pretrial risk assessment tools in use nationwide.

Information presented is not summarized; instead, it is a compilation of the most updated, publicly available material. Tools and studies for states and localities no older than 2016 are included. As a result, for some tools entire validation reports are included; for others, merely the tool description; and, for others, only the tool itself. While there is a pretrial risk assessment tool used by several states and/or counties (the Arnold Public Safety Assessment, PSA),⁴ others use state specific tools or tools employed by just a few states (for example, the Ohio Risk Assessment System- Pretrial Assessment Tool, ORAS- PAT) and others employ tools that been developed specifically for their county. Readers are encouraged to reach out to the individual states or counties for more information about specific tools.

¹ Full report is available at:

<http://www.supremecourt.ohio.gov/Boards/Sentencing/resources/commReports/bailPretrialSvcs.pdf>

² See full report here: <http://www.sc.ohio.gov/Publications/bailSys/report.pdf>

³ Amendments to Criminal Rule 46 can be found here:

<http://www.supremecourtofohio.gov/ruleamendments/documents/4.22.20%20Posting.pdf>

⁴ See <https://advancingpretrial.org/psa/research/> for links to research specifically about the PSA tool in various locations.

Additionally, several resources provide links to additional state/county and federal pretrial risk assessment tools, research about their effectiveness, and discussions about their strengths and weaknesses. For example: the [National Institute of Corrections](#), the [University of Pretrial](#), and [Mapping Pretrial Injustice](#).

The Commission recommends the use of a risk assessment tool for pretrial release decisions, but does not endorse one particular tool. This resource is created as a snapshot of available information and research about existing pretrial risk assessment tools and is **not** the list of validated risk assessments that will be created later by the Commission. Every jurisdiction and/or court is encouraged to fully evaluate available risk assessment tools and determine the tool that best suits their locality. Finally, this is not exhaustive information; pretrial services and the use of risk assessment tools is a nationally trending, dynamic topic. Jurisdictions continue to share and engage in evidence informed best practices and may adopt new or revise current risk assessment tools. As we learn of new or revised tools and information, we will update this resource and in the future create a separate list of validated risk assessment tools. It is also likely that information is not included here, because it is not available or publicly accessible. Please contact us (sara.andrews@sc.ohio.gov) if there is a tool, information or resource that should be added or removed from this snapshot resource.

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MEDIA ADVISORY
Tuesday, March 14, 2017

Sentencing Commission Ad Hoc Committee Unveils Bail, Pre-Trial Recommendations

COLUMBUS – A special committee of the Ohio Criminal Sentencing Commission will present its recommendations to reform bail and pre-trial services in the state at a March 16 meeting.

The ad hoc group sought to examine the current state of bail and pre-trial services and issue recommendations that maximize public safety, appropriate placement for defendants, and appearance at court hearings and protect the presumption of innocence.

The Commission intends only to consider the recommendations at the March meeting and a vote to accept the final report will be at its next quarterly meeting on June 15, 2017. The Commission also invites public comment on the report and recommendations via its [website](http://www.supremecourt.ohio.gov/Boards/Sentencing/default.asp) (<http://www.supremecourt.ohio.gov/Boards/Sentencing/default.asp>) through May 15, 2017.

“As a prosecutor, my primary concern about “bail reform” was to ensure that the community is safe from further harm. The Committee considered the risk of reoffending and the risk of flight as significant factors in pre-trial detention. The ad hoc committee’s proposals appropriately balance these concerns against the rights of the defendant. The time is right for reform of the money bail system.” – Dave Phillips, Union County Prosecutor and Ad Hoc Committee Member

“The recommendations target changing the bond and bail from a one-size fits all fixed amount bond schedule to a method of release at the pretrial stage utilizing evidence based practices and tailoring any pretrial release conditions to the individual. The hoped for result will be that individuals will no longer be incarcerated simply because they did not have the financial resources to post bond. The Report is the result of a collaborative effort by various stakeholders in the judicial system with the goals of transparency, fairness, and equity.” – Judge Beth Cappelli, Fairborn Municipal Court and Ad Hoc Committee Member

“As criminal justice systems across the nation reexamine bail practices, the Ohio Criminal Sentencing Commission has engaged in a collaborative, thoughtful process in developing recommendations that address public safety and court appearance concerns by shifting the bail decision from a money-based decision to an individualized defendant risk-based system. The result of these recommendation is a system that more fairly considers a defendant’s risk of failing to appear or to the safety of the community rather than the amount of money they or their families have.” – Dan Peterca, past President of the Ohio Association of Pretrial Services Agencies and Ad Hoc Committee Member.

What: Bail and Pre-Trial Services Recommendations

When: 10 a.m., Thursday, March 16, 2017

**Where: Thomas J. Moyer Ohio Judicial Center, Room 101, 65 S. Front St.,
Columbus**

Contact: Sara Andrews at 614.387.9305.

Ohio Criminal Sentencing Commission. 2017. *Ad Hoc Committee on Bail and Pretrial Services: Final Report and Recommendations*. Ohio Criminal Sentencing Commission: Supreme Court of Ohio.

Appendix A

PRETRIAL SYSTEM REFORMS

	Use of *Arnold Tool Risk Assessment	Use of Other Risk Assessment Tool	Contains a *SJC Site	*EJUL Case to Challenge Bond Schedules	*EJUL Case/Other Efforts to Promote Bail Reform	*Smart Pretrial State/Site	Rewritten Bail Statutes	*EBDM Practices
Alabama					X			
Alaska		X						X
Arizona	X		X					
California	X		X	X				
Colorado		X	X			X	X	X
Connecticut			X		X			
Delaware		X				X		
Florida	X	X	X					
Georgia				X				
Idaho			X					
Illinois	X		X					
Indiana								
Kansas								
Kentucky		X						X
Maine					X			
Maryland					X			
Massachusetts								
Mississippi					X			
Missouri			X	X				
Nevada								
New Jersey					X		X	
New Mexico							X	
New York			X		X			
North Carolina	X		X		X			
Ohio	X	X	X					
Oregon			X					
Pennsylvania	X		X					
Tennessee			X					
Texas			X	X				
Utah		X			X			
Virginia		X						X
Washington			X		X	X		
Washington D.C.								
Wisconsin	X		X					X

***Arnold Tool:** Entirely objective risk assessment tool developed to help judges make accurate evidence-based decisions about which defendants should be released or detained pending trial.

***SJC Site:** State that promotes the Safety and Justice Challenge initiative to reduce overpopulation in jails through the

establishment of more effective and just alternatives to excessive incarceration.

***Smart Pretrial State/Site:** States/sites participating in the Pretrial Justice Institute Smart Pretrial Demonstration initiative to research effective ways to reduce jail costs, while maintaining public safety, through the improvement of pretrial policies and practices

***EJUL:** Cases represented by the non-profit Equal Justice Under the Law organization that provides pro bono legal representation to individuals in extreme need

***EBDM:** Evidence-based decision making



DECEMBER 2019

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Pretrial Risk Assessment in California



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SUMMARY

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Technical appendices to this report are available on the PPIC website.

The policies governing California’s pretrial system are undergoing substantial change. Amid recent correctional reforms and ongoing challenges to the state’s bail system, pretrial risk assessment has emerged as a way to help counties make decisions about whether arrested individuals should remain in the community or be detained until any charges stemming from that arrest are resolved.

This report presents an overview of pretrial risk assessment in California and offers considerations for using, evaluating, and improving the effectiveness of local pretrial risk assessment systems.

- **Forty-nine of California’s 58 counties use pretrial risk assessment tools alongside bail.** These tools rely on criminal history, demographic, and/or socioeconomic information to make “risk predictions” of whether individuals are likely to be arrested during the pretrial period or to miss their court date.
- **A risk assessment tool is only one component of informed pretrial decision making.** A comprehensive pretrial policy framework also includes an explanation of why a particular tool was chosen and how it should be used—as well as guidance regarding how risk assessment results should translate into decisions about release with or without supervisory conditions, or detention, in individual cases.
- **Equity is an ongoing concern.** Critics argue that risk assessment tools that use criminal history could propagate preexisting inequities in the criminal justice system for racial minorities and homeless, unemployed, and impoverished individuals. However, proponents maintain that these tools offer new opportunities for monitoring and evaluating accuracy—which could ultimately help mitigate inequities.
- **Counties may face data challenges in testing a tool’s accuracy and equity.** Local testing is critical, in part because many tools were not developed with populations that include Latinos and Asian Americans. Since the criminal history data used in these tools may be housed in different agencies and many counties may not process enough cases to properly test their tool on their own, data-sharing agreements and cross-county collaboration may be necessary.
- **Transparent decision making is essential.** By carefully tracking the risk predictions made by their assessment tool—as well as how these predictions are translated into release or detention decisions—counties can identify any patterns of inconsistency, inaccuracy, and inequity. To promote transparent decision making, judges and pretrial services officers should explicitly state their reasoning if they override the prescribed recommendation.

Developing a pretrial risk assessment system that balances an arrested individual’s right to liberty and the need to preserve victim and public safety, while also promoting equity, is an ongoing endeavor. With transparent decision making, as well as consistent and complete data collection, counties will be in a strong position to conduct the routine monitoring, testing, and evaluation necessary to identify areas of weakness and ensure their pretrial decisions align with local policy objectives.

Introduction

The pretrial period begins with an arrest and ends when the charges stemming from that arrest are resolved through plea bargain, trial, or dismissal—a process that can last a few hours or persist over many months.¹ The fundamental decision made during this time is whether the arrested individual should be detained until the charges are resolved. In California, several actors in the criminal justice system can make the decision to release or detain individuals at different stages in the pretrial process—law enforcement officers at arrest and booking; pretrial services officers prior to arraignment; and judges at arraignment (Tafoya 2015; Tafoya et al. 2017). The purpose of pretrial risk assessment is to inform these decisions—particularly those made by judges at arraignment.

In California, most counties use pretrial risk assessment tools in concert with the bail system, which includes money or cash bail, to make decisions about pretrial release and detention (PDRW 2017). These risk assessment tools predict the likelihood that pretrial misconduct—generally referring to a new arrest or failure to appear in court—will occur based on a person’s demographic, criminal history, and/or socioeconomic background.²

Under the bail system, people who have been arrested or charged with a crime can offer a financial guarantee that they will appear for their court dates in exchange for their pretrial release, with the bail amount typically based on the severity of the offense. Critics have argued that this system fails to protect public safety and privileges wealthy people who can afford bail over poorer people who cannot (BRWG 2016; PDRW 2017). Advocates of the current system argue that bail is an effective means of ensuring court appearances.

Across the United States, policies governing pretrial release and detention—especially money bail—are being challenged, evaluated, and revised.³ Since 2012, every state has adopted new pretrial policies. In 2017 alone, 14 states made provisions to adopt or investigate the use of pretrial risk assessment tools (Widgery 2018). In addition, two states, New Jersey and Alaska, have nearly, but not completely, eliminated money bail.⁴

Challenges to the bail system are also cropping up in California. In January 2018, the First District Court of Appeals in San Francisco ruled the pretrial detention of Kenneth Humphrey unconstitutional because “a defendant may not be imprisoned solely due to poverty.” Should the ruling be upheld, it may constitute an existential challenge to the state’s bail system. Concurrent challenges—motivated in part by high rates of pretrial detention in California relative to the rest of the nation—have been posed by the Judicial Council and state legislature.

In October 2016, the Judicial Council founded a Pretrial Detention Reform Workgroup (PDRW) to “identify ways to make release decisions that will treat people fairly, protect the public, and ensure court appearances” (PDRW 2017, 1). The PDRW (2017, 2) made ten recommendations intended to better “balance the protection of public safety” with the rights of arrested individuals, particularly their right to liberty, by increasing the number of people who are released pretrial. Their recommendations included eliminating money bail, establishing pretrial services in each county, and using pretrial risk assessment tools that have been proven accurate to help judges make decisions about release and detention based on “objective factors” (PDRW 2017, 50).

¹ Although California lacks statewide statistics regarding the average length of the pretrial period, in Santa Clara County, for example, the average length of pretrial detention was one month for those charged with misdemeanors and seven months for those charged with felonies (BRWG 2016, 2).

² In this report, any discussion of risk assessment tools refers specifically to pretrial risk assessment tools. The research and analysis provided here about pretrial risk assessment tools are not intended to apply to other contexts in the criminal justice system.

³ Under the bail system, individuals who are offered bail and who can afford to pay a fee are released during the pretrial period, whereas those who cannot are detained. Bail schedules assign a pecuniary price on release that is based solely on the seriousness of the arrest offense—a proxy for threat to public safety (Tafoya 2013). Most people who are released on bail in California pay the predetermined fee listed in the bail schedule, although judges can weigh other factors to set bail at their discretion (Tafoya 2015; Tafoya et al. 2017).

⁴ For example, New Jersey’s system, instituted in 2017, does not outlaw bail. However, it seems to have obviated the need for it. In 2018, bail was imposed in only 102 of 44,383 cases—mainly after defendants missed court dates while on pretrial release (Grant 2019).

Each of these proposed reforms was codified by the state legislature in Senate Bill 10 (SB 10). SB 10 was signed into law in August 2018, but challenged immediately by the bail bond industry. Although its fate will be decided in a voter referendum in November 2020, SB 10 clearly signals the intent of state legislators: they sought to establish a system enabling pretrial decisions that would more effectively protect public safety, while also maintaining individuals' right to liberty and eliminating their potential to be detained "solely due to poverty."⁵ In addition, in October 2019, the governor signed SB 36, which requires pretrial service agencies that use risk assessment tools to test the tool on a regular basis and requires that the Judicial Council publish an annual report on the outcomes and potential biases in pretrial release.

Although they are sometimes portrayed as mutually exclusive alternatives, pretrial risk assessment and money bail can be compatible, as the current pretrial justice system in California illustrates. This report focuses on pretrial risk assessment and considerations for improving existing assessment systems. The broader question of whether pretrial risk assessment should replace bail is one that rests with the voters, the legislature, the courts, or some combination thereof.

We begin this report by describing the current landscape of pretrial services in California. We then present an overview of the most common risk assessment tools used across the state and ways to mitigate racial inequity. Lastly, we identify several key considerations for counties as they seek to improve their pretrial risk assessment systems and provide guidance for routine monitoring and testing of these systems to ensure they are performing as intended.

Background on Pretrial Services

Pretrial services is the arm of the criminal justice system responsible for conducting pretrial risk assessments, making recommendations for pretrial release or detention, supervising and providing services to released individuals, and locating those who do not show up for court appearances. These services have existed in California since the 1960s. However, most counties established pretrial services in the wake of public safety realignment in 2011 (CSJ 2015). Realignment reduced the prison population but expanded jail populations because many individuals who would have previously served time in state prisons due to supervision violations instead served that time in county jails (Bird et al. 2018; Grattet et al. 2017).⁶

Jail overcrowding prompted many counties to reexamine their pretrial policies and led the state legislature to explore bail reforms (Tafoya 2013, 2015). Though none of those early reforms made it through the legislative process, the passage of Proposition 47 in 2014 again reshaped pretrial justice. Individuals charged with drug and property crimes that had been downgraded from felonies to misdemeanors were more likely to be released pretrial (Bird et al. 2016). By 2015, 46 California counties had established pretrial services as independent agencies; units within law enforcement, probation, or the courts; or multi-agency collaborations (CSJ 2015).

⁵ Importantly, most of California's counties have already instituted some of these reforms. By 2017, 49 counties were using pretrial risk assessment tools to inform at least some pretrial release or detention decisions (PDRW 2017).

⁶ For every three inmates released from state prison, one was admitted to jail (Lofstrom and Raphael 2013).

Goals of Pretrial Justice

Practitioners and policymakers refer to four main goals of pretrial justice: maximizing individuals' right to liberty, public safety, court appearances, and equity (e.g., PDRW 2017; Mahoney et al. 2001, 1). Releasing as many people as possible under the fewest conditions maximizes individuals' right to liberty. Minimizing behavior that endangers individual victims or the general public maximizes public safety. Maximizing court appearances protects the efficiency of the justice system. Finally, ensuring that pretrial policies apply equally to all people—that some people are not treated disparately relative to others—maximizes equity.

For pretrial services to function effectively, practitioners and policymakers must determine how to balance these objectives. Because pretrial risk assessment tools enable stakeholders to monitor the accuracy and equity of release and detention decisions, these tools can help counties strike their desired balance between releasing as many people as possible while protecting victim and public safety and ensuring court appearances.

In August 2019, the Judicial Council awarded funding for two-year pilots in 16 counties to either implement new pretrial programs or enhance existing programs across the state. The pilot programs share many of the same goals, including seeking to assess more people more quickly; collect and store data more efficiently; and create “graduated supervision levels” so that individuals deemed low risk receive minimal or no supervision during the pretrial period, while higher-risk individuals receive more supervision or are detained. All of the pilots leverage risk assessment tools to meet these challenges and will include an evaluation of the program (Balassone 2019).

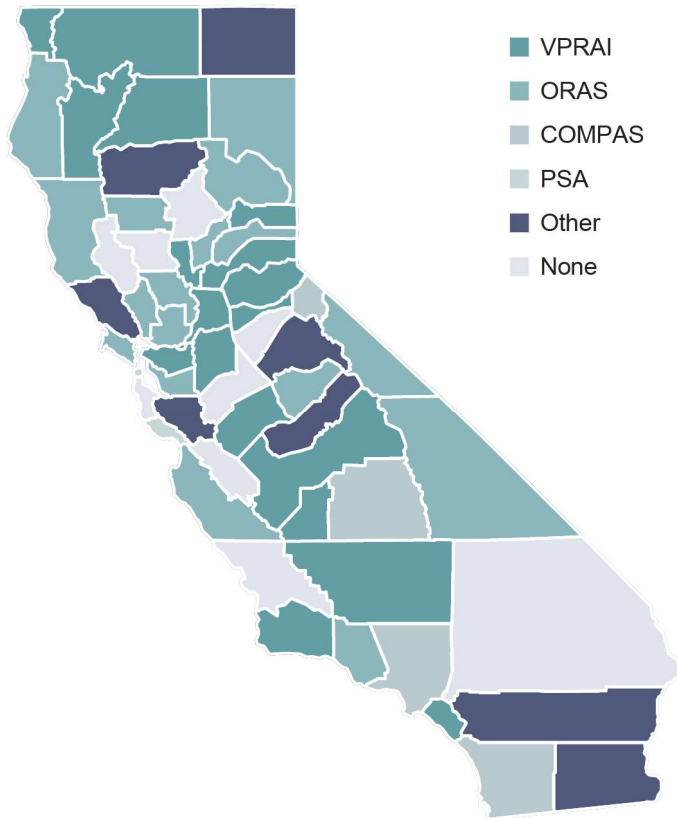
How much counties spend on pretrial services is unclear, particularly when these responsibilities are embedded in other agencies. Notably, personnel levels drive pretrial costs (Clark and Henry 2003), and personnel levels vary because counties have different arrest rates and provide different services (CSJ 2015; Lofstrom et al. 2018). Funding amounts for the pretrial pilot programs suggest a wide range in costs. Funding to establish new programs ranged from \$531,000 in Calaveras County to \$9.59 million in Sacramento County. Alameda County received \$14.4 million to restore its defunct program. Costs in counties expanding their programs also varied widely, with allocations between \$330,000 for a collaboration between Nevada and Sierra Counties, and \$17.3 million in Los Angeles County.

The Role of Pretrial Risk Assessment Tools

As shown in Figure 1, 49 of California's 58 counties currently use a pretrial risk assessment tool to inform at least some pretrial decision making. Only four counties—Santa Clara, Sonoma, Riverside, and Tuolumne—developed their own tools. By contrast, the vast majority of counties use a tool that was developed outside of California. Most counties use the Virginia Pretrial Risk Assessment Instrument (VPRAI; 18 counties) or the Ohio Risk Assessment System tool (ORAS; 17 counties). The COMPAS and PSA tools are used by four counties and two counties, respectively.

FIGURE 1

Most counties use a pretrial risk assessment tool developed outside of California



SOURCE: Author illustration based on PDRW (2017) and personal communication.

Counties also use these tools in different ways: in some counties, all eligible arrested and booked individuals undergo pretrial risk assessment, while in others, only those charged with specific crimes do (PDRW 2017). These differences are likely attributable to variation in how developed the county’s system of pretrial justice is, how long the county has been using a particular risk assessment tool (or whether it uses a tool at all) to inform release or detention decisions, and the resources available to make risk assessments and administer pretrial justice more generally. Some counties have been using pretrial risk assessment tools to inform at least some pretrial release or detention decisions for years, whereas others have never used such tools.

Comparing Pretrial Risk Assessment Tools

Table 1 presents key attributes for the four most common pretrial risk assessment tools used in California. When tested by developers, each has about a 65 percent chance of distinguishing a person at high risk of committing pretrial misconduct from a person who is at low risk.⁷ While this accuracy rate may not seem especially high, it should be compared to the current standard—judges’ risk predictions. The best evidence indicates that pretrial

⁷ The most common measure of accuracy is called the area under the curve (AUC). The AUC, which ranges from 0.00 to 1.00, indicates the probability that a risk assessment tool can distinguish people who are highly likely to commit pretrial misconduct from people who are not. Most tools used in California have an AUC of 0.65, which means they have about a 65 percent chance of distinguishing a high-risk person from a low-risk person. More information on the AUC is presented in [Technical Appendix D](#).

risk assessment tools make more accurate pretrial risk predictions than judges (Baradaran and McIntyre 2012; Berk et al. 2018; Kleinberg et al. 2017).⁸

An important difference between the tools is that they define pretrial misconduct in different ways, though each tool predicts some combination of failure to appear in court and a new arrest. Ideally, pretrial risk assessment tools should predict each pretrial misconduct outcome separately (Gouldin 2016; Kleinberg et al. 2019; PAI 2019). PSA predicts three outcomes separately: failure to appear, new arrest, and new violent arrest. However, VPRAI, ORAS, and COMPAS do not predict failure to appear and new arrest separately. ORAS and VPRAI predict failure to appear *or* new arrest, while COMPAS predicts any new felony arrest *or* failure to appear in court. These “compound” prediction outcomes make it impossible for county policymakers to distinguish people at high risk of arrest from people at high risk of missing a court date. This could lead to misleading risk predictions and could make it difficult to tailor pretrial recommendations appropriately (Gouldin 2016). See additional considerations regarding how pretrial misconduct can be defined in the textbox on page 9.

TABLE 1
Select characteristics of pretrial risk assessment tools currently used in California

	VPRAI	ORAS	COMPAS	PSA
Number of counties	18	17	4	2
Pretrial misconduct outcome	Failure to appear	Failure to appear	Failure to appear	Failure to appear
	New arrest	New arrest	New felony arrest	New arrest
				New violent arrest
Compound prediction outcome	Yes	Yes	Yes	No
Predictor domains	Criminal behavior	Criminal behavior	Criminal behavior	Criminal behavior
	Employment	Employment	Employment	Age
	Substance Use	Substance Use	Substance Use	
	Supervision	Residence	Residence	
		Age		
Interview required (length of interview)	Yes (20 minutes)	Yes (10-15 minutes)	No	No
Transparent risk prediction model	Yes	Yes	No	Yes
Free to use	Yes	Yes	No	Yes

SOURCES: Personal communication; Arnold Ventures (n.d.); BJA (n.d.); Danner et al. (2016); DeMichele et al. (2018b); Equivant (n.d.); Latessa et al. (2009); PDRW (2017); VDCJS (2018).

NOTES: Counties may be using different versions of each tool. The information presented represents the current versions of each tool: COMPAS-PRRS II, ORAS-PAT, and VPRAI-R. We show the full range of predictors for each instrument in [Technical Appendix B](#). PSA refers to a new arrest as “new criminal activity” and to a new violent arrest as “new violent criminal activity.”

⁸ In a national sample, Baradaran and McIntyre (2012) found that, relative to judges’ decisions, their probit regression model would release 25 percent more defendants while also decreasing the probability of pretrial violent arrest by more than one-third, from 1.9 percent to 1.2 percent, and the probability of any pretrial arrest by 18.8 percent, from 17.0 percent to 13.8 percent. Similarly, Kleinberg et al. (2017) found that, relative to judges’ decisions, their machine learning algorithm could reduce detention rates in New York City by 41.9 percent without increasing crime rates.

The four tools use different predictors—criminal history, demographic, and/or socioeconomic indicators—to predict whether individuals will commit pretrial misconduct (see [Technical Appendix B](#)).⁹ Some tools use demographic indicators such as age; however, factors such as race/ethnicity or gender are not used in any of these tools. Notably, VPRAI, ORAS, and COMPAS use socioeconomic factors to predict risk. As described further below, critics have expressed concern that including these characteristics can systematically disadvantage certain marginalized groups. For example, if factors like unemployment, homelessness, and mental illness increase an individual’s chance of being classified as high risk, then these groups could be disproportionately detained. Likewise, racial minorities who are overrepresented in these populations could also be systematically and disproportionately classified as high risk and detained (Starr 2014).¹⁰

Defining pretrial misconduct

According to California law, whether individuals pose a threat to victim or public safety should be the primary consideration when making pretrial release and detention decisions (Karnow 2008; Tafoya 2013). In practice, there is a wide range in how pretrial misconduct is defined. As shown in Table 1, most risk assessment tools adopt fairly expansive definitions of pretrial misconduct, such as any new arrest and failure to appear. They also often predict those outcomes over two years—far longer than the average felony pretrial period, even for serious and violent crimes.

In contrast, some legal scholars indicate that narrower interpretations of pretrial misconduct that focus on the individuals’ threat to public safety are more appropriate when predicting risk. According to a Judicial Council report, California law allows pretrial detention only as a means of preventing serious violent crimes (PDRW 2017). Similarly, Mayson (2018, 501) concluded that “the threshold [for detention] cannot be less than a substantial risk of serious violent crime in a six-month span.”

It is important to note that counties can develop their own assessment tools, as a few counties have, which may provide them with more latitude in how they define pretrial misconduct. Regardless of what counties choose, it is critical that county agencies be explicit and transparent about this definition. The primary tradeoff to consider is that defining pretrial misconduct broadly and over a longer time period could lead to risk predictions that overestimate the threat people pose to public safety, thereby inhibiting counties from achieving objectives related to preserving individuals’ right to liberty. In contrast, narrowly defining pretrial misconduct would allow more individuals to be released pretrial but could lead to risk predictions that do not take into account the potential for new non-violent offenses and failures to appear in court.

⁹ The statistical models that underlie most tools assign numerical values called weights to each predictor by assessing the strength and direction of its relationship to an outcome such as an arrest during the pretrial period. For example, predictors that strongly increase the chance of pretrial misconduct receive large positive weights; those that weakly decrease the chance of pretrial misconduct receive small negative weights. During assessment, the weights for the predictors associated with each assessed individual are tallied to calculate risk scores (Picard-Fritsche et al. 2017).

¹⁰ However, the pragmatic way to understand whether including a predictor in a risk prediction model systematically disadvantages one group of people relative to another is through testing. If adding or subtracting a predictor promotes disparity in risk predictions between groups of people or introduces disparity in rates of misclassification between groups of people, its inclusion should be questioned.

The data collection required for these assessments takes time and resources. In addition, the ORAS and VPRAI tools require interviews—which may make them more expensive to administer. Although there is a lack of comprehensive information on this topic, in Kentucky, completing the PSA assessment takes up to 45 minutes (PDRW 2017, 81). Meanwhile, “conducting an interview, reviewing a defendant’s records, and electronically submitting a report to the court takes approximately one hour” in Santa Clara County, which uses its own tool (BRWG 2016, 27). Finally, how an assessment tool predicts risk is key to understanding whether and how it can help counties achieve their policy objectives. According to the Chief Probation Officers of California (CPOC 2019, 9), “jurisdictions should be wary of proprietary assessments that do not disclose weighting and scoring.” The ORAS, PSA, and VPRAI transparently report how they were developed and how they predict risk. By contrast, the COMPAS risk prediction model is proprietary. [Technical Appendix B](#) contains additional information about these tools.

Concerns of Racial Inequity

Critics of pretrial risk assessment tools argue that they exacerbate past and current inequity—especially racial inequity—in the criminal justice system (Angwin et al. 2016; Mayson 2019; Starr 2014; Tonry 2014). But proponents maintain that implementing risk assessments in a transparent and deliberate way could actually help correct inequities in pretrial decision making (Kleinberg et al. 2019; Picard et al. 2019).

One central concern involves the fact that assessment tools use criminal history information—such as previous arrests, convictions, and incarceration—to predict the probability that an individual will commit an offense during the pretrial period. However, these metrics do not only reflect individual behavior—they also reflect the operations of the criminal justice system. Research has found that racial minorities and other marginalized groups are overrepresented in criminal justice data in part because they are subject to greater surveillance and enforcement (Alexander 2010; Braga et al. 2019).

Although we cannot know with certainty the degree to which criminal history data reflect differences in individuals’ behavior versus differences in enforcement, research indicates that these data overstate the involvement of racial minorities in crime (Weaver et al. 2019). This disparity begins at arrest and is propagated through each stage of the criminal justice system (Harris et al. 2009; Lofstrom et al. 2018). If past criminal history data are used to predict future criminal behavior, those predictions could thus overstate the probability of racial minorities committing a crime. The same could be true of other socioeconomic characteristics that might be associated with disparities in the criminal justice system, such as being homeless, unemployed, or in poverty.

Yet pretrial risk assessment tools also present opportunities for greater transparency, which could serve to mitigate inequities in pretrial decision-making processes. Developing a transparent and consistent pretrial decision-making system makes it possible to evaluate whether release or detention decisions are accurate and equitable (Berk et al. 2018; DeMichele et al. 2018a; Koepke and Robinson 2019). Furthermore, if patterns of inconsistency, inaccuracy, or inequity become evident during monitoring and evaluation, pretrial risk assessment systems can be modified accordingly (PAI 2019; Kleinberg et al. 2019; Mayson 2019; Picard et al. 2019).

Considerations for Improving Pretrial Risk Assessments

Pretrial risk assessment is often equated with the use of pretrial risk assessment tools, but the latter do not advance the goals of pretrial justice on their own. To accomplish local policy objectives, counties should develop broader policy frameworks that govern:

- **How pretrial misconduct is defined and how risk is predicted.** This involves selecting or designing a tool that aligns with local objectives for how pretrial misconduct should be defined (see textbox on page 9), ensuring that the necessary data are available, and allocating the resources needed to conduct the assessments.
- **How risk predictions are interpreted and translated into release or detention decisions.** This involves providing guidance for pretrial services officers and judges regarding how the results of risk assessment tools should be mapped onto decisions about release with or without supervisory conditions, or detention.

A pretrial risk assessment tool is only one component of what is ideally a comprehensive infrastructure that supports the entire pretrial risk assessment process. This section describes several factors for counties to consider as they seek to build upon and improve these systems, including potential limitations in the available data, challenges in interpreting risk predictions, and the importance of transparency in the decision-making process.

Data Challenges in Using Risk Assessment Tools

Some of the data required for pretrial risk assessment tools may prove challenging to collect because different criminal justice agencies track different information. At the county level, for example, law enforcement agencies track arrests and jail incarcerations, the courts track convictions, and probation offices track supervision violations. Each of these agencies may need to collaborate, individually or jointly through an integrated countywide data system, to share data and implement pretrial risk assessment. Depending on whether incarceration is measured locally or statewide, to assess risk using the COMPAS, ORAS, and PSA, data-sharing agreements with state agencies might also be necessary.

Additionally, the data required to make some risk predictions may not be available. In particular, most risk assessment tools use past failures to appear in court to make predictions about future behavior. Yet many California counties do not systematically collect information about failures to appear (PAI 2019). When they do, they may measure failures to appear inconsistently. For example, failures to appear can be recorded for every nonappearance, only when a bench warrant is issued, or as self-reported by defendants (Clark and Henry 2003; Gouldin 2018). Such vast inconsistency in measurement can lead to risk predictions that vary less with individual behavior and more with how that behavior is recorded (Myburgh et al. 2015).

Regardless of which agency collects and stores the data, how the data are collected matters. Data collection processes should be systematized so that they are as similar as possible for everyone. For example, failures to appear should be recorded under the same circumstances for all individuals (Gouldin 2018; Myburgh et al. 2015). Likewise, efforts should be made to ensure that pretrial services officers characterize information solicited in interviews similarly (e.g., clarifying the difference between heavy drug use and drug use) (Cohen 1960; Fleiss 1971).

Interpreting Risk Predictions

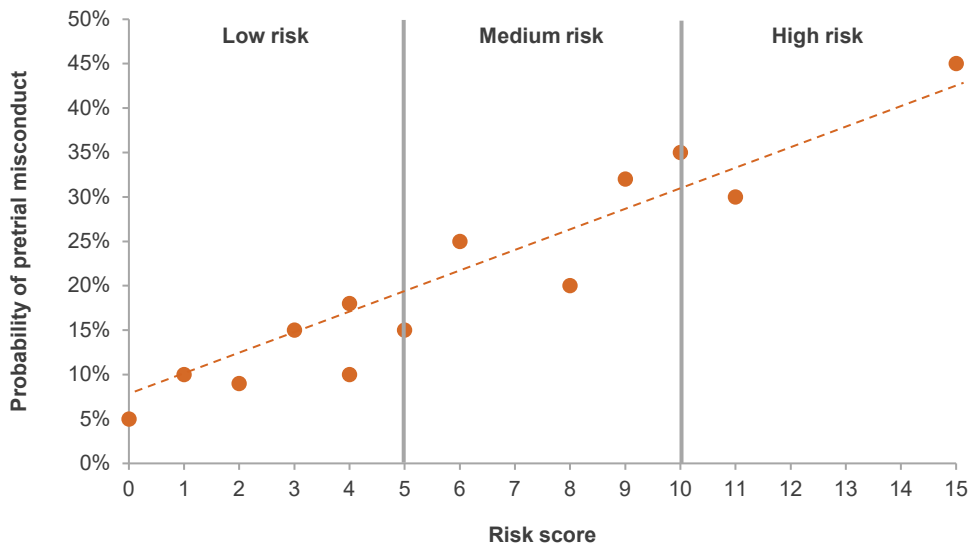
Pretrial risk assessment tools generally report risk scores—weighted sums based on the underlying probability that an individual will commit pretrial misconduct—and descriptive risk categories, which characterize people as low, medium, or high risk. Risk categories are typically translated, often directly, into release or detention

decisions.¹¹ In fact, one objective of California’s pretrial pilot programs is to create graduated supervision levels based on risk predictions—for example, the lowest-risk individuals might be released on their own recognizance with a reminder sent to them about their court date, while medium-risk individuals might be released on their own recognizance with additional supervisory conditions (see [Technical Appendix F](#)).

It is important to recognize that although descriptive risk levels can be helpful, they can also obscure the underlying probability of pretrial misconduct, which could lead to inappropriate decisions. Figure 2 shows probabilities of pretrial misconduct plotted against risk scores. Cut points delineated by vertical lines divide individuals into high, medium, and low risk levels. In general, people classified as high risk have a higher probability of pretrial misconduct than people classified as low risk—a logical and desired result.

FIGURE 2

Hypothetical risk categories based on the probability of pretrial misconduct and associated risk scores



SOURCE: Author illustration.

However, this figure also illustrates some of the pitfalls of risk categories:

- They can make different people look similar and similar people look different. A person who scores 5 has a 20 percent chance of pretrial misconduct, whereas a person who scores 9 has a 30 percent chance. Yet both will be classified as medium risk. Individuals whose risk scores lie on either side of a cut point will be classified differently even though they have similar probabilities of pretrial misconduct.
- Risk categories can also heighten perceptions of how “risky” people are. Risk predictions rarely span the full range of probabilities. In fact, the average probability of committing pretrial misconduct is usually well below 50 percent even at the highest risk level.¹²

¹¹ Translating risk predictions into pretrial release or detention decisions requires interpretation, which can be challenging because most tools do not report the actual probability that a person will commit pretrial misconduct. Importantly, risk predictions reflect how people similar to the assessed individual behaved on average. If an assessed individual has a 20 percent chance of pretrial arrest, that risk prediction means that when the tool was last validated, one in five people who resemble the assessed individual were arrested during the pretrial period.

¹² According to Mayson (2018, 514), less than 15 percent of those classified high risk by some pretrial risk assessment tools were rearrested during the pretrial period.

- Finally, people may incorrectly assume similar numbers of people are classified into each risk level. Instead, in most scenarios, we would expect that far more people should be released than detained because far more people are likely to be classified as low risk.

Three key pieces of information can help combat these challenges. First, sharing risk scores and not just risk categories would allow pretrial services officers and judges to see whether or not an individual is near a cut point. Second, emphasizing the range of probability of pretrial success, rather than misconduct, for each risk category would highlight the fact that most people are more likely to succeed than not if released (DeMichele et al. 2018a).¹³ Third, information about how many people are likely to be classified into each risk level can help pretrial services officers and judges make decisions that adhere to local policy objectives.

These pieces of information work together to help judges make decisions. For example, if the policy objective is to release as many people as possible under the fewest restrictions possible, but a large proportion of individuals are classified as moderate risk, judges will need to differentiate within the moderate category. With information on risk scores, judges might release without conditions all those classified as low risk, as well as those who are classified as moderate risk but are near the low-risk cut point.

The Importance of Transparent Decision Making

A pretrial risk assessment tool uses the same predictors and the same statistical model to predict risk for all assessed individuals. For non-proprietary tools, how risk predictions are made is transparent—the information and the process used to make them is known. Moreover, those risk predictions are consistent—people with identical predictors have identical risk predictions. Similarly, all else being equal, people with the same risk predictions should experience the same release or detention decisions. If they do not, those decisions can be challenged on the grounds that they are inconsistent, inaccurate, or inequitable.

Judges make pretrial release or detention decisions based on risk predictions and recommendations made by pretrial services officers, who gather additional information to facilitate those decisions.¹⁴ Well-designed pretrial risk assessment systems structure decision-making to help judges and others translate risk predictions into decisions that reflect local policy objectives. Structure can take the form of written policies, decision trees, and/or decision matrices to indicate whether people who meet certain criteria should be released or detained (Koepeke and Robinson 2019).¹⁵

Overrides occur when judges or pretrial services officers make decisions that conflict with the recommendations of the pretrial risk assessment system. Even in well-designed and seemingly comprehensive pretrial risk assessment systems, research has found that judicial overrides are commonplace (e.g., BRWG 2016). Although judges or others often override with good reason (e.g., to address a credible threat to a particular victim), if the reasons for those overrides are unknown, research indicates that the goals of pretrial justice can be compromised. Overrides without explicit explanations run the risk of introducing ambiguity, inconsistency, inaccuracy, and inequity into assessment systems (Garrett and Monahan 2018; Kleinberg et al. 2017; PDRW 2017; Mamalian

¹³ One helpful approach would be reporting predictions as probabilities bounded by ranges of uncertainty (PAI 2019). For example, reporting that someone has a 20 percent chance of committing pretrial misconduct with a range of uncertainty between 15 and 25 percent is different than reporting the same chance with a range of uncertainty between 5 and 35 percent. None of the pretrial risk assessment tools used in California present risk predictions as bounded probabilities.

¹⁴ Pretrial services officers (PSOs) can also override recommendations from pretrial risk assessment systems. They can do so in two ways: by changing their recommendations to judges or by themselves choosing to release or detain a person against the recommendation of the system. Like judicial overrides, overrides by PSOs should also be monitored, evaluated, and addressed.

¹⁵ It is important to understand that arraignment court judges are often under pressure to make hundreds of decisions each day (Ottone and Scott-Hayward 2018). When people must make decisions quickly, they may often rely on immediate and intuitive associations rather than considered and complex analyses (Kahneman 2011). Decision-making based on such associations may in turn reinforce implicit biases—unconscious, socially determined stereotypes about others—that could disadvantage racial minorities and the poor in criminal justice proceedings (DeMichele et al. 2018a; Guthrie et al. 2007).

2011; Stevenson 2019). For this reason, judges and pretrial services officers should be required to explicitly state why they override each time they do so.

Altogether, transparency in pretrial decision making entails a record of the information that contributed to each release or detention decision, including which risk category was predicted; how it was predicted (e.g., the predictors and the assessment tool used); the recommendation to release or detain; whether that recommendation was overridden and why; and the final release or detention decision (PAI 2019). This information will help enable evaluation of whether pretrial decision-making processes align with local policy objectives.

Defining accuracy

Accuracy in risk assessment can be defined in terms of error rates. Risk assessment tools can make two kinds of errors. **False positives** occur when people are misclassified as high risk. When these types of errors occur, arrested individuals and their families primarily bear the costs because people classified as high risk are more likely to be detained. In addition, the public pays the costs associated with pretrial incarceration. **False negatives** occur when people are misclassified as low risk. Victims and communities primarily bear the costs of this kind of error because people classified as low risk are more likely to be released and therefore have the opportunity to commit crimes in the community.

During validation and evaluation, assessing how many false positives there are relative to false negatives can help counties strike the appropriate balance between protecting public safety and protecting arrested individuals' right to liberty. Allowing fewer false positives than false negatives prioritizes individuals' right to liberty over public safety and vice versa.

However, the rates at which false negatives and false positives occur can only be assessed among those who have been released pretrial. Determining the number of low- and medium-risk people who were detained is key because those individuals potentially could have been released without threatening victim or public safety. Understanding why they were detained can help counties assess whether the decision-making process aligns with local objectives.

See [Technical Appendices D and E](#) for more information.

Evaluating Pretrial Risk Assessment Systems

This section describes how counties can test and evaluate their pretrial risk assessment systems to ensure that they are performing as intended. We focus on data challenges in testing and evaluation as well as considerations for promoting equity.

Data Challenges in Evaluation

Pretrial risk assessment tools must be tested to understand how they perform for the local population and within the local system of pretrial justice. This testing, also referred to as “validating” the tool, involves assembling a dataset, using it to determine the accuracy of the risk predictions made by the tool, and evaluating the equity of the decisions that resulted from those predictions.

Pretrial risk assessment tools that have not been locally tested can classify people inaccurately and lead to inequitable pretrial decisions because how a tool performs reflects the policy objectives and the pretrial misconduct patterns in which it was validated. Lack of testing could lead to misleading assumptions about a tool’s accuracy.¹⁶ Most pretrial risk assessment tools have not been validated for populations like California’s. For instance, 11 California counties are rural, according to the US Census Bureau. Yet most tools have been validated only in urban areas (Mamalian 2011). Likewise, Latino and Asian Americans make up large shares of the population in many California counties. Yet most tools used in California, including the ORAS, VPRAI and PSA, were not initially tested on populations that included these racial/ethnic groups (DeMichele et al. 2018b; Latessa et al. 2009; VanNostrand 2003).

Counties may struggle to assemble data that include enough observations to properly test their assessment tool. For instance, individuals’ criminal history is a key input. Yet policy contexts shift over time, and major changes in the criminal justice landscape have affected pretrial justice at the state level. Importantly, in 2014 Proposition 47 reduced pretrial detention rates for individuals charged with some crimes.¹⁷ Although past and future policy contexts cannot be perfect mirrors, the policy context that produced the test data should be as similar as possible to the policy context in which the tool will be used (Koepeke and Robinson 2019). Although there are no established standards regarding how large these datasets should be, both the ORAS and the VPRAI were initially tested using sample sizes of about 2,000, which seems commonplace (Latessa et al. 2009; VanNostrand 2003).¹⁸ Less populous counties may be able to use fewer observations, but probably not fewer than 500.¹⁹

These challenges are likely to affect many counties in California, as can be seen when we examine the frequency with which pretrial misconduct outcomes might occur. COMPAS, for example, uses new felony arrests to construct its pretrial misconduct measure. Figure 3 shows California Department of Justice (DOJ) data on the number of felony arrests that occurred in each county for the three most recent years (2016–18).

More than a quarter of counties (16) processed fewer than 2,000 felony arrests during this three-year period and would likely find it difficult to evaluate and monitor their pretrial data because they do not process enough arrests.²⁰ Importantly, the DOJ data do not distinguish pretrial arrests from all arrests, so the number of pretrial

¹⁶ For example, VPRAI developers reported an accuracy rate of 65 percent, whereas researchers in Riverside County found that the accuracy rate was 61 percent—a difference that translates to four additional inaccurate risk predictions per 100 risk predictions (Lovins and Lovins 2015).

¹⁷ County policies can similarly affect pretrial justice. For example, many counties now send text messages to remind defendants about their court dates (Balassone 2018). Pretrial misconduct rates prior to such policies may differ from pretrial misconduct rates afterward.

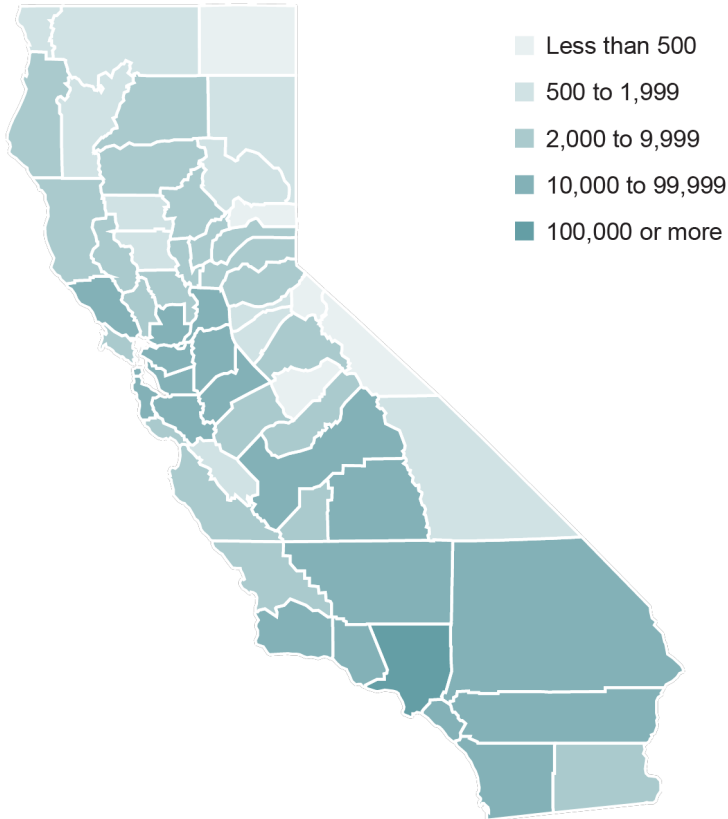
¹⁸ In the published literature, validation datasets range in size from about 500 to more than 30,000 observations (Lovins and Lovins 2015; PJI 2009; Siddiqi 2009).

¹⁹ With smaller samples validating for population subgroups will be challenging. For example, if African Americans are only 10 percent of the population, a 500-person sample will include about 50 blacks, which limits the potential for statistical modeling to evaluate equity.

²⁰ Narrowing the timeframe to 2018, more than half (32) of California’s counties did not process 2,000 felonies.

felony arrests is certainly less than the total number of felony arrests shown in Figure 3, even with repeat offenders present in the data.

FIGURE 3
Many counties in California processed fewer than 2,000 felony cases between 2016 and 2018



SOURCE: California Department of Justice

NOTE: These numbers reflect all felony arrests, not just those that occurred during pretrial periods.

These data limitations are all the more significant in light of recent legislation (SB 36) mandating that counties test their pretrial risk assessment tool at least once every three years. Counties may also be experiencing concurrent data challenges in implementing these tools, as described earlier. Prior research and case studies suggest some approaches to overcome various challenges in using, testing, and evaluating these tools with limited data:

- Counties that process a reasonable volume of cases, but that have not collected the historical data necessary to test a pretrial risk assessment before it is used, can pilot a tool and test it afterward. Similarly, counties that are missing data for some predictors or outcomes (e.g., failure to appear) can verify the tool’s predictive accuracy without those variables. The Riverside County case study in [Technical Appendix A](#) illustrates these options.
- Counties can develop their own pretrial risk assessment tools, as illustrated by the Santa Clara County and Sonoma County case studies in [Technical Appendix A](#). For counties with very limited data, Dressel and Farid (2018) illustrate how a tool might be developed using only two predictors.

- Smaller counties that are similarly sized and relatively homogenous can collaborate to test or develop a risk assessment tool (Vetter and Clark 2013). As the research in this area is scant, we look forward to the evaluation of the ongoing collaborative pretrial pilot project in Nevada and Sierra Counties.
- Counties that process too few cases to develop or test pretrial risk assessment tools can still achieve more transparency, consistency, and equity by structuring pretrial decisions through decision matrices and decision trees, as shown in [Technical Appendix F](#).

Defining equity

In pretrial risk assessment, there are two commonly used standards for measuring equity between groups of people. **Predictive parity** measures how often risk predictions were not followed by the expected outcome. For example, this standard requires that individuals who are deemed high risk commit pretrial misconduct at the same rate for each racial/ethnic group. **Statistical parity** measures how often pretrial misconduct outcomes were not preceded by the appropriate risk prediction. For example, this standard requires that the percentage of people who did not commit pretrial misconduct but were classified as high risk be the same for each racial/ethnic group.

Failure to meet predictive parity means risk classifications will be more accurate for some groups compared to others, while failure to meet statistical parity means that certain groups will be more likely to be classified as high risk (see the ProPublica-COMPAS case study in [Technical Appendix A](#)). Since the two standards cannot be maximized simultaneously, county stakeholders should determine which form of equity they wish to prioritize and measure in their evaluation and testing.

See [Technical Appendices D and E](#) for more information.

Promoting Equity

An essential aspect of the evaluation process is examining whether pretrial risk assessment systems compromise equity between groups of people (see textbox above for how equity can be measured).²¹ If a risk assessment tool makes inequitable predictions, there are several options for practitioners and policymakers. More equity might be achieved by, for example, shifting cut points to classify fewer people as high risk or by removing predictors that might exacerbate inequity from the risk prediction model.²² If more equity in risk prediction cannot be achieved or if the tradeoffs between accuracy and equity or individuals' right to liberty and victim and public safety are too high, the policies that translate risk predictions into pretrial release or detention decisions can be modified to

²¹ As described in the textbox on page 14, accuracy in risk prediction can be measured in more than one way, which means that equity in risk prediction, which is defined in terms of accuracy, can also be measured in multiple ways. In the textbox on this page, we define two standards of equity, predictive parity and statistical parity. Correcting inequity in either standard involves tradeoffs that are a consequence of group average differences in the probability of committing pretrial misconduct (Berk et al. 2018; Kleinberg et al. 2016). First, predictive parity and statistical parity cannot be simultaneously maximized. But they can be balanced in relation to each other (Huq 2019). Even a "balanced" system is likely to have slight inequities by one standard or the other. Second, equity is defined as a function of accuracy. Therefore, regardless of how the equity standards are balanced, increasing equity in risk prediction will generally come at the expense of decreasing accuracy. Again, slight inaccuracies and inequities will be present, which is why their consequences need to be evaluated and addressed (Berk et al. 2018; Chouldechova 2017; Huq 2019; Kleinberg et al. 2016; Mayson 2019). We elaborate on these issues in [Technical Appendices D and E](#).

²² In Figure 2, for example, raising the first cut point from 5 to 6 could increase individual liberty, but decrease public safety. Individuals with a 25 percent chance of pretrial misconduct will now be classified as low risk and likely released, whereas before they would have been classified as medium risk and more likely to be detained.

mitigate the degree to which inequity is propagated, as shown in the Center for Court Innovation case study in [Technical Appendix A](#) (Picard et al. 2019).

One approach is to alter graduated supervision levels to expand the conditions under which people can be released. For instance, when Kentucky instituted a pretrial risk assessment system based on the PSA, judges initially followed the recommendations from the system. As a result, pretrial detention rates decreased from 69 percent to 65 percent. But ongoing evaluation showed that judges returned to making their own release and detention decisions within six months, after which pretrial detention rates rose. A research study found that the judges' decisions systematically disadvantaged African Americans such that racial disparity in pretrial release without financial conditions increased by 8 percentage points relative to levels prior to the implementation of the pretrial risk assessment system (Stevenson 2019, 363). To remedy this situation, state policymakers modified policies to allow pretrial services officers to release more people before arraignment. By expanding the conditions under which individuals were released by pretrial services officers prior to arraignment, they reduced the number of cases in which judges had the opportunity to make decisions about pretrial release and detention (Stevenson 2017).

In addition to demonstrating how a jurisdiction might mitigate racial inequity in a pretrial risk assessment system, Kentucky's experience also highlights the need for routine testing of pretrial risk assessment tools and routine evaluation of pretrial risk assessment systems to ensure that the goals of pretrial justice are achieved.²³

Conclusion

Amid potential reforms to the state's bail system, pretrial risk assessment offers the opportunity to make release or detention decisions that might better balance arrested individuals' right to liberty with the need to maintain victim and public safety. When used effectively, pretrial risk assessment can help make pretrial decisions more transparent, consistent, and equitable. Since most counties already have pretrial services and are already using a risk assessment tool, this report focuses on ways to improve existing systems and practices, as well as considerations for evaluating whether pretrial programs meet local policy objectives.

To function effectively, all stakeholders should understand how pretrial risk assessment works, what risk predictions mean in the local policy context, and how to translate risk predictions into release or detention decisions. Local collaboration—among pretrial services, the police, probation officers, the courts, social services, and the larger community—is critical. Creating a public forum that allows for the improvement of pretrial policies that are collectively agreed upon, communicated through training, and easy to administer can promote the success of these policies (CPOC 2019; DeMichele et al. 2018a; Myburgh et al. 2015; PAI 2019). To that end, the Community Corrections Partnerships, established to implement realignment, provide models of public and transparent policymaking that can be replicated.²⁴

Lack of sufficient data may present challenges to the implementation of effective pretrial risk assessments and their ongoing evaluation. First, the criminal history data often used in assessment tools—such as incarceration, arrests, and failures to appear—may be housed in different local or state agencies. It is critical that agencies work

²³ Several of the case studies presented in [Technical Appendix A](#) further illustrate this point.

²⁴ Transparency requires a record of information that contributed to each release or detention decision, including which risk category was predicted; how it was predicted (e.g., the predictors and the assessment tool used); the recommendation to release or detain; whether that recommendation was overridden and why; and the final release or detention decision (PAI 2019).

together to store and collect the necessary data, and that the data are collected in a uniform manner. Second, data collection is necessary for evaluating and monitoring whether pretrial risk assessment systems are achieving the desired objectives. However, many counties in California may not process enough cases to ensure the accuracy of these tools with the data they have available or for their own local populations. Options for addressing these challenges range from piloting and evaluating the accuracy of the tools with the available data to collaborating with neighboring counties that have similar populations on data collection and testing.

Racial equity is a key concern for practitioners and policymakers involved in pretrial services and risk assessment. In particular, pretrial risk assessment tools have raised questions about whether the use of criminal history information will systematically disadvantage racial minorities and other marginalized groups. However, when implemented effectively, pretrial risk assessment systems also enable transparency and consistent decision-making processes—which can offer an important avenue for identifying and addressing potential inequities in pretrial justice. Stakeholders should track accuracy and equity rates across race/ethnicity and other socioeconomic characteristics during ongoing testing and evaluation of pretrial risk assessment tools—and, if needed, adjust decision-making protocols based on these findings.

Ensuring that pretrial risk assessment systems balance arrested individuals' right to liberty with victim and public safety, while also promoting equity, is an ongoing process that requires transparency as well as consistent and complete data collection. In addition, routine monitoring, testing, and evaluation of pretrial risk assessment systems are essential to identify areas of weakness and develop strategies that will enable counties to offer pretrial services that align with their policy objectives.

REFERENCES

- Alexander, Michelle. 2010. *The New Jim Crow: Mass Incarceration in the Age of Colorblindness*. New York: New Press.
- Angwin, Julia, Jeff Larson, Surya Mattu, and Lauren Kirchner. 2016. "Machine Bias." ProPublica, May 23.
- Arnold Ventures. n.d. "[Public Safety Assessment](#)."
- Austin, James. Vincent Schiraldi, Bruce Western, and Anamika Dwivedi. 2019. *Reconsidering the "Violent Offender."* New York: Square One Project.
- Balassone, Merrill. 2018. "[Can We Text You? Californians Are Looking at New Ways to Provide Services By Text](#)." California Courts Newsroom, May 30.
- Balassone, Merrill. 2019. "[Judicial Council Funds 16 Pretrial Pilot Programs](#)." California Courts Newsroom, August 9.
- Baradaran, Shima, and Frank L. McIntyre. 2012. "Predicting Violence." *Texas Law Review* 90: 497–570.
- Berk, Richard. 2012. *Criminal Justice Forecasts of Risk: A Machine Learning Approach*. New York: Springer-Verlag.
- Berk, Richard. 2019. *Machine Learning Risk Assessments in Criminal Justice Settings*. New York: Springer International.
- Berk, Richard, Justin Bleich, Adam Kapelner, Jaime Henderson, Geoffrey Barnes, and Ellen Kurtz. 2014. "[Using Regression Kernels to Forecast a Failure to Appear in Court](#)."
- Berk, Richard, Hoda Heidari, Shahin Jabbari, Michael Kearns, and Aaron Roth. 2018. "[Fairness in Criminal Justice Risk Assessments: The State of the Art](#)." *Sociological Methods & Research*.
- Bird, Mia, Sonya Tafoya, Ryken Grattet, and Viet Nguyen. 2016. *How Has Proposition 47 Affected California's Jail Population?* Public Policy Institute of California.
- Bird, Mia, Magnus Lofstrom, Brandon Martin, Steven Raphael, and Viet Nguyen. 2018. *The Impact of Proposition 47 on Crime and Recidivism*. Public Policy Institute of California.
- BJA (Bureau of Justice Assistance). n.d. "[Public Safety Risk Assessment Clearinghouse](#)."
- Braga, Anthony A., Rod K. Brunson, and Kevin M. Drakulich. 2019. "[Race, Place, and Effective Policing](#)." *Annual Review of Sociology* 45: 535–555.
- BRWG (Bail Reform Work Group). 2016. *Consensus Report on Optimal Pretrial Justice*. County of Santa Clara.
- Chouldechova, Alexandra. 2017. "Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments." *Big Data* 5 (2): 153–163.
- CJI (Crime and Justice Institute). 2017. *Pretrial Assistance to California Counties (PACC): Riverside County Technical Assistance Report*.
- Clark, John W., and D. Alan Henry. 2003. *Pretrial Services Programming at the Start of the 21st Century: A Survey of Pretrial Services Programs*. US Department of Justice, Office of Justice Programs, Bureau of Justice Assistance.
- Cohen, Jacob. 1960. "A Coefficient of Agreement for Nominal Scales." *Educational and Psychological Measurement* 20 (1): 37–46.
- CPOC (Chief Probation Officers of California). 2019. *Effective Pretrial Practices Implementation Toolkit*. Pretrial Justice Institute.
- CSJ (Californians for Safety and Justice). 2015. *Pretrial Progress: A Survey of Pretrial Practices and Services in California*. Boston: Crime and Justice Institute.
- Danner, Mona J.E., Marie VanNostrand, and Lisa M. Spruance. 2016. *Race and Gender Neutral Pretrial Risk Assessment, Release Recommendations, and Supervision: VPRAI and Praxis Revised*. Luminosity, Inc.
- Dawes, Robyn M., David Faust, and Paul E. Meehl. 1989. "Clinical versus Actuarial Judgment." *Science* 243 (4899): 1668–1674.
- DeMichele, Matthew, Megan Comfort, Shilpi Misra, Kelle Barrick, and Peter Baumgartner. 2018a. "[The Intuitive-Override Model: Nudging Judges toward Pretrial Risk Assessment Instruments](#)."
- DeMichele, Matthew, Peter Baumgartner, Michael Wenger, Kelle Barrick, Megan Comfort, and Shilpi Misra. 2018b. "[The Public Safety Assessment: A Re-Validation and Assessment of Predictive Utility and Differential Prediction by Race and Gender in Kentucky](#)."
- Dieterich, William, Christina Mendoza, and Tim Brennan. 2016. *COMPAS Risk Scales: Demonstrating Accuracy Equity and Predictive Parity*. Northpointe, Inc.
- Dressel, Julia, and Hany Farid. 2018. "The Accuracy, Fairness, and Limits of Predicting Recidivism." *Science Advances* 4 (1).
- Equivant. n.d. "COMPAS Scale Documentation." Unpublished document.

- Fleiss, Joseph L. 1971. "Measuring Nominal Scale Agreement among Many Raters." *Psychological Bulletin* 76 (5): 378–382.
- Garrett, Brandon L. and Monahan, John. 2018. "[Judging Risk](#)." Virginia Public Law and Legal Theory Research Paper No. 2018-44.
- Gouldin, Lauryn P. 2016. "Disentangling Flight Risk from Dangerousness." *Brigham Young University Law Review* 2016 (3): 837–898.
- Gouldin, Lauryn P. 2018. "Defining Flight Risk." *The University of Chicago Law Review* 85: 677–742.
- Grant, Glenn A. 2019. Jan. 1-Dec. 31 2018 Report to the Governor and the Legislature. New Jersey Judiciary.
- Grattet, Ryken, Mia Bird, Viet Nguyen, and Sonya Tafoya. 2017. "California Jails under Realignment and Proposition 47." *California Journal of Politics and Policy* 9 (3): 1–15.
- Guthrie, Chris, Jeffrey J. Rachlinski, and Andrew J. Wistrich. 2007. "Blinking on the Bench: How Judges Decide Cases." *Cornell Law Review* 93 (1): 1–43.
- Harris, Casey T., Darrell Steffensmeier, Jeffrey T. Ulmer, and Noah Painter-Davis. 2009. "Are Blacks and Hispanics Disproportionately Incarcerated Relative to Their Arrests? Racial and Ethnic Disproportionality between Arrest and Incarceration." *Race and Social Problems* 1 (4): 187–189.
- Hester, Rhys. 2019. "Risk Assessment at Sentencing." In *Predictive Sentencing: Normative and Empirical Perspectives*. Edited by Jan W. de Keijser, Julian Roberts, and Jesper Ryberg. Hart Publishing.
- Huq, Aziz. 2019. "Racial Equity in Algorithmic Criminal Justice." *Duke Law Journal* 68: 1043–1134.
- Johnson, Brian D. and Ryan D. King. 2017. "Facial Profiling: Race, Physical Appearance, and Punishment." *Criminology* 55 (3): 520–547.
- Jones, Michael R. and Timothy R. Schnacke. 2013. *Colorado Decision Tree for Setting Bond Type*. Center for Legal and Evidence Based Practices.
- Kahneman, Daniel. 2011. *Thinking, Fast and Slow*. New York: Farrar, Strauss, and Giroux.
- Karnow, Curtis E. 2008. "Setting Bail for Public Safety." *Berkeley Journal of Criminal Law* 13 (1): 1–30.
- Kleinberg, Jon, Sendhil Mullainathan, and Manish Raghavan. 2016. "[Inherent Trade-offs in the Fair Determination of Risk Scores](#)."
- Kleinberg, Jon, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan. 2017. "Human Decisions and Machine Predictions." *The Quarterly Journal of Economics* 133 (1): 237–293.
- Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Cass R. Sunstein. 2019. "[Discrimination in the Age of Algorithms](#)." National Bureau of Economics Working Paper 25548.
- Koepke, John Logan, and David G. Robinson. 2019. "Danger Ahead: Risk Assessment and the Future of Bail Reform." *Washington Law Review* 93: 1725–1807.
- Latessa, Edward, Paula Smith, Richard Lemke, Matthew Makarios, and Christopher Lowenkamp. 2009. "[Creation and Validation of the Ohio Risk Assessment System: Final Report](#)." University of Cincinnati.
- Levin, David. 2012. Santa Clara County, California Pretrial Risk Assessment Instrument. Pretrial Justice Institute.
- Lofstrom, Magnus, and Steven Raphael. 2013. *Impact of Realignment on County Jail Populations*. Public Policy Institute of California.
- Lofstrom, Magnus, Brandon Martin, Justin Goss, Joseph Hayes, and Steven Raphael. 2018. *New Insights into California Arrests: Trends, Disparities, and County Differences*. Public Policy Institute of California.
- Lovins, Brian, and Lori Lovins. 2015. Riverside Pretrial Assistance to California Counties (PACC) Project: Validation of a Pretrial Risk Assessment Tool. Correctional Consultants Inc.
- Mahoney, Barry, Bruce D. Beaudin, John A. Carver III, Daniel B. Ryan, and Richard B. Hoffman. 2001. Pretrial Services Programs: Responsibilities and Potential. National Institute of Justice.
- Mamalian, Cynthia A. 2011. State of the Science of Pretrial Risk Assessment. Pretrial Justice Institute.
- Mayson, Sandra Gabriel. 2018. "Dangerous Defendants." *The Yale Law Journal* 127 (3): 490–568.
- Mayson, Sandra Gabriel. 2019. "Bias In, Bias Out." *The Yale Law Journal* 128 (8): 2218–2300.
- Miller, Marc, and Martin Guggenheim. 1990. "Pretrial Detention and Punishment." *Minnesota Law Review* 75: 335–426.
- Myburgh, John-Etienne, Carolyn Camman, and J. Stephen Wormith. 2015. "Review of Pretrial Risk Assessment and Factors Predicting Pretrial Release Failure." Center for Forensic Behavioral Science and Justice Studies. University of Saskatchewan.

- Ottone, Sarah, and Christine S. Scott-Hayward. 2018. "Pretrial Detention and the Decision to Impose Bail in Southern California." *Criminology, Criminal Justice, Law, and Society* 19 (2): 24–43.
- PAI (Partnership on AI). 2019. Report on Algorithmic Risk Assessment Tools in the U.S. Criminal Justice System.
- PDRW (Pretrial Detention Reform Workgroup). 2017. Recommendations to the Chief Justice. Judicial Council of California.
- Picard, Sarah, Matt Watkins, Michael Rempel, and Ashmini Kerodal. 2019. *Beyond The Algorithm: Pretrial Reform, Risk Assessment, and Racial Fairness*. New York: Center for Court Innovation.
- Picard-Fritsche, Sarah, Michael Rempel, Jennifer A. Tallow, Julian Adler, and Natalie Reyes. 2017. *Demystifying Risk Assessment: Key Principles and Controversies*. New York: Center for Court Innovation.
- PJI (Pretrial Justice Institute). 2009. *Overview of Pretrial Risk Assessment Validation Study Findings*.
- PJI (Pretrial Justice Institute). (n.d.) *Pretrial in America: A Brief History*.
- Robertson, Jim, and Michael R Jones. 2013. Sonoma Pretrial Risk Assessment Tool (SPRAT) Report. Sonoma County.
- Siddiqi, Qudsia. 2009. Predicting the Likelihood of Pretrial Failure to Appear and/or Rearrest for a Violent Offense Among New York City Defendants: An Analysis of the 2001 Dataset. New York Criminal Justice Agency.
- Sonoma County. 2014. Sonoma County Pretrial Release and Detention Guidelines.
- Starr, Sonja B. 2014. "The Risk Assessment Era: An Overdue Debate." *Federal Sentencing Reporter* 27(5): 205–206.
- Stevenson, Megan. 2017. "Risk Assessment: The Devil's in the Details." *The Crime Report*, August 3.
- Stevenson, Megan. 2019. "Assessing Risk Assessment in Action." *Minnesota Law Review* 103: 303–384.
- Tafoya, Sonya. 2013. *Assessing the Impact of Bail on California's Jail Population*. Public Policy Institute of California.
- Tafoya, Sonya. 2015. *Pretrial Detention and Jail Capacity in California*. Public Policy Institute of California.
- Tafoya, Sonya, Mia Bird, Viet Nguyen, and Ryken Grattet. 2017. *Pretrial Release in California*. Public Policy Institute of California.
- Tonry, Michael. 2014. "Legal and Ethical Issues in the Prediction of Recidivism." *Federal Sentencing Reporter* 26 (3): 167–176.
- VanNostrand, Marie. 2003. "Assessing Risk among Pretrial Defendants in Virginia: The Virginia Pretrial Risk Assessment Instrument." Virginia Department of Criminal Justice Services.
- VDCJS (Virginia Department of Criminal Justice Services). 2018. "Virginia Pretrial Risk Assessment Instrument (VPRAI) – Instruction Manual Version 4.3."
- Vetter, Stephanie, and John Clark. 2013. *The Delivery of Pretrial Justice in Rural Areas: A Guide for Rural County Officials*. Pretrial Justice Institute.
- Weaver, Vesla M., Andrew Papachristos, and Michael Zanger-Tishler. 2019. "The Great Decoupling: The Disconnection between Criminal Offending and Experience of Arrest across Two Cohorts." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 5 (1): 89–123.
- Widgery, Amber. 2018. Trends in Pretrial Release: State Legislation Update. National Conference of State Legislatures.
- Yang, Crystal S. 2017. "Toward an Optimal Bail System." *New York University Law Review*, 92: 1399–1493.

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Pretrial Risk Assessment in California

Technical Appendices

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Heather M. Harris, Justin Goss, and Alexandria Gumbs

Appendix A. Case Studies

Introduction

In this supplementary section, we present six two-page case studies that draw on the work of local governments, journalists, and researchers who encountered and overcame challenges as they sought to implement or understand pretrial risk assessments tools. For each case, we provide a summary and several key “takeaways.” The cases provide concrete examples that support the key points made in main report.

In the first case we describe how officials in Riverside County updated their Pretrial Services Division. The case illustrates the advantages of locally validating and modifying a pre-existing risk assessment tool. It also highlights the need for jurisdictions to clearly define the objectives they want to achieve through their pretrial risk assessment systems because technical and policy decisions made during the development of those systems can either promote or undercut those objectives (CJI 2017; Lovins and Lovins 2015).

The Santa Clara County case allows us to highlight several key points from the main report. Risk level classifications from pretrial risk assessment tools can be misleading, which highlights the importance of developing policy frameworks—what we call pretrial risk assessment systems—to transparently and consistently translate risk level classifications into pretrial release or detention recommendations. The county’s commitment to routine monitoring and regular evaluation of its pretrial risk assessment system also highlights the importance of addressing overrides. Overrides can negatively impact the transparency, consistency, and equity of pretrial release or detention decisions. To understand why overrides occur, what their impact is, and how they can be addressed, the reasons for overrides must be consistently recorded (BRWG 2016; Levin 2012).

We then describe how Sonoma County created a pretrial risk assessment tool and system, highlighting the advantages of a transparent local process. We discuss the challenges of such an ambitious undertaking, including how to define and measure risk, whether to include predictors such as socioeconomic and mental health status, and what can happen when pretrial risk assessment tools classify too many people as medium risk. In addition, Sonoma County’s recent evaluation of its pretrial risk assessment tool and system provide an excellent example for other counties to follow (PJI n.d.; Feld and Halverson 2019; Robertson and Jones 2013).

Next we describe the work of two researchers who developed their own pretrial risk assessment tool using only two predictors. Their work demonstrates that even jurisdictions with limited resources or data, may be able to develop a pretrial risk assessment tool for use within a pretrial risk assessment system (Dressel and Farid 2018).

Our final two case studies focus on equity—and whether it can be achieved by any measure—that have been raised as the use of pretrial risk assessment tools has proliferated. We begin by describing ProPublica’s conflict with Northpointe, the proprietors of the COMPAS. Their disagreement illustrates, first, that there are multiple ways to quantitatively define equity; second, that not all definitions of equity can be satisfied simultaneously; and third, that racial inequity originates in the historical criminal justice data that pretrial risk assessment tools rely on to make risk predictions (Angwin et al. 2016; Dieterich, Mendoza, and Brennan 2016; Mayson 2018).

Finally, we summarize findings from a recent Center for Court Innovation study. This case presents an example of how pretrial risk assessment tools and systems can be evaluated and adjusted to promote local policy objectives related to equity. It illustrates how California’s counties can, first, determine the degree of racial and other forms of inequity that pretrial risk assessment tools might propagate *and*, second, how that inequity can be mitigated by developing and testing alternative policies for interpreting risk predictions and making pretrial release or detention decisions based on them (Picard et al. 2019).

Riverside Case Study

Riverside County began using the Virginia Pretrial Risk Assessment Tool (VPRAI) in 2014 and validated it locally two years later. A Pretrial Steering Committee (PSC) comprised of representatives from the Probation Department, Pretrial Services Unit, the Court, Sheriff’s Department, and offices of the Public Defender and District Attorney oversaw validation.

The PSC set three clearly defined pretrial policy objectives: to release more people on own recognizance; to ensure release decisions correspond to assessed risk; and to develop a continuum of supervision options (i.e., “graduated sanctions”), from release on own recognizance for the lowest risk individuals, to detention for the highest risk individuals. To achieve these objectives the PSC validated the VPRAI locally, invested in electronic monitoring to supervise released individuals, and automated court date reminders to reduce failure to appear rates.

During validation, the VPRAI was modified to create the Riverside PRAI (RPRAI). The RPRAI maintained the same definition of pretrial misconduct—a compound outcome of either failure to appear in court or pretrial arrest—but reduced the number of predictors of pretrial misconduct from nine to five. The five predictors measured criminal history, housing status, and substance use. In addition, the number of risk level classifications was reduced from five to three. As a result of these changes the overall accuracy of the RPRAI improved slightly relative to the VPRAI, increasing from 0.609 to 0.614. However, the performance of the RPRAI varied for different demographic subgroups of individuals. The RPRAI was slightly more accurate for females than for males and for nonwhites relative to whites.

How people were classified using the RPRAI may have undermined the local policy objectives defined by the PSC because high risk individuals, on average, were still less likely to commit pretrial misconduct than not and most individuals were classified as moderate risk—common outcomes in pretrial risk assessment. Individuals classified as low risk under the RPRAI had pretrial misconduct rates of 13 percent, while those classified as moderate and high risk committed pretrial misconduct at rates of 27 percent and 43 percent respectively. Nearly 60 percent of assessed individuals fell into the moderate risk level classification, whereas 14 percent fell into the low risk level classification and 28 percent were classified as high risk. Judges overrode the pretrial release or detention recommendations from the RPRAI 30 percent of the time.

Takeaways

Validation of an existing tool can lead to performance improvements.

By adopting the VPRAI, Riverside avoided the challenges associated with developing a bespoke tool from scratch. By modifying the tool Riverside demonstrated that the local performance of VPRAI could be improved and also generated information regarding how the tool performed on different local demographic subgroups, which is crucial to assessing equity in risk prediction and pretrial release or detention decisions.

Risk level classifications should enable pretrial decisions that support policy objectives.

Only about one in ten individuals assessed using the RPRAI were classified as low risk and, thus, clearly eligible for release. This likely contributed to the county’s failure to release a higher share of its pretrial population, as evidenced by rising proportions of pretrial detainees in the county jail in recent years (BSCC Jail Profile Survey). To create the conditions under which the objective of releasing more people on their own recognizance can be met, the PSC could adjust the cut points to classify more people as low risk.

Robust pretrial risk assessment systems interpret ambiguous risk level classifications.

Similarly, the RPRAI classified so many individuals as moderate risk that judges likely could not differentiate between moderate risk individuals who should be released and moderate risk individuals who should be detained. To facilitate those decisions, the PSC could provide more guidance to judges. Specifically, the conditions under which medium risk people should be released can be broadened by expanding graduated sanctioning options.

Policies should be developed to address risk assessment overrides.

The absence of a strong pretrial risk assessment system to inform pretrial release or detention decisions based on the RPRAI also likely contributed to high rates of judicial overrides. Although the county tracked overrides, it neither evaluated how those overrides impacted the accuracy and equity of the RPRAI nor responded by taking steps to minimize them. For example, the PSC could track the reasons for overrides and use that information to develop a decision matrix that relates risk level classifications to information omitted from the RPRAI. Such a framework might promote more consistency and transparency in judges' decisions.

Santa Clara County Case Study

About a decade ago, the Pretrial Justice Institute helped Santa Clara County develop a pretrial risk assessment tool that includes three risk prediction models that predict three pretrial misconduct outcomes—new arrest, failure to appear, and technical violations—for assessed individuals. A workgroup comprised of local criminal justice officials also created a pretrial risk assessment system to interpret risk predictions from the tool. The workgroup developed a scoring manual and created a decision matrix that associated risk level classifications with pretrial release or detention decisions and supervision conditions.

Santa Clara County engaged in a collaborative process to develop a pretrial risk assessment tool and a pretrial risk assessment system. Yet two aspects of the risk level classifications produced by the tool illustrate potential challenges associated with making informative classifications. First, some pretrial misconduct outcomes were rare. For example, 99 percent, 93 percent, and 89 percent of individuals classified at levels one (lowest), two, and three (highest), respectively, were not arrested during the pretrial period. As discussed in Technical Appendix C, rare outcomes are difficult to predict, which led to a second problem. Most classified individuals fell into one risk level classification—a sign that the risk prediction model could not differentiate between high and low risk individuals. For instance, 93 percent of individuals were classified at level two by the failure to appear model.

Santa Clara County evaluates its pretrial risk assessment system regularly. Those regular evaluations include examination of overrides—departures from the recommendations of the system—by judges and pretrial services officers (PSOs). According to the Santa Clara County Bail and Release Workgroup, Santa Clara allows PSOs to override 15 percent of the time and only after they specify reasons for overrides, which are reviewed by a supervisor. Yet judges can override PSOs recommendations without specifying why. Judges overrode the recommendations of PSOs 25 percent of the time in 2015.¹ “Anecdotal information” indicates that judges override in response to additional information provided by the prosecutor, a process that could be formalized to account for different types of information (BRWG 2016: 45).

Takeaways

Use separate risk prediction models to predict each pretrial misconduct outcome.

According to a report from the Partnership on AI, an organization dedicated to studying best practices in artificial intelligence, different pretrial misconduct outcomes should be predicted using separate risk prediction models (PAI 2019). Yet many existing pretrial risk assessment tools predict compound outcomes (e.g., failure to appear and arrest) using a single risk prediction model. By contrast, Santa Clara County’s pretrial risk assessment tool predicts three outcomes using separate risk prediction models, which allows policymakers to differentiate between risks of pretrial misconduct and to create graduated sanctions based on those differences.

Understand what “high” and “low” risk mean in the local population.

To make appropriate pretrial release or detention decisions, judges and PSOs should understand what “high” and “low” risk mean in terms of the chance that a person will commit pretrial misconduct. In Santa Clara County, pretrial misconduct was rare, which may have distorted the meaning of high risk. Only 11 percent of individuals classified as high risk were arrested after being released during the pretrial period. Put another way, people

¹ By 2019, judges’ decisions were in concordance with the pretrial risk assessment system in at 90 percent of cases—although they still do not record the reasons for their overrides (personal communication 2019).

assessed at high risk had 89 percent probability of *not* being arrested. Thus, in Santa Clara County, even many individuals classified as high risk may have been safe to release.

When risk level classifications do not inform pretrial release or detention decisions, pretrial risk assessment systems should.

The pretrial risk assessment tool used in Santa Clara County classified most individuals as medium risk. In fact, the failure to appear model classified people as medium risk with such high prevalence that it provided judges with little information about how to determine who should be released and who should be detained. Although Santa Clara County developed a decision matrix to inform judges' and PSOs' release or detention decisions, those recommendations are regularly overridden—suggesting a misalignment between the risk assessment system and the individuals who make those decisions. This misalignment can be addressed by adjusting the policies within the pretrial risk assessment system to accommodate or eliminate overrides—but only if more information about them is collected.

Routinely monitor and regularly evaluate pretrial risk assessment tools and systems.

Santa Clara County routinely monitors and regularly evaluates its pretrial risk assessment system, which has resulted in higher pretrial release rates and lower pretrial misconduct rates. However, override rates have increased over time in Santa Clara County. Although the county has taken steps to address overrides, more could be done to understand why they are occurring, how they might impact consistency and equity in pretrial release or detention decisions, and to refine the pretrial risk assessment system in response.

Require judges to record why they override.

High override rates among PSOs and judges threaten the transparency, equity, and consistency of pretrial risk assessment systems. Although PSOs in Santa Clara County are required to provide their supervisor with written justifications for overrides, the same does not seem to be true for judges (BRWG 2016). Collecting data on the reasons for overrides will enable evaluators to characterize the situations in which they happen, determine whether they introduce inconsistency or inequity in the administration of pretrial justice, and redesign the pretrial risk assessment system to ameliorate or accommodate them. An example of this is Sonoma County's system of "enhancements," which is described in the following case.

Sonoma County Case Study

Sonoma County redesigned its pretrial policy framework by creating a risk assessment system around a locally developed pretrial risk assessment tool. The locus of the redesign was the Community Corrections Partnership (CCP), a local policymaking workgroup comprised of representatives from county administrative, criminal justice, and social services agencies. Prior to public safety realignment, the CCP was formed to reduce recidivism to state prisons and then maintained as an advisory body.

Sonoma County designed its risk assessment system with the objective of helping judges make more consistent and transparent pretrial release or detention decisions. A pretrial risk assessment tool—the Sonoma County Pretrial Risk Assessment Tool (SPRAT)—was designed to predict the likelihood that individuals will commit pretrial misconduct. Then a policy framework was developed to facilitate interpretation of those risk predictions.

To create the SPRAT, researchers defined pretrial misconduct as a compound outcome of either arrest for a new crime or failing to appear in court and used existing criminal justice data to determine which factors predicted pretrial misconduct. The most predictive factors were criminal history, gang affiliation, homelessness, employment, and potentially violent mental health disorders.

To interpret the SPRAT risk predictions, CCP members collaborated with the courts to create a decision matrix that related risk level classifications and current offenses to pretrial release or detention decisions. The level of supervision increased with the SPRAT score and the severity of the offense. For instance, an individual who scored a 2 (of 4) on the SPRAT and who was booked for a petty theft could be released on own recognizance, while a person scoring a 3 who was arrested for domestic violence would be subject to stricter supervision.

Although Sonoma County has decided to transition from their SPRAT-based pretrial risk assessment system to one centered on the PSA, their experience provides valuable lessons for counties that may want to develop and evaluate their own pretrial risk assessment tools. In particular, the county evaluates the performance of their pretrial risk assessment system annually. The most recent report from 2018 examined overrides and “enhancements,” which are conditions (e.g., threats to victims) that elevate risk classification levels above those predicted by the SPRAT. The analysis revealed that enhancements increased the number of people recommended for detention or enhanced supervision by 230 percent in 2018. Overrides by pretrial services officers also increased the number of people recommended for detention or enhanced supervision—but only by 13 percent—and mainly because the person was charged with a new crime. Judges also overrode SPRAT recommendations. Unlike pretrial services officers, they did so in both directions—some individuals who might have been detained were released and vice versa. Unfortunately, why judges departed from the SPRAT recommendations is unknown. Importantly, Sonoma County also examined racial inequity at six decision points in their pretrial risk assessment system, from whether an arrest resulted in a booking to whether a released defendant committed pretrial misconduct. Blacks were 5 times as likely as whites to be booked and 50 percent more likely to be recommended for detention or enhanced supervision before enhancements.

Takeaways

Convene a local stakeholder group.

Sonoma County repurposed an existing policymaking body to ensure that the relevant parties participated publicly in the development of its pretrial risk assessment system.

Be transparent.

The SPRAT was developed in a public forum, so the process used to develop the SPRAT was transparent. Likewise, the process through which individuals are classified is also transparent. How much each risk factor contributes to the overall risk score is explicitly stated. In addition, the decision matrix clearly illustrates how risk predictions are translated into pretrial release or detention decisions—and it is available online.

Avoid compound definitions of pretrial misconduct.

Creating a compound measure of pretrial misconduct reduced the transparency of the SPRAT. Compound outcomes are less transparent because it is unclear whether a person classified as high risk threatens public safety, is likely to miss a court date, or both. In addition, failure to appear and pretrial arrest are distinct outcomes with distinct predictors. Using the same variables to predict both outcomes simultaneously assumes that the predictors explain both outcomes similarly. Thus, the accuracy of the SPRAT may also have been negatively impacted.

Socioeconomic predictors may introduce inequity.

Of the SPRAT predictors, homelessness and mental health correlated most strongly with higher risk of pretrial misconduct. However, the Judicial Council has indicated that it may prohibit using these factors as “exclusions” because doing so can increase detention rates for people who are disadvantaged, rather than criminal. Before such factors are used in a risk prediction model, they can be tested to determine whether they propagate disadvantage.

Do not double-weight predictors.

Although the decision matrix transparently facilitates pretrial decisions, it double counts the same measure of criminal history by using it both to predict risk and as a component of the decision matrix. In addition, that weighting is often counteractive. For example, the SPRAT classifies individuals arrested for DUIs as very low risk of pretrial misconduct, but the decision matrix elevates an arrest for a DUI to a higher supervision status.

Revalidation is critical to assessing and addressing inequity in risk predictions.

Sonoma County’s 2018 report highlights pretrial decision points where racial inequity can materialize. Their assessment indicated racial inequity at several of them. For the tool’s performance, the most concerning are the inequities in pretrial risk predictions and pretrial release or detention recommendations. To address these inequities, the county can explore how alternative policies might exacerbate or ease them, as illustrated in the Center for Court Innovation case.

Regular evaluation is critical to understanding how systems perform over time.

Although pretrial release following a SPRAT assessment increased by 16 percent between 2016 and 2018, overrides and enhancements generally led to more restrictive pretrial release conditions. Enhancements are policies external to the pretrial risk assessment tool that affect how the system performs. If the county wants to release more people under less restrictive conditions, enhancement modifications may be required. Judicial downgrades present an opportunity to examine whether enhancements can be modified to allow release under certain circumstances.

Dressel and Farid Case Study

Transitioning to a pretrial risk assessment tool can create unique difficulties for counties that do not currently operate robust data collection systems. For example, using a pretrial risk assessment tool such as COMPAS, which uses 8 predictors that may be sourced from a core questionnaire that includes 137 items, may not initially be feasible for counties that currently collect only basic criminal justice and demographic information. Identifying additional predictors, hiring and training staff to collect them for each assessed person, and standardizing their use may be too steep a curve to overcome initially.

Dressel and Farid (2018) showed that more parsimonious and less resource intensive risk assessment tools can be developed. For counties with limited data resources seeking to transition to a risk based method of making pretrial release or detention decisions, the methods and models Dressel and Farid (2018) described may offer a more viable starting point for the local development a pretrial risk assessment tool. Using standard logistic regression methods for a sample of about 7,000 people, they created a risk prediction model using two predictors: age and total number of prior convictions.

Takeaways

Simpler risk prediction models can rival the accuracy of more complex models.

When Dressel and Farid (2018) compared their model to the COMPAS, they found that their tool correctly predicted outcomes 66.8 percent of the time, whereas the COMPAS correctly predicted outcomes 65.4 percent of the time. Although the overall accuracies of the two tools were similar, the types of errors they made were slightly different. The Dressel and Farid (2018) model incorrectly detained people at slightly higher rates than the COMPAS but also incorrectly released slightly fewer people.

Simpler risk prediction models can be similarly equitable across racial groups.

Dressel and Farid's (2018) two-predictor model was also similarly accurate for black and white individuals. Their model correctly predicted outcomes for whites 66.4 percent of the time compared to 67.0 percent for the COMPAS, and correctly predicted outcomes for 66.7 percent of blacks compared to 63.8 percent for the COMPAS.

More complicated pretrial risk assessment tools maintain certain advantages.

Pretrial risk prediction tools that use more information to predict risk tend to more accurately classify the most and least risky individuals because very high and very low risk classifications are made based on more robust information. Similarly, more complicated tools are able to make more accurate predictions when faced with individuals charged with less prevalent forms of criminal behavior, such as those charged with violent offenses.

ProPublica-COMPAS Case Study

In 2016 ProPublica published an article questioning the equity of the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) pretrial risk assessment tool. According to ProPublica the COMPAS classified blacks as higher risk than whites even when they had similar criminal histories. Northpointe, the proprietor of COMPAS, argued that their tool was not inequitable or biased because the higher predicted risk for blacks accurately reflected the reality that blacks were more likely than whites to be arrested. Both parties were correct because each applied a different standard of equity (Mayson 2018).

Northpointe emphasized *predictive parity*, meaning a pretrial risk assessment tool should predict misconduct outcomes equally well for all individuals classified at a given risk level. For example, COMPAS expects about 60 percent of men of both races who are classified as high risk to be rearrested. ProPublica found that both black and white males classified by COMPAS as high risk were rearrested at about that rate. By this standard, the COMPAS pretrial risk assessment tool is not racially biased—the likelihood of correctly predicting rearrest is the same for both black and white men.

However, ProPublica applied a different standard of equity. *Statistical parity* expects individuals who experience particular pretrial misconduct outcomes to have been classified similarly. The COMPAS did not meet this standard. Among individuals who were not rearrested, 45 percent of blacks were classified as high risk, whereas only 23 percent of whites were. Similarly, among individuals who were rearrested, 48 percent of whites were classified as low risk, whereas only 28 percent of blacks were. By this standard, COMPAS is racially biased—more black men who are not rearrested are classified as high risk and fewer black men who are not rearrested are classified as low risk.

Takeaways

Policymakers need to consider the implications of failing to meet each standard of equity.

Failing to satisfy either standard of equity can have serious consequences for assessed individuals. Failing to achieve predictive parity means that risk classifications will be more accurate for one group than for the other—the predictions for whites are more likely to be correct than the predictions for blacks—which can lead to inappropriate pretrial detention or release for one group of people relative to the other. Failing to meet statistical parity can result in inequitable classification rates between groups—blacks are more likely than whites to be classified as high risk—which can lead to more pretrial detention in one group relative to the other.

County pretrial workgroups need to determine which standard of equity best promotes local policy objectives.

Simultaneously maximizing predictive parity and statistical parity is impossible because, as Northpointe noted, arrest rates vary for different groups of people. Although some balance between standards of equity can be achieved, policymakers will ultimately need to choose which standard to prioritize (Berk et al. 2018; Kleinberg et al. 2016; Mayson 2018). Which standard is prioritized should be decided publicly, so that the public understands the implications and tradeoffs of that decision.

Promoting either standard requires tradeoffs—specifically accuracy tradeoffs.

Increasing the equity—by either standard—of a pretrial risk assessment tool generally comes at the expense of reduced accuracy. For example, to increase the statistical parity of the COMPAS, whites could be classified as if

they were black, but doing so would mean detaining some whites who otherwise would be released—and thereby compromising their right to liberty. Conversely, blacks could be classified as if they were white, which would mean releasing some blacks who otherwise would be detained—and potentially threatening public safety. How to weigh these tradeoffs, again, should be considered in a public forum.

Criminal justice data reflect historical bias in the criminal justice system.

Arrest rates may differ for different groups of people because criminal justice data reflect historical bias in the criminal justice system. Historically blacks have been policed more heavily than whites, so it is unclear whether they are actually more likely to commit crime or just more likely to be arrested because they are monitored more closely. Yet pretrial risk assessments use these data to predict risk of pretrial misconduct as if there were not uncertainty in how they were created. Although there are limitations to how well such biases can be addressed, validation can help policymakers understand how accurate and equitable their pretrial risk assessments will be for different groups of people. From that baseline understanding, decisions can be made about how to interpret those risk predictions for all people and for protected classes of people, such as racial minorities. The Center for Court Innovation Case Study illustrates how racial bias can be mitigated—and at what cost.

Center for Court Innovation Case Study

Partly in response to the ProPublica-COMPAS debate, the Center for Court Innovation (CCI) determined whether their independently-developed pretrial risk assessment tool exhibits racial bias and whether it could be mitigated by policies that describe how to interpret and act on risk level classifications (Picard et al. 2019). CCI's recently released report illustrates how California's counties can validate their chosen pretrial risk assessment tools and evaluate their pretrial risk assessment systems to assess and mitigate racial inequity—and other potential inequities—that may emerge as pretrial risk assessment systems mature.

CCI tested their 9-item tool, which does not include race, but does include other demographic, criminal history, and current case information, using data from New York City. The tool classified individuals into five risk categories according to their predicted probability of being rearrested within two years: minimal, low, moderate, moderate-high, and high risk. When they initially tested their tool, CCI found that it classified individuals of all races—blacks, Latinos, and whites—with similar accuracy ($AUC \geq 0.72$).

However, CCI found evidence of racial inequity in risk level classifications, which can lead to racial inequity in pretrial detention rates. Blacks and Latinos were more likely than whites to be classified as moderate-high or high risk: 37 percent of blacks and 29 percent of Latinos were classified as moderate-high or high risk, but only 18 percent of whites were. If pretrial release or detention decisions were made based solely on these risk level classifications, fewer than 1 in 5 whites, but more than 1 in 3 blacks would be detained. Moreover, when they examined rearrest rates, CCI also found racial inequity in false positive rates. Blacks and Latinos classified as moderate high and high risk were more likely to *not* be rearrested than similarly classified whites: 23 percent of blacks and 17 percent of Latinos, but only 10 percent of whites were incorrectly classified.

CCI then tried to develop policies to mitigate these inequities by assessing how different alternatives would impact racial inequity in detention and false positive rates. First, CCI examined a policy of detaining only people classified as high risk. Under this alternative, both detention rates and false positive rates declined, but racial inequity remained. Detention rates were 22 percent for blacks, 10 percent for Latinos, and 16 percent for whites. False positive rates were 10 percent for blacks, 7 percent for Latinos, and 3 percent for whites. CCI then examined what would happen under a policy that limited detention to people classified as moderate-high and high risk who also were charged with a violent felony or domestic violence—by interpreting risk level classifications in concert with additional criminal history information. Relative to the first scenario, racial inequity was mitigated and detention rates declined—but false positive rates increased. Detention rates were 13 percent for blacks and whites and 14 percent for Latinos. False positives rates were 16 percent for blacks and Latinos and 14 percent for whites.

Takeaways

Pretrial risk assessment tools are likely to exhibit inequity—especially racial inequity.

People who have more prior arrests but are not more likely to commit crimes are more likely to be misclassified as high risk and are more likely to be needlessly detained as a result. Some demographic groups, especially racial minorities, are arrested at higher rates—even though they may not be more likely to commit crimes.

Validation helps counties determine the degree of racial inequity in risk prediction.

The CCI case illustrates how counties can determine the following across racial groups: (1) how a pretrial risk assessment tool will classify individuals; (2) to what degree those classifications are likely to be accurate; (3) and the consequences those classifications can have for pretrial release or detention decisions.

Pretrial risk assessment systems can be designed to promote equity.

After testing the performance of the risk assessment tool and finding racial inequity in potential detention rates and false positive rates, CCI created and tested policy alternatives to see whether they could reduce those inequities. Ultimately, they found a policy with the potential to promote racial equity by combining information from the pretrial risk assessment tool with an additional condition that recommends detention only when individuals have violent charges in their criminal histories.

Increased equity will generally come at the expense of reduced accuracy.

Risk assessment combined with detaining only potentially violent criminals increased equity in this case. But relative to a policy of only detaining the highest risk people, it comes at the cost of reduced accuracy. Although fewer people of all races are detained under the policy that creates more racial equity, false positive rates are higher for people of all races. Local pretrial policy objectives will determine whether this is an appropriate tradeoff, which is why those objectives need to be determined prior to validation.

Without robust pretrial risk assessment systems, pretrial decisions are likely to be more inequitable and inaccurate.

When CCI assumed that risk predictions would be translated directly into pretrial release or detention decisions, nearly 1 in 5 whites and more than 1 in 3 blacks would have been detained—and 1 in 4 blacks and 1 in 10 whites would have been incorrectly detained. CCI showed that detention rates could be reduced to less than 1 in 15 for all racial groups and that fewer than 1 in 15 people of all races would be incorrectly detained.

Pretrial risk assessment tools can be part of pretrial justice systems that lead to more transparent, consistent, accurate, and equitable pretrial release or detention decisions.

Non-proprietary pretrial risk assessment tools ensure that all people are evaluated in the same way, using the same criteria. How risk predictions are made is therefore transparent and consistent. The policies that govern how to interpret and act on those risk predictions should be similarly unambiguous and systematically applied. Under those conditions, pretrial release or detention decisions will be similarly transparent and consistent. As the CCI case illustrates, those policies can also be designed to ensure as much equity and accuracy as possible in pretrial release or detention decisions.

Appendix B. Predictors in Risk Assessment Tools

TABLE B1

Select characteristics of commercially available pretrial risk assessment tools currently used in California

	COMPAS PRRS-II	ORAS-PAT	VPRAI-R	PSA FTA	PSA NCA	PSA NVCA
Current Offense	Category representing most serious current charge		Current charge is felony drug, or theft			Current violent charge Current violent charge and age 20 or younger
Pending Charges	Number of pending charges or holds		Has pending charges	Has pending charges	Has pending charges	Has pending charges
Prior Pretrial Misconduct	Number of FTAs Number of times arrested or charged for new crimes during pretrial release	FTA warrants in the past 24 months: 0, 1, or more than 2	Has of two or more FTAs as an adult	Has FTA in the past two years Has FTA more than two years old	Has FTA in the past two years	
Prior Convictions			Has one or more past felony or misdemeanor convictions as an adult Has two or more violent convictions as an adult	Has prior felony or misdemeanor conviction	Has prior felony conviction Has prior misdemeanor conviction Has prior violent conviction	Has prior felony conviction Has prior misdemeanor conviction Has prior violent conviction
Prior Incarceration	Number of incarcerations that exceed 30 days	Has three or more prior incarcerations			Has prior sentence to incarceration	
Supervision Status			On community criminal justice supervision			
Age		Over or under age 33 at first arrest			Age at current arrest	
Employment	Employment status: full time, part time, unemployed, not in labor force	Employment status: full time, part time, unemployed	Employment status: employed, unemployed, student, caregiver, retiree, none			
Living Situation	Time in current neighborhood	Same residence for last six months				
Substance Use	Has history of drug use	Used illegal drugs in the last six months Drug use caused life problems in last six months	Has history of any drug use			

SOURCES: COMPAS Scale Documentation, Creation and Validation of the Ohio Risk Assessment Final Report, Virginia Pretrial Risk Assessment Tool - (VPRAI) Instruction Manual – Version 4.3, Public Safety Assessment Website

NOTES: FTA = FTA is failure to appear, NCA is new criminal act, and NVCA is new violent criminal act. The points assigned for NCA and FTA in the PSA risk assessment tool are totaled in two separate scales, whereas the total points for NVCA are converted to a binary “yes” or “no” outcome. The COMPAS pretrial release risk scale can be paired with the Violence Risk Scale to determine an individual’s risk to the community.

Appendix C. Developing “State of the Art” Pretrial Risk Assessment Tools using Machine Learning: A Brief Introduction

Instead of validating existing pretrial risk assessment tools counties can develop and test their own. “State-of-the-art” risk assessment tools rely on algorithms (Berk 2019: 6). Algorithms are systematically applied decision rules. Algorithms can be very basic, generating a risk prediction using one or two pieces of information (e.g., Dressel and Farid 2018). Algorithms can also be very complex. For example, “decision trees,” are processes that sequentially consider dozens or hundreds of variables to predict the likelihood of an outcome (Berk 2012, 2019; Kleinberg et al. 2017). Complex algorithms, including the decision trees that have been used to predict pretrial outcomes, are identified using “machine learning” techniques, meaning a computer is supplied with data and directed to predict an outcome using a specified methodology. The computer adaptively creates and revises the algorithm as it incorporates more data. Like the comparison between clinical and actuarial assessments, pretrial risk assessment tools based on machine learning algorithms have been shown to be more accurate than those based on statistical models, such as logistic regression (Berk et al. 2014; Kleinberg et al 2017).²

Using Machine Learning to Develop Pretrial Risk Assessment Tools

Developing a pretrial risk assessment tool begins with at least three decisions. First, local policy objectives must be established. Second, the outcome to be predicted must be defined. Third, the data used to predict the outcome must be selected to reflect the local population and policy environment. Each of these steps is described in the main report, so we only briefly summarize them here. After those decisions are made, the processes of developing and validating the risk prediction model that will undergird the pretrial risk assessment tool can begin.

Define Pretrial Policy Objectives

Pretrial policy objectives operationalize the goals of pretrial justice, which include maximizing individual liberty, public safety, court appearances, and equity. How counties operationalize these goals will influence the design of the pretrial risk assessment system, from defining pretrial misconduct to making pretrial release or detention decisions. When county pretrial workgroups convene, they should begin by defining these objectives.

Precisely Define the Pretrial Misconduct Outcome to Predict

Risk prediction models can only predict well-defined outcomes and they are “*exceedingly sensitive*” to the choice of outcome (Kleinberg et al. 2019: 5, emphasis in original). As described in the main report, counties will need to precisely define the pretrial misconduct outcomes they want to predict. Current legal scholarship indicates that individuals should be detained only to prevent serious violent crimes during the pretrial period (Mayson 2019; PDRW 2017).

² The distinction between machine learning algorithms and statistical models is not always clear. A useful distinction may be that machine learning algorithms typically impose less structure on the data than statistical methods because they do not assume an underlying model, whereas statistical methods typically do (Berk 2019). However, there are statistical methods that also do not impose structure on the data.

Rare Outcomes

Accurately predicting rare outcomes is a fundamental challenge for all risk prediction models. The best available data indicates that violent crimes are committed during the pretrial period very rarely. For example, between 1990 and 2009 only 1.4 percent of felony defendants in California were arrested for a violent felony during the pretrial period (Tafoya 2015). As a result, those forms of pretrial misconduct that pose the greatest threat to public safety are also the most difficult to predict accurately.

Rare outcomes pose two key problems for algorithmic risk assessment tools: they limit the number of similar cases that can be used to train the model and they make calibrating the tool to appropriately reflect the rarity of the outcome challenging. We discussed the first problem at length in the main report: for a pretrial risk assessment tool to make accurate risk predictions for future arrested individuals, it must have a robust sample of past similar arrestees. Rare outcomes like violent felonies make for a small sample—particularly in less populated counties—and may not provide enough observations to create unique training and testing datasets.

The second calibration problem is subtler. Because violent felonies occur so rarely, it is difficult for a tool to both assign a probability that reflects their rarity and be appropriately sensitive to their occurrence. For example, if a county has a violent felony arrest rate of 300 per 100,000 residents, then the risk prediction model should (at most) predict that 3 percent of individuals will commit a violent felony while on pretrial release. Therefore, the predicted probability of pretrial violence should be near zero for most assessed individuals. And those with non-zero predicted probabilities of pretrial violence should still have low probabilities overall. Setting a threshold to separate low from very low probabilities of pretrial violence will tend to lead to either too many (i.e., over-sensitivity) or not enough (i.e., under-sensitivity) people predicted to commit a violent felony.

In addition, traditional performance metrics like accuracy, which are intended to reflect how well tools predict risk, can provide deceptive information (Hester 2019). Referring to our previous example, if the risk assessment tool never predicts anyone will commit a violent felony, it will still be accurate 97 percent of the time because it will make incorrect predictions only for the 3 percent of individuals who do commit violent felonies. Yet the tool will fail to predict violence for 100 percent of the instances in which it occurs. Similarly, the tool could grossly over predict the number of people likely to commit a violent felony, and still result in a very high accuracy. As a result, researchers and practitioners responsible for validating the performance of risk assessment tools should carefully examine the different types of errors the tool makes in predicting rare outcomes, rather than relying on more general diagnostics that reflect the overall performance of the tool. We describe how to do this in Technical Appendix D.

Collect Representative Data to Develop and Test a Risk Prediction Model

Pretrial risk assessment tools unavoidably use information from the past to predict the future. When gathering data to develop and test tools, counties should try to gather past data that best represents the current local policy landscape and the current local pretrial population. As described in the main report, important considerations include whether there have been substantial demographic shifts or shifts in the policy environment that may affect pretrial misconduct outcomes (e.g., Bird et al. 2016).

To build a representative dataset, information on all pretrial release or detention decisions and pretrial misconduct outcomes in a county over a relevant time period should be gathered, as should additional systematically collected data that can be used to make pretrial risk assessments (e.g., demographic, criminal history, and socioeconomic information). Counties should gather as much information as possible and include it in the dataset—no predictors should be excluded a priori (e.g., due to equity concerns). Machine learning models perform better when more data is available to them. Whether including particular predictors compromises equity can be evaluated later.

Developing and Testing a Risk Prediction Model

In a machine learning framework, developing a risk assessment tool essentially amounts to developing (and choosing) the best performing risk prediction model and then testing it. Both developing (i.e., training) a risk prediction model and validating (i.e., testing) it require unique samples or subsets of the representative dataset.³ How much data—meaning how many observations—the dataset contains therefore determines whether and which machine learning techniques can be used to develop the tool. In jurisdictions with larger volumes of pretrial release or detention decisions and misconduct outcomes (e.g., 10,000 or more), machine learning techniques that rely on “big data” are feasible (e.g., Kleinberg et al. 2017). In jurisdictions with fewer pretrial release or detention decisions and pretrial misconduct outcomes (e.g., 1,000), the methods differ, but may still exploit recently developed machine learning techniques (e.g., Berk et al. 2014).

Large Sample Machine Learning Techniques

To apply machine learning techniques in large samples, the representative dataset will be divided into a minimum of two subsets. The first subset is used for “training.” In the training stage, the data are used to incrementally improve upon a risk prediction model until a version of the model that best predicts the desired pretrial misconduct outcome while also satisfying the local policy objectives is identified. The second subset is used to test the chosen risk prediction model, meaning to reassess its performance using data it has not yet seen. This process is akin to the validation process that we described in the main report. A third “verification” subset is often desirable (but not strictly required) because it enables a second independent test of the chosen risk prediction model (e.g., Kleinberg et al. 2017; Berk 2012, 2019).⁴

Small Sample Machine Learning Techniques

Berk et al. (2014) developed the only machine learning process for small samples (n~1500) of which we are aware. Their process, which is available as an R package, relies on kernel methods and requires three unique subsets of the data. Training data are used to identify several promising risk prediction models. A second “specification” dataset is used to identify the best performing risk prediction model from among the promising models. Finally, testing data is used to assess the performance of the chosen risk prediction model on new data.

Limitations of Machine Learning: Transparency and Complexity

Although machine learning algorithms often outperform simpler statistical models, they are less transparent in how they reach their predictions. For statistical models, analysts can directly examine the predictors and the risk prediction model to understand how a risk prediction will be reached. That is not possible with machine learning algorithms. Machine learning algorithms can be adjusted. But to understand what happens when a machine learning risk prediction model runs, it must be run (Kleinberg et al. 2019).

Finally, county agencies that are already overwhelmed with administrative tasks, policy development, and policy evaluation may find it difficult to allocate the time and resources necessary to learn and applying machine learning techniques to the development of pretrial risk assessment tools. Counties may therefore find it fruitful to collaborate with academic institutions or research consulting firms to develop such tools.

³ Ideally, each subset will include unique observations: the available data will be divided so that each observation appears in only one of the subsets. Alternatively, random samples can be taken from the available data. In the later scenario, each subset will be unique, but some observations will be repeated across the subsets.

⁴ Berk (2012) steps through these processes, provides some examples of machine learning code, and provides additional references for deeper learning.

Appendix D. Performance of Risk Assessment Tools

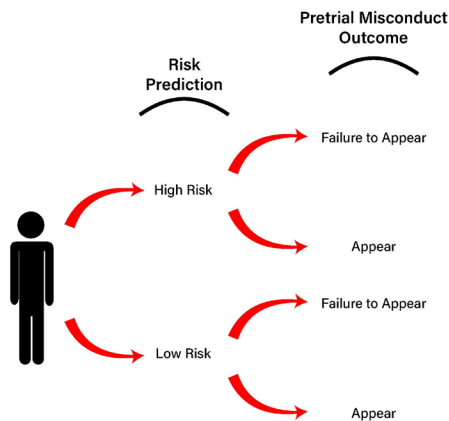
Risk assessment tools are validated by considering different aspects of their performance, meaning how well the predictions made by the risk assessment tool conform to future behavior on the part of the assessed individuals. In the sections that follow, we present the most common performance measures and illustrate how they are derived. We then explain the intuition behind each measure.

Relationships between Risk Predictions and Pretrial Misconduct Outcomes

When there are two risk predictions, high risk or low risk, and two pretrial misconduct outcomes, failure to appear (FTA) or appear, the paths from risk prediction to pretrial misconduct outcomes can be depicted as in Figure D1. Figure D1 can then be translated into what is called a confusion table, as depicted in Table D1. A confusion table relates the risk predictions made by risk assessment tools to the behavior observed after the prediction was made.

FIGURE D1.

Relating risk predictions to pretrial misconduct outcomes



SOURCE: Author illustration

The four cells at the center of the confusion table reflect the four potential relationships between pretrial risk predictions and pretrial misconduct outcomes shown in Figure D1: two ways of making correct risk predictions and two ways of making incorrect risk predictions. In this framework, “true” means correct, “false” means incorrect, “positive” indicates the predicted behavior (in our example, failure to appear), and “negative” indicates the opposite of the predicted behavior (in our example, appear).

TABLE D1

Confusion table that represents the relationship between predicted risk and actual behavior on pretrial release

	Actual Pretrial Misconduct Outcome			Equity (Outcome Oriented)
		Fail to Appear	Appear	Statistical Parity
Pretrial Risk Prediction	High Risk	True Positive TP	False Positive FP	False Positive Rate $FP/(FP+TN)$
	Low Risk	False Negative FN	True Negative TN	False Negative Rate $FN/(FN+TP)$
Equity (Prediction Oriented)	Predictive Parity	False Discovery Rate $FP/(FP+TP)$	False Omission Rate $FN/(FN+TN)$	
Accuracy	Accuracy	$(TP+TN)/(TP+FP+FN+TN)$		
	Calibration	Percent Appear	Percent Low Risk	

SOURCE: Author illustration

In the sections that follow, we first review the most common overall performance metric, the area under the curve. We then review more fine-grained indicators of performance. We introduce two different perspectives on the performance of risk assessment tools and show why they matter for the measurement of performance. The same tool can be said to perform well or poorly, depending on the perspective adopted. Finally, we highlight the consequences for accuracy and equity of measuring performance from each perspective.

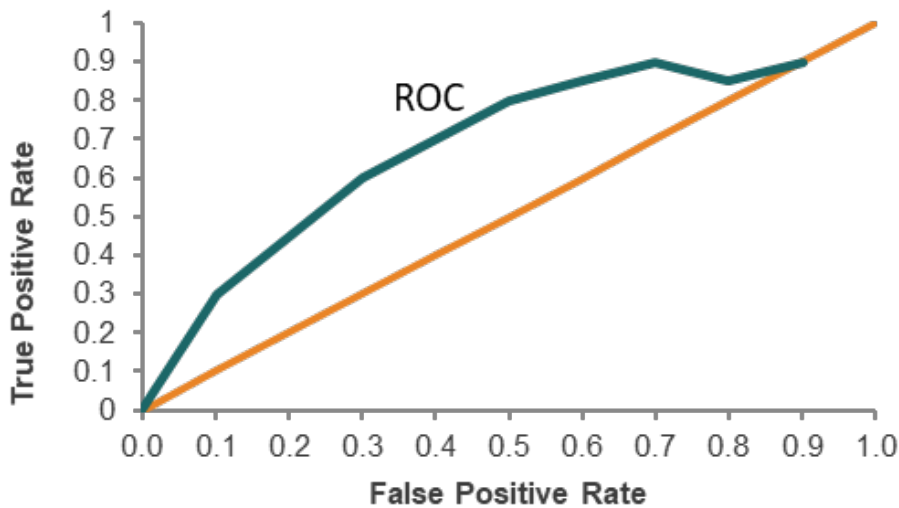
Overall Performance: Area under the Curve

The most common performance measure is called the *area under the curve* (AUC). The “curve” is the *receiver operating characteristic* (ROC) curve, which is a plot of the true positive rate (on the y-axis) as a function of the false positive rate (on the x-axis), as depicted by the blue line in Figure D2. The ROC curve visually represents the tradeoff between assigning a high risk classification to individuals likely to commit pretrial misconduct (i.e., making a correct prediction) and assigning a high risk classification those who are unlikely to commit pretrial misconduct (i.e., making an incorrect prediction). The AUC measures the distance between the ROC and an idealized relationship between the correct and incorrect predictions, which is represented by the orange line in Figure D2. This line represents a 1:1 ratio between correct and incorrect predictions.

Intuitively, a risk prediction model performs better by making more correct than incorrect predictions: the ratio between correct and incorrect predictions is greater than 1:1. When that occurs, the ROC line will lie above the idealized line, as shown in Figure D2. The greater the distance between the ROC line and the idealized line, the more true positives the risk prediction model assigns relative to false positives. Taking the integral of the ROC relative to the idealized line produces the AUC.

FIGURE D2

Hypothetical area under the curve plot



SOURCE: Author illustration

AUCs can range from 0.0 to 1.0, with 1.0 indicating perfectly accurate prediction and 0.0 indicating perfectly inaccurate prediction. An AUC of 0.5 means that the tool has a 50 percent chance of distinguishing a high risk person from a low risk person—no better than flipping a coin. An AUC of 1.0 means that the tool has a 100 percent chance of distinguishing a high risk person from a low risk person. Generally, an AUC value greater than 0.7 signals that the risk prediction model makes adequately accurate predictions, whereas values below 0.6 suggest that it does not.

Perspectives on Performance

Using the four basic relationships at the heart of the confusion table, we can examine the performance of a risk assessment tool from two perspectives. Within each perspective both correct and incorrect predictions are possible. However, analysts typically evaluate the performance of risk assessment tools in terms of the false or incorrect predictions, rather than the true or correct predictions. In other words, they want to understand prediction errors so that they can be corrected. The key fact to recognize is that false positives and false negatives can be measured in two ways, from two perspectives.

Prediction-Oriented Perspective

A *prediction-oriented perspective* looks forward from predictions to outcomes and asks: at what rate did the risk predictions fail to materialize? At what rate did high risk people appear; and at what rate did low risk people fail to appear? The former is called the *false discovery rate* (mathematically: $FP/FP+TP$). The latter is called the *false omission rate* (mathematically: $FN/FN+TN$).⁵

⁵ These false rates have corresponding true rates: at what rate did the risk predictions materialize as actual outcomes? For two-by-two confusion tables, the true rates oppose the false rates.

Outcome-Oriented Perspective

Alternatively, an *outcome-oriented perspective* looks backward from outcomes to predictions and asks: at what rate were the outcomes predicted incorrectly? At what rate were the people who failed to appear predicted to appear; and at what rate were the people who appeared predicted to fail to appear? The former is called the *false negative rate* (mathematically: $FN/(FN+TP)$). The latter is called the *false positive rate* (mathematically: $FP/(FP+TN)$).⁶

Defining Accuracy and Calibration

Accuracy in risk assessment is most often defined as the proportion of correct predictions: the number of true positives plus the number of true negatives, divided by the total number of predictions (mathematically: $(TP+TN)/(TP+TN+FP+FN)$).⁷ Defined in this way, accuracy depends on each of the four core relationships between risk predictions and actual behavior. This is also a very intuitive definition of accuracy.

However, accuracy can be defined in more than one way. Another definition of accuracy has been called “calibration” (Kleinberg et al. 2016: 4). Calibration asks whether the proportion of people predicted to appear matches the proportion of people who actually appear regardless of whether those predictions are correct or incorrect (mathematically: $(FP+TN)/(TP+TN+FP+FN)$).

To see why calibration is an important alternative measure of accuracy, consider a population in which only 80 percent of people appear but the tool predicted that 50 percent are at high risk for failing to appear. The performance of the tool is immediately called into question because it predicts that far more people will fail to appear than actually do fail to appear. Thus, calibration is an important initial test of the performance of a risk assessment tool. It requires that risk scores “mean what they claim to mean” even if the predictions are sometimes incorrect (Kleinberg et al. 2016: 4).

Predictive Parity and Statistical Parity

In Technical Appendix E, we discuss seven standards of equity. Here, we discuss in more detail the two we highlighted in the main report. *Statistical parity* adopts an outcome-oriented perspective by looking backward from an outcome to ask how many people in each group were predicted to experience it. *Predictive parity* adopts a prediction-oriented perspective by looking forward from a prediction to ask how many people in each group experienced the outcome.

A tool achieves statistical parity when the false positive rate and the false negative rate are the same for both groups of people.⁸ More intuitively, the percentage of people who appeared and who were initially classified high risk should be the same in both groups. Likewise, the percentage of people who failed to appear and who were initially classified as low risk must be the same in both groups.

Predictive parity requires the false discovery rate and the false omission rate to be the same for both groups of people. More intuitively, the percentage of people classified as high risk and who go on to appear must be the same in both groups. Likewise, the percentage of people classified low risk and who go on to fail to appear must be the same in both groups.⁹

⁶ Similarly these false rates have corresponding true rates: at what rate were the actual outcomes predicted?

⁷ The complementary measure to accuracy is the misclassification rate, defined as proportion incorrect predictions (mathematically: $FP+FN/(TP+TN+FP+FN)$).

⁸ Berk et al. (2018) refer to this as “conditional procedure accuracy equality.” We chose a term that references more commonly used terms in the broader risk assessment literature.

⁹ Berk et al. (2018) refer to this as “conditional use accuracy equality.” We chose to follow Chouldechova’s (2017) lead because her terminology references the common definitions of the true composite terms: positive predictive value ($TP/(TP+FP)$) and negative predictive value ($TN/(TN+FN)$).

Like accuracy, statistical parity and predictive parity rely on each of the four relationships between risk predictions and actual behavior. Intuitively, these relationships suggest that there will be tradeoffs between accuracy, statistical parity, and predictive parity. To demonstrate why those tradeoffs are inevitable in real-world situations, we introduce two more concepts: base rates and error weights.

Accuracy, Equity, and Base Rates of Pretrial Misconduct

Base rates refer to the underlying probability that an outcome will occur in a population or in subsets of that population. Different subsets of a population (e.g., groups delineated by race, age, or socioeconomic status) do not necessarily have equal probability of experiencing pretrial misconduct outcomes. Their base rates of failing to appear or committing a crime during pretrial release differ.

The potential for underlying variation in base rates of experiencing pretrial misconduct outcomes complicates the notions of equity and accuracy that we have been discussing. To understand why consider the tables in Panels A, B, and C of Figure D3. The tables in each panel are laid out as in Table D1, but with additional cells that indicate the total number of assessed individuals, the number of individuals who were predicted high and low risk, and the number of individuals who failed to appear and appeared.

In Panel A, we present an idealized hypothetical situation that allows us to discuss some features of risk assessment tool performance that can help counties compare how risk assessment tools perform for different population subgroups. First, notice that the tool that produced these results is *calibrated*: the base rate of appearing in Group 1 is 50 percent and half of the people in Group 1 are classified as low risk. Second, notice that the false positive and false negative rates are the same. Moreover the number of false positive and false negatives is the same, suggesting that policymakers value both false positives and false negatives similarly. This is rarely the case in real-world applications. Finally, note that the false discovery and false omission rates are also the same. Again, this rarely occurs in real-world situations.

In Panel B, we present the performance of the same risk assessment tool for Group 2, another hypothetical situation intended to illustrate how base rates can impact notions of equity between groups of people. Base rates of failing to appear in Group 2 (67 percent) are higher than in Group 1 (50 percent). Mathematically, this is achieved simply by multiplying the rightmost column by 2, which means there are 3000 people in Group 2, whereas there were 2000 people in Group 1. Note what happens to the performance measures. False positive and false negative rates remain equal and, in fact, are the same as for Group 1. Statistical parity is also achieved. However, predictive parity is compromised. More Group 1 members appear (50 percent versus 33 percent) and fewer fail to appear (50 percent versus 67 percent) than Group 2 members. Yet fewer Group 1 members are classified as low risk (40 percent versus 57 percent) and more are classified as high risk (40 percent versus 25 percent) than Group 2 members. Calibration is partly to blame: the tool predicts that 47 percent of Group 2 members will appear when in fact only 33 percent will. The calibration problem can be fixed. However, as Panel C illustrates, fixing the calibration problem increases the accuracy of the predictions for Group 2 but does not necessarily increase equity relative to Group 1.

In Panel C, some Group 2 members who eventually fail to appear are shifted from the low risk level classification to the high risk level classification. A shift like this seems appropriate and, intuitively might be accomplished by moving the rightmost line in Figure 2 in the main report to the left. As Panel C illustrates, this shift achieves calibration for Group 2. Thirty-three percent of Group 2 members appear and 33 percent of Group 2 members are classified as low risk. However, the predictive parity gains that accompany this shift come at the expense of statistical parity. False omission rates are the same for both groups and the false discovery rate for Group 2 is

closer to that of Group 1 than it had been. But the false negative rate is lower for Group 2 than it is for Group 1, even though false negatives and false positives are again valued equally in both groups.

FIGURE D3

How different base rates of failing to appear can impact policy decisions related to accuracy and equity

Panel A: Risk Assessment Performance for Group 1					
		Actual Behavior			
		Fail to Appear	Appear	N	Statistical Parity
Predicted Risk	High Risk	600	400	1000	0.40
	Low Risk	400	600	1000	0.40
	N	1000	1000	2000	
	Predictive Parity	0.40	0.40		
	Accuracy	0.60			
	Calibration	0.50	0.50		

Panel B: Risk Assessment Performance for Group 2 (Only Base Rates Differ)					
		Actual Behavior			
		Fail to Appear	Appear	N	Statistical Parity
Predicted Risk	High Risk	1200	400	1600	0.40
	Low Risk	800	600	1400	0.40
	N	2000	1000	3000	
	Predictive Parity	0.25	0.57		
	Accuracy	0.60			
	Calibration	0.33	0.47		

Panel C: Risk Assessment Performance Calibrated for Group 2					
		Actual Behavior			
		Fail to Appear	Appear	N	Statistical Parity
Predicted Risk	High Risk	1600	400	2000	0.40
	Low Risk	400	600	1000	0.20
	N	2000	1000	3000	
	Predictive Parity	0.20	0.40		
	Accuracy	0.73			
	Calibration	0.33	0.33		

SOURCE: Adapted from Berk et al. (2018)

Finally, a different kind of equity also seems to be compromised: the overall accuracy of the tool improved from 60 percent to 73 percent for Group 2, which far exceeds the accuracy of the tool for Group 1 (60 percent). If accuracy is greater for Group 2 than for Group 1, it means that the members of Group 1 are more likely to be treated inequitably because the classifications applied to them are more likely to be incorrect.

Figure D3 illustrates a proven “impossibility theorem” (Berk et al. 2018: 17; Kleinberg et al. 2016). In the absence of perfect prediction, if base rates are unequal it is impossible to maximize *both* statistical parity, and predictive parity simultaneously. Although they can be better balanced as the shifts between panels illustrate, policymakers must choose which to sacrifice in service to the other.

The Cost of Making Mistakes: Accuracy, Equity, Liberty, and Safety

Variation in base rates is not the only factor policymakers need to consider as they decide how to predict risk and translate those risk predictions into pretrial release or detention decisions. Risk classification choices assign value to prediction errors—false negatives and false positives—which reflect choices about how individual liberty is valued in relation to public safety.

To begin to understand this, consider Panels A and C of Figure D3. In Panel C, the *cost ratio*, meaning the ratio of false negatives to false positives, is 1:1. The risk prediction model allows the same number of the different types of errors. In Panel B, however, the cost ratio is 2:1. The risk prediction model allows twice as many false negative as false positives. The implication in Panel A is that public safety and individuals’ right to liberty are valued equally. In Panel C, the implication is that public safety is half as valuable as individuals’ right to liberty, because false negatives are most likely to impact public safety, whereas false positives are most likely to impact individuals’ right to liberty.

The notion of “valuing errors” might seem overly technical. But people intuitively understand and implicitly “value” false negatives and false positives. If a person classified as low risk is released and commits a new crime, the victim, the victim’s family, and the local community primarily bear the consequences of the false negative—public safety is compromised. Likewise, if a person classified as high risk is detained, but would not have committed a new crime, he, his family, and his community primarily bear the consequences of the false positive—the individual right to liberty is compromised. Thus, the exercise of placing value on errors and estimating the consequences of that valuation can help policymakers better understand the tradeoffs inherent in predicting risk and making decisions based on those predictions that impact their constituents’ liberty and safety.

Appendix E. Equity Standards in Pretrial Risk Assessment

Equity can be understood as a measure of whether a risk assessment tool treats different types of people equally. In the pretrial literature discussions of equity have largely centered on race but can also be extended other classes of people (e.g., gender, socioeconomic status, and health). Below we review seven standards of equity, which are primarily referred to as standards of “fairness” in the academic literature, to provide policymakers with a sense of the tradeoffs they may face when deciding which to promote.

Predictive Parity

Predictive parity requires the positive predictive value (precision) and the negative predictive value to be the same for both groups. Predictive parity also implies that the false discovery and false omission rates should be the same for both groups, which we distinguish with “1” and “2” subscripts in the following equations (Berk et al. 2018).

$$\frac{FP_1}{TP_1 + FP_1} = \frac{FP_2}{TP_2 + FP_2}$$

and

$$\frac{FN_1}{TN_1 + FN_1} = \frac{FN_2}{TN_2 + FN_2}$$

Statistical Parity

Statistical parity requires that the false positive and false negative rates be the same for the two groups. Statistical parity also implies sensitivity-specificity parity, meaning that the true positive rate (sensitivity) and the true negative rate (specificity) should be the same for both groups.

$$\frac{FP_1}{FP_1 + TN_1} = \frac{FP_2}{FP_2 + TN_2}$$

and

$$\frac{FN_1}{FN_1 + TP_1} = \frac{FN_2}{FN_2 + TP_2}$$

Accuracy Equality

Accuracy equality requires the proportion of correct predictions to be the same in each group. In other words, the accuracy of prediction should be the same for both groups.

$$\frac{TP_1 + TN_1}{TP_1 + TN_1 + FP_1 + FN_1} = \frac{TP_2 + TN_2}{TP_2 + TN_2 + FP_2 + FN_2}$$

Demographic Parity

Demographic parity requires the proportion of people predicted to be high risk to be the same for both groups.

$$\frac{TP_1 + FP_1}{TP_1 + TN_1 + FP_1 + FN_1} = \frac{TP_2 + FP_2}{TP_2 + TN_2 + FP_2 + FN_2}$$

and

$$\frac{TN_1 + FN_1}{TP_1 + TN_1 + FP_1 + FN_1} = \frac{TN_2 + FN_2}{TP_2 + TN_2 + FP_2 + FN_2}$$

Treatment Parity

Treatment parity requires the “cost ratio” of false negatives to false positives be the same for both groups.

$$\frac{FN_1}{FP_1} = \frac{FN_2}{FP_2}$$

Calibration Parity

Although they do not include it among their definitions of equity, Berk et al. (2018) adopt Kleinberg et al.’s (2016) definition of calibration as correctly predicting the probability of experiencing an outcome regardless of prediction errors. They argue that calibration parity is an important definition of equity, so we include it here.

$$\frac{FP_1 + TN_1}{TP_1 + TN_1 + FP_1 + FN_1} = \frac{FP_2 + TN_2}{TP_2 + TN_2 + FP_2 + FN_2}$$

Total Equity

Total equity occurs when all parity measures are achieved. This occurs only in the trivial and not realistic case in which different groups have identical base rates.

Appendix F. Example Decision Matrixes and Decision Tree

FIGURE F1

New Jersey's Pretrial Release Recommendation Decision Making Framework

**Pretrial Release Recommendation Decision Making Framework (DMF)
[March 2018]**

DMF MATRIX

	NCA 1	NCA 2	NCA 3	NCA 4	NCA 5	NCA 6
FTA 1	Risk Level Green – Recommendation ROR	Risk Level Green – Recommendation ROR				
FTA 2	Risk Level Green – Recommendation ROR	Risk Level Green – Recommendation ROR	Risk Level Light Green – Recommendation PML 1	Risk Level Yellow – Recommendation PML 2	Risk Level Light Orange – Recommendation PML 3	
FTA 3		Risk Level Light Green – Recommendation PML 1	Risk Level Light Green – Recommendation PML 1	Risk Level Yellow – Recommendation PML 2	Risk Level Light Orange – Recommendation PML 3	Risk Level Red – No Release Recommended
FTA 4		Risk Level Light Green – Recommendation PML 1	Risk Level Light Green – Recommendation PML 1	Risk Level Yellow – Recommendation PML 2	Risk Level Light Orange – Recommendation PML 3	Risk Level Red – No Release Recommended
FTA 5		Risk Level Yellow – Recommendation PML 2	Risk Level Yellow – Recommendation PML 2	Risk Level Light Orange – Recommendation PML 3	Risk Level Dark Orange – Recommendation PML 3 + EM/HD	Risk Level Red – No Release Recommended
FTA 6				Risk Level Red – No Release Recommended	Risk Level Red – No Release Recommended	Risk Level Red – No Release Recommended

SOURCE: <https://njcourts.gov/courts/assets/criminal/decmakframwork.pdf>

FIGURE F2

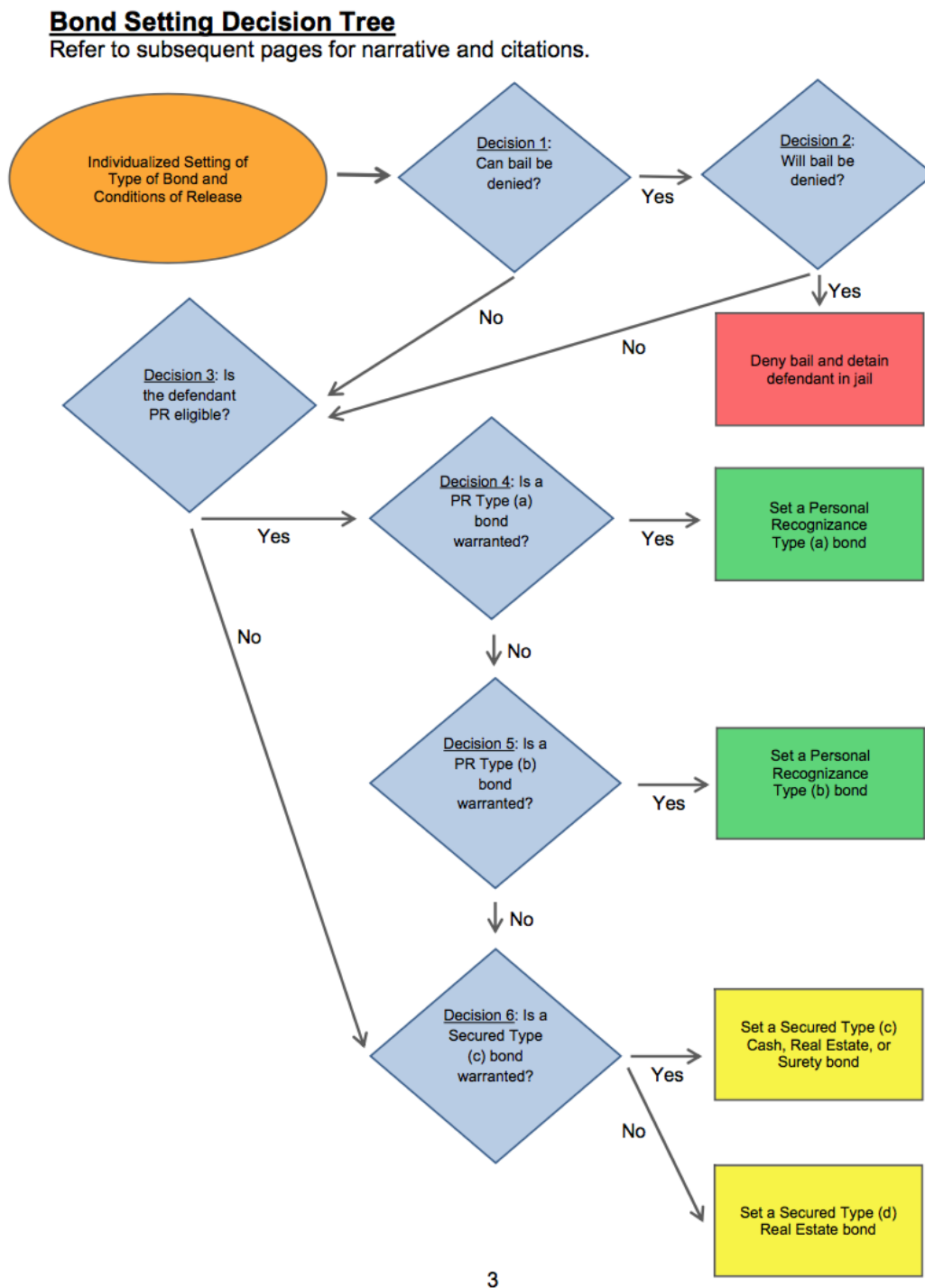
Example Decision Matrix from Chief Probation Officers of California and the Pretrial Justice Institute

MOST SERIOUS CHARGE						
PRETRIAL RISK CATEGORY	LESS SERIOUS MISDEMEANOR	MORE SERIOUS MISDEMEANOR	LESS SERIOUS OR NON-VIOLENT FELONY	DRIVING UNDER THE INFLUENCE	DOMESTIC VIOLENCE	SERIOUS OR VIOLENT FELONY
LOWER	Recognizance Release with Court Reminder	Recognizance Release with Court Reminder	Recognizance Release with Court Reminder	Recognizance Release with Basic Supervision	Recognizance Release with Basic Supervision	Recognizance Release with Enhanced Supervision (if Released); or Detained
MEDIUM	Recognizance Release with Basic Supervision	Recognizance Release with Basic Supervision	Recognizance Release with Basic Supervision	Recognizance Release with Enhanced Supervision	Recognizance Release with Enhanced Supervision	Recognizance Release with Enhanced Supervision (if Released); or Detained
HIGHER	Recognizance Release with Basic Supervision	Recognizance Release with Enhanced Supervision	Recognizance Release with Enhanced Supervision	Recognizance Release with Enhanced Supervision (if Released); or Detained	Recognizance Release with Enhanced Supervision (if Released); or Detained	Recognizance Release with Enhanced Supervision (if Released); or Detained

SOURCE: CPOC (2019)

FIGURE F3

Colorado's Bond Setting Decision Tree



SOURCE: Jones and Schnake (2013)



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RISK ASSESSMENT FACTSHEET

Colorado Pretrial Assessment Tool (CPAT)

LAST UPDATED: May 6, 2019

REVIEWED BY: Sue Ferrere (Pretrial Justice Institute), Victoria Terranova (University of Northern Colorado, Department of Criminology and Criminal Justice), and Michael Jones (Pinnacle Justice Consulting, formerly Pretrial Justice Institute)

Who created the risk assessment? Are they a public or private organization?

CPAT was created through a joint partnership between the Pretrial Justice Institute, the JFA Institute, and 10 Colorado counties.

How large was the training data set?

The initial data set contained 2,000 samples of defendants who were booked into a county jail. Only 1,315 of these samples were used to build the model (discussed later).

How was the training data set collected and assembled (i.e., what jurisdiction(s) is it from)?

Training data came from 10 Colorado counties. Each county was to contribute a specific number of samples to ensure the sample was representative of the overall populations of the 10 counties. Pretrial services staff conducted interviews and collected the data.

Over what time frame was the data collected?

The data was collected over a 16-month time period; samples were collected each day of the week and at all times of day.

What factors (i.e., defendant characteristics) were included in the data set? This question pertains to all the factors that were available about defendants, not necessarily all the factors that were used to train or develop the model.

There were over 100 factors included in the initial data set (though not all 100 were used to develop the model). These factors included information about criminal history, mental health, drug and alcohol use, housing and employment, as well as defendant demographics.

Does the dataset include instances of defendants who were detained? If so, does the data include outcomes for those people (i.e., was counterfactual estimation involved; if so, how)?

Of the 2,000 defendants, 1,315 (66%) were released from jail on pretrial status and 655 (33%) were held in jail until case closure. However, the researchers did not include the 655 detained defendants in the set of samples used to build the model (because outcome information was not available for these defendants).

Are there any known issues or errors with the data?

Some counties did not hit their target number of samples, so other (larger) counties collected more samples and contributed those samples to the data to accommodate.

In what year was the risk assessment created?

2012

What factors, among all the factors in the training data, were considered in the development of the risk assessment? If not all factors were considered, how were those that were considered chosen?

From the original set of more than 100 factors, 29 factors were considered in the development of the risk assessment. The 29 factors were chosen by examining simple correlations between each of the factors in the original set and the outcome variables. The 29 chosen factors had significant correlations that were not skewed.

How were factors that were considered ultimately chosen for exclusion or inclusion in the final model (the risk assessment itself)?

Logistic regression was used to estimate the relationship between each of the 29 predictors and the outcomes (failure to appear, new filings, and either). The predictors with a statistically significant relationship to the outcomes were chosen. A significance level of .30 was used (the researchers chose this level over the more common .05 level because “the sample size was too small to yield a sufficient number of predictors” using the .05 level).¹ 12 factors were selected for use in the final model.

Does the final model include as a factor(s) arrests that did not lead to convictions? Does the final model include socioeconomic factors such as housing and employment status? Does the final model include personal health factors such as mental health or substance abuse?

Yes. The model does consider housing status, whether the defendant has a phone, whether the defendant contributes to residential payments, history of problems with alcohol and mental health history, and whether the defendant has other pending cases, among other factors.

How were weights assigned to each factor included in the final model? (rounding correlation coefficients, Burgess Method, etc.)

The weights were assigned based on “marginal increase in pretrial misconduct risk attributable to each category. For example, if having a prior jail sentence increased the risk of pretrial misconduct by 4 percentage points relative to not having this history, then this category was assigned a weight of 4.”²

How does the final model define outcomes (i.e., during the model development process, was there a distinct outcome defined for each type of failure (failure to appear, new crime, new violent crime, etc.) or were outcomes compounded?

The final model defines a compound outcome of “Any Failure,” which includes failure to appear and new criminal filings. The researchers considered using separate models for each of these outcomes but ultimately concluded to use a single model to predict both outcomes, noting that “Additional diagnostics showed that the model assessing the likelihood of “Any Misconduct” is able to assess the likelihood of both of the individual outcomes as well as any models developed to assess the likelihood of only one of the individual outcomes.”³

What does the output of the model look like (i.e. a score on a scale of 1-10, etc.)?

The output is a total score, on a scale of 0 to 82.

¹ See Source 1, page 11

² See Source 1, page 13

³ See Source 1, pages 12-13

Does the model output risk level designations or convert raw scores into risk level designations such as “low risk,” “moderate risk,” and “high risk”?

The model classifies defendants into risk “categories” based on their score (for example, a score between 0 and 17 classifies a defendant as “Risk Category 1.” The categories were selected using the “natural breaks” method.⁴

What proportion of samples in the training data set failed at each risk score and/or level (for example, what percentage of people with a score of 5 or a label of “moderate risk” actually failed to appear)?

Failure rates from the training data (n = 1315):⁵

Risk level	Public Safety Failure Rate	Court Appearance Failure Rate	Overall Combined Failure Rate
1	9%	5%	13%
2	20%	15%	29%
3	31%	23%	42%
4	42%	49%	67%

Did the model developers assess the predictive validity of the model? If so, how (reported AUC, FPR, TPR, etc.)?

The researchers plotted pretrial misconduct rate as a function of risk scores in the training set (rounded to the nearest ten). The plot showed that “the misconduct rate increases as a defendant’s score on the tool increases.”⁶

Where is the risk assessment used?

As of May 2019, the CPAT is used in 22 counties throughout the state of Colorado.

Are the factors and weights of the risk assessment publicly available?

Yes

Does the risk assessment cost money for a jurisdiction to adopt?

No

Does the adoption of the risk assessment require training? If so, by who?

Training is not required, but it is highly advised by the tool developers and the pretrial services agencies that use the tool. The Colorado Association of Pretrial Services (CAPS) published a publicly-available training manual in June 2015 (Source 3).

Does the risk assessment come with any sort of software or software package?

No

⁴ See Source 1, pages 14 and 18

⁵ See Source 1 page 15

⁶ See Source 1, page 14

Does the risk assessment involve or require an in-person interview?

Yes - 8 of the 12 factors on the CPAT are based on a defendant's answers in an in-person interview.

How does the risk assessment account for missing information?

An administration manual includes guides for answering specific questions as "Yes" or "No" when information is unknown.⁷

Has the risk assessment been analyzed on non-training data for predictive validity? Has the risk assessment been analyzed with training data or non-training data with regard to performance for different race groups? Has the risk assessment been analyzed with training data or non-training data with regard to performance for different genders? If so, by who, when, and using what data?

Researchers at the University of Northern Colorado are working on a validation (and possible revision) of the CPAT. They expect to release the full validation report in mid-2020.

Information retrieved from:

- [1] CPAT Revised Report dated October 19, 2012
- [2] CPAT FAQs Document dated October 2012
- [3] CPAT Administration, Scoring and Reporting Manual Version 2 dated June 2015
- [4] Information from Sue Ferrere (Pretrial Justice Institute)
- [5] Information from Victoria Terranova (University of Northern Colorado, Department of Criminology and Criminal Justice)
- [6] Information from Michael Jones (Pinnacle Justice Consulting, formerly Pretrial Justice Institute)

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⁷ See Source 3, pages 5-8



Process Evaluation of the IRAS-PAT Pilot Program Implementation

Report to the Indiana Office of Court Services



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BACKGROUND

In 2014, the Indiana Supreme Court Committee to Study Evidence-Based Pretrial Release was tasked with the development and implementation of a pilot project to assess the feasibility, efficacy, economics and methodologies of establishing an evidence-based system for pretrial release decisions in Indiana (Supreme Court Cause No. 94S00-1312-MS-909 and No. 94S00-1412-MS-757). The committee partnered with the National Institute of Corrections (NIC) to develop the pilot project. In spring 2016, the Indiana Office of Court Services (IOCS), in collaboration with the Evidence Based Decision Making policy team (EBDM), entered into agreements with select courts to participate in a pilot program of the Indiana Risk Assessment System – Pretrial Assessment Tool.

The pretrial period occurs after arrest and before a disposition has been determined by the court. One of the critical decisions made during this period is whether a defendant should be released back into the community or remain detained in jail pending trial. This decision is multifaceted; should the court decide to release a defendant to the community, the terms and conditions of bail must also be set. One of the main factors used to inform these decisions is the risk of failure-to-appear (FTA) in court. Generally speaking, bail systems are used to offset the risk of defendants failing to appear. In this system, defendants can secure a release from jail pending trial if they are able to meet the bail amount set by the court. Posting money or property is thought to assure that defendants will stand trial as these financial means would be returned if defendants attend court appearances or forfeited if defendants fail to appear.

Release or detain decisions are important for a number of reasons. First, these decisions must be consistent with the constitutional rights of defendants. Due process, equal protection, safety from the imposition of excessive bail, and the presumption of innocence are all key considerations that must be taken into account by the court. Second, decisions are being assessed in relation to emerging pretrial practice standards. The American Bar Association (2007) and National Association of Pretrial Service Agencies (2004) have specified a set of benchmarks consistent with Bail Reform Act of 1984 and best practices to improve the efficiency and effectiveness of pretrial efforts. Third, pretrial decisions have significant downstream justice system consequences. Defendants who are detained prior to court disposition are more likely to plead guilty, receive prison sentences, and be incarcerated for longer periods of time than defendants who were released to the community (Heaton et al., 2017; Lowenkamp et al., 2013b; Reaves, 2013). These front-end system decisions impose substantial system costs to state and local governments as well as direct or intangible costs to defendants and their families.

In 2010, Indiana adopted the Indiana Risk Assessment System (IRAS), a suite of five separate instruments, created by researchers at the University of Cincinnati, which are designed to be used at specific points in the criminal justice process to identify an offender’s risk of a FTA or reoffend and, for some instruments also identify criminogenic needs. One of these instruments, the IRAS Pretrial Assessment Tool (IRAS-PAT) is intended for use during the pretrial period. It was designed to be short but also contain measures that are predictive of both a defendant’s FTA and risk of violating pretrial supervision with a new offense. Exhibit 1 shows the items captured from the IRAS-PAT. In keeping with the idea of brevity, the IRAS-PAT consists of seven risk items in three dimensions (criminal history, employment and residential stability, and drug use). Only trained staff can administer the IRAS-PAT which requires a brief face-to-face interview (approximately 10 minutes) with arrestees and follow-up verification of information by pretrial supervision staff.

Exhibit 1. IRAS-PAT Instrument

INDIANA RISK ASSESSMENT SYSTEM: PRETRIAL ASSESSMENT TOOL (IRAS-PAT)

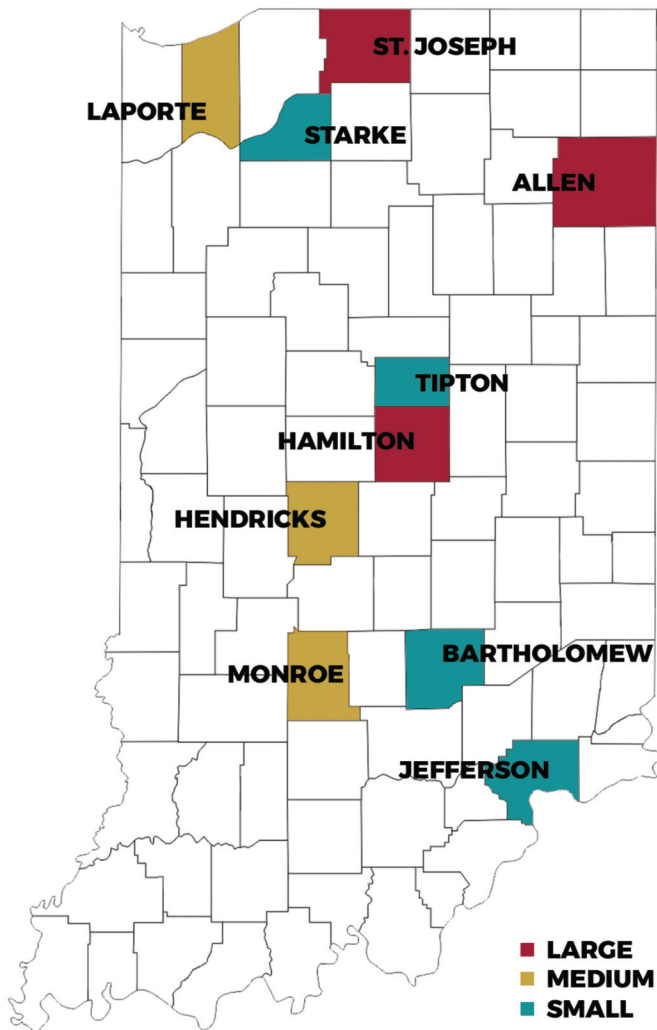
Name: _____ Date of Assessment: _____
 Case#: _____ Name of Assessor: _____

Pretrial Items	Verified			
1. Age at First Arrest 0=33 or older 1=Under 33	<input type="checkbox"/> <input type="checkbox"/>			
2. Number of Failure-to-Appear Warrants Past 24 Months 0=None 1=One Warrant for FTA 2=Two or More FTA Warrants	<input type="checkbox"/> <input type="checkbox"/>			
3. Three or more Prior Jail Incarcerations 0=No 1=Yes	<input type="checkbox"/> <input type="checkbox"/>			
4. Employed at the Time of Arrest 0= Yes, Full-time 1= Yes, Part-time 2= Not Employed	<input type="checkbox"/> <input type="checkbox"/>			
5. Residential Stability 0=Lived at Current Residence Past Six Months 1=Not Lived at Same Residence	<input type="checkbox"/> <input type="checkbox"/>			
6. Illegal Drug Use During Past Six Months 0=No 1=Yes	<input type="checkbox"/> <input type="checkbox"/>			
7. Severe Drug Use Problem 0=No 1=Yes	<input type="checkbox"/> <input type="checkbox"/>			
Total Score: <input type="checkbox"/>				
Scores	Rating	% of Failures	% of Failure to Appear	% of New Arrest
0-2	Low	5%	5%	0%
3-5	Moderate	18%	12%	
6+	High	29%	15%	17%

CURRENT PILOT STUDY

With public safety always being the highest priority, the goal of the pilot project is to develop and implement an effective pretrial release system that supports judicial officers in making evidence-based pretrial release decisions under Indiana law. Ideally, the pilot program will reduce pretrial incarceration for defendants with lower risk levels and provide suitable levels of detention for high risk defendants. Furthermore, should defendants secure pretrial release, supervision terms will be structured in accordance to defendants’ level of risk. While participating courts were afforded a reasonable degree of flexibility in determining the best approach to utilizing the IRAS-PAT in their communities, pilot counties were asked to consider the expectations of the Indiana evidence-based decision making (EBDM) Policy Team (see Appendix A). During the implementation phase of the pilot program, IOCS requested the assistance of researchers from the Indiana University Center for Criminal Justice Research (CCJR) in conducting a process evaluation of the IRAS-PAT program implementation in the 10 participating pilot counties: Allen, Bartholomew, Hamilton, Hendricks, Jefferson, Monroe, Porter, St. Joseph, Starke, and Tipton (see Exhibit 2).

Exhibit 2. Map of Pretrial Pilot Counties



This formative report summarizes research activities and related findings from this evaluation and includes the following:

- Review of the research literature that pertains to pretrial risk assessments and the IRAS-PAT;
- Summary of pilot county data collection and data sharing efforts;
- Stakeholder interview findings, examination of pilot county implementation process, and emerging themes regarding implementation of the IRAS-PAT;
- Cross-county comparisons of implementation process;
- Preliminary analysis of INCite IRAS-PAT data linked to Odyssey data; and,
- Conclusions and recommended next steps.

During the initial year of pilot program implementation, the focus of this study was to develop a baseline understanding of the criteria used by pilot sites in administering the IRAS-PAT, the number of IRAS-PAT instruments administered

among arrestees, and the level to which IRAS-PAT results are being utilized by courts in determining the need for pre-trial jail commitment in each of the pilot counties.

LITERATURE REVIEW: NATIONAL TRENDS IN PRETRIAL CASE PROCESSING

Research has consistently shown that a majority of jail inmates who are currently incarcerated have yet to receive a court disposition. Nationally representative samples of jail inmates find that 55-63% of inmates are awaiting trial (Minton & Zeng, 2015). These national estimates have been relatively stable since 2000. Similar proportions are to be expected across the state of Indiana, although simple averages may mask wide degrees of variation between jurisdictions. For instance, a recent report on the operations of the Marion County criminal justice system found that 84% of jail inmates were awaiting trial (BKD, 2016).

Court processing data can also provide some insights about release and detain decision-making. Among felony defendants in a nationally representative sample of courts serving urban jurisdictions, 62% of defendants were released into communities prior to case disposition, 38% were detained until disposition, and 4% were denied bail (Reaves, 2013)¹. Sixty percent of defendants were released to the community with financial terms and conditions. Four out of every five defendants posting a financial bond did so through a private surety bond. Twenty percent of defendants were released on own recognizance terms. Half of those who were released were out of custody within one day of arrest and 75% were released within one week. Among defendants who remained in jail, 90% had a bail amount set by the court but were unable to meet the financial conditions to secure release.

Pretrial Risk Assessment Basics

Innovations and experiments continue to be implemented by jurisdictions across the country to release bail-able defendants, reduce disparities in pretrial release or detention decisions, decrease the length of time defendants are held in pretrial detention, and integrate evidence-informed practices (Tsarkov, 2017). One approach to achieve these objectives while mitigating the risk of defendant flight and danger to the community or specific individuals is to employ risk assessment tools. The potential promise of these tools is to standardize the risk of pretrial arrestees and inform release, detention, terms, or conditions decisions through structured decision matrices. A large body of research has demonstrated that standardized risk assessment tools more accurately identify who will or will not be successful on a variety of outcomes in relation to unstructured assessments or a reliance on professional judgement alone (Mamalian, 2011). Unstructured or professional judgement decisions result from real experiences, but this knowledge does not necessarily translate to or represent broader patterns experienced within and across jurisdictions. *By improving the accuracy of behavioral predictions, risk assessment tools can increase public safety and reduce costs.*

Generally, pretrial risk assessment tools consist of 8 to 10 factors that are associated with FTAs and rearrest while case disposition is pending. The most common factors are: current offense charge, prior convictions, prior incarcerations, pending offense charge(s), history of FTA, community ties, residential stability, substance abuse, employment, education, and age. Common items integrated into

¹Unfortunately, comparable data collections on suburban and rural jurisdictions are not available from the U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics.

risk assessment tools are often included on the basis of empirical support. However, this is not always the case. Items can also be included because of statutory or consensus guidelines. For example, the seriousness of the current offense charge has long been used as a critical factor in informing release or detain decisions (Phillips, 2004). Yet, this factor is unable to accurately predict future pretrial misconducts (Lowenkamp & Wetzel, 2009). Similarly, community or family ties are thought to be key factors in determining whether a defendant will or will not attend scheduled court hearings. At best, these items are weakly correlated with pretrial misconduct (Myburgh et al., 2015).

Comparing Factors among Risk Assessments

Exhibit 3 presents a summary of the factors used in available (and accessible) pretrial risk assessment tools and compares these to the factors on the IRAS-PAT. Criminal history record information is one of the most prominent factors. Employment status or history is the next most prominent factor and is followed by an array of metrics on substance use behaviors. Next are factors affiliated with residential stability. The number of factors included on an assessment tool ranges from six (Iowa's Fifth Judicial District; Prell, 2008) to over 50 (District of

Columbia; Lotze et al., 1999) with estimated time needed to administer ranging from 15 to 28 minutes per individual (Desmarais et al. 2016). As illustrated in Exhibit 3, the IRAS-PAT contains the factors most commonly captured on pretrial risk instruments.

Bechtel et al. (2016) have conducted a meta-analysis of 16 studies testing the predictive validity of pretrial risk assessment tools. The researchers found that available pretrial risk assessment tools are able to predict FTAs and a combined measure of failures to appear and rearrest; however, the relative strength of the ability to predict pretrial misconduct (FTA and rearrest) outcomes is modest. Desmarais et al (2016) also conducted a meta-analysis of 19 different risk assessment tools and found that no one tool stood out as being more accurate than another. *Relevant to this discussion is the inclusion of the ORAS-PAT in the study sample—which is the same instrument as the IRAS-PAT. Similar to the Bechtel et al. (2016) study, findings from Desmarais et al. (2016) suggest a positive association between ORAS-PAT scores and pretrial misconduct. That is, higher ORAS-PAT scores were correlated with an increased likelihood of pretrial misconduct, while lower scores were affiliated with relatively infrequent pretrial misconduct.*

Exhibit 3. Comparison of Risk Assessment Instruments

	IRAS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
Defendant Characteristics																										
Age	•	•				•	•	•				•	•	•		•				•	•	•		•		
Mental health history									•			•		•	•										•	
Substance abuse	•				•		•	•	•	•	•	•	•	•	•	•	•							•	•	•
Criminal History																										
Criminal history	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Past release failures	•	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Pending cases		•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Current offense		•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Financial Indicators																										
Employment history	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Education									•							•	•								•	
Financial assets			•	•	•				•		•			•	•	•	•									•
Home owner							•									•	•									•
Phone Access												•		•		•					•					•
Social Ties																										
Residential stability	•		•		•	•		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Residential arrangement			•			•		•																		•
Marital status			•					•				•			•						•					•
Available guarantors			•		•				•		•				•						•					•
Number of Items	7	9	7	6	9	9	9	22	6	9	12	11	7	12	11	30	8	13	7	8	16	7	9	12	14	
Predictive Validity Metric	--	62%	2%	--	--	77%	--	80%	--	--	--	--	64%	--	--	--	--	--	--	--	--	--	--	--	--	--

- | | | |
|--|--|---|
| 1. Public Safety Assessment (PSA) Tool (aka Arnold Instrument) | 9. Virginia Pretrial Risk Assessment Instrument. | 17. Lee County (FL) Risk Assessment Tool. |
| 2. Philadelphia (PA) Bail Experiment (aka Vera Instrument) | 10. Kentucky Pretrial Risk Assessment Instrument. | 18. Maryland Pretrial Risk Assessment Tool. |
| 3. New York City (NY) Pretrial Risk Assessment Instrument. | 11. Florida Pretrial Risk Assessment Instrument. | 19. Harris County (TX) Pretrial Services Point Scale. |
| 4. Lake County (IL) Pretrial Risk Assessment Instrument. | 12. Ohio Risk Assessment System (Same as IRAS-PAT). | 20. Ramsey County (MN) Pretrial Evaluation Point Scale. |
| 5. Minnesota 4th Judicial District Pretrial Evaluation Scale. | 13. Colorado Pretrial Risk Assessment Tool. | 21. Monroe County (NY) Pretrial services Point Scale. |
| 6. Allegheny Pretrial Services Risk Assessment. | 14. Connecticut Pretrial Risk Assessment Instrument. | 22. Summit County (OH) Pretrial Risk Assessment. |
| 7. District of Columbia Pretrial Risk Assessment. | 15. Coconino County (AZ) Pretrial Services Risk Assessment. | 23. County of Orange (CA) Pretrial Risk Assessment. |
| 8. Iowa 5th Judicial District Pretrial Release Point Schedule. | 16. Mecklenburg County (NC) Pretrial Risk Assessment Praxis. | 24. Connecticut Pretrial Risk Assessment. |

Implementation of Pretrial Risk Assessment

One significant gap in knowledge about pretrial risk assessment tools is how the integration of these tools affect traditional pretrial service operations. The implementation of any innovation requires significant investment in resources, mobilization of personnel, and courage to self-assess progress and learn from the issues that arise. Some important lessons have been experienced across the country. In response to jail overcrowding and a reliance on cash bonds, Lake County (IL) established a pretrial services division and integrated a pretrial risk assessment tool to inform release and bond decisions (Coopridge, 2009; Coopridge et al., 2003). One of the initial challenges with the tool was the wide assortment of scores that were generated. No two pretrial services staff were able to reach agreements on risk scores for similar defendants. Training and reaching consensus on the definitions and scoring of risk assessment items were offered as being key factors to improve the quality of the assessment and gain staff support for the use of the local tool. The county experienced increases in the proportion of defendants who bonded to non-financial release options after integrating their tool. Further, the county experienced reductions in FTA rates.

Despite evidence of anticipated benefits, there also have been issues associated with the implementation of pretrial risk assessment tools. In a Maryland pilot, Kentucky's statewide pretrial risk assessment tool was integrated into the pretrial operations of a single jurisdiction (Governor's Commission to Reform Maryland's Pretrial System, 2014). The study found that defendants assessed as low risk were more likely to be released to the community on an own recognizance bond in comparison to defendants assessed as being high risk. However, bail amounts were set to larger monetary values for low risk defendants than higher risk defendants. As a result, only a small proportion of low risk defendants were able to post bond and secure release. In Philadelphia and Pittsburgh, researchers found that judges continued to set discrepant bail amounts for similar misdemeanor defendants despite the integration of pretrial risk assessment tools and decision matrices (Gupta et al., 2016; Stevenson, 2016). In turn, defendants in front of a judge who tends to order monetary bonds were more likely to be detained pending trial, plead guilty, and receive lengthier sentences than defendants who were in front of judges who are presumed to follow more closely to decision matrices.

Formative Evaluation

The research literature highlights the importance and effectiveness of using risk assessments and also suggests that the IRAS-PAT contains the necessary core elements of an evidence-based risk assessment tool. However, the literature also highlights potential issues that can arise during implementation. This is particularly relevant to pretrial risk assessments in Indiana as counties are able to use other instruments in conjunction with the IRAS-PAT. Additionally, each of the counties developed their own plans for implementation into existing criminal justice operations. Thus, as part of the CCRJ study we aimed to understand the county implementation process by conducting interviews with key stakeholders.

IRAS-PAT IN PILOT COUNTIES

As part of the project scope of work, CCJR proposed to conduct stakeholder interviews with representatives in each of the pilot counties. The overall goal of

the interviews was to determine: (1) the court's previous experience, if any, with pretrial assessment tools; (2) the process and extent to which the IRAS-PAT is being administered (i.e., individuals responsible for administering the instrument, frequency of IRAS-PAT usage, method of sharing IRAS-PAT results with judge(s), ways in which judge(s) use results in making decisions, etc.); and, (3) potential barriers in IRAS-PAT implementation and needed resources to overcome these barriers. Stakeholders were selected based on the recommendations of IOCS and a total of 34 stakeholders participated in the process. Most interviews were conducted in November and December, 2016. CCJR performed qualitative analysis of stakeholder feedback provided in the interviews and also asked stakeholders to complete a brief online survey. While participants were allowed flexibility to follow their own train of thought and to introduce topics of significance related to their own work experience, stakeholder discussions focused primarily on the following broad topics:

- Use of IRAS-PAT results to make release decisions
- Use of additional information (e.g., criminal histories) to make release and supervision decisions
- Challenges counties face incorporating and administering the IRAS-PAT
- Any legal or ethical issues of concern regarding use of the assessment tool

IRAS-PAT Implementation and Administration

Results from interviews and surveys are summarized in Appendix B and Appendix C. With regards to target populations, four of the pilot counties (Hamilton, Hendricks, Monroe, and Tipton) reported including all arrestees in their implementation plan. While most counties had a pilot program start date between June and October 2016 it is important to note that many of the counties were administering the IRAS-PAT prior to this start date. This illustrates an important finding in that county-level implementation is not only about administering the IRAS-PAT but also using the results in the pretrial release decision.

In order to examine trends in the administration of the IRAS-PAT across the pilot counties we examined data from INcite; a Trial Court Technology data management system for the IRAS. INcite data were examined from January 2014 through December 2016. Because the criminal caseload size of the counties ranged dramatically (from an estimated 360,000 in Allen County to 16,000 in Tipton County²) we grouped the counties into *large* (200,000 and over: Allen, Hamilton, and St. Joseph), *medium* (100,000 to 200,000: Porter, Hendricks, and Monroe), and *small* (100,000 and less: Bartholomew, Jefferson, and Starke) jurisdictions based on county level population estimates based on U.S. Census data.

The number of IRAS-PAT's administered were examined by quarterly periods over the three-year period are displayed in Exhibit 4-6. The overall patterns suggest that many counties increased the number of instruments administered after July 2016; for example, Starke, Jefferson, and Bartholomew all went from nearly no IRAS-PAT administrations in 2014 to 140, 250, and 134 completed instruments in 2016 respectively. Similarly, post October 2016 Monroe County had a dramatic increase and administered 450 instruments in three months

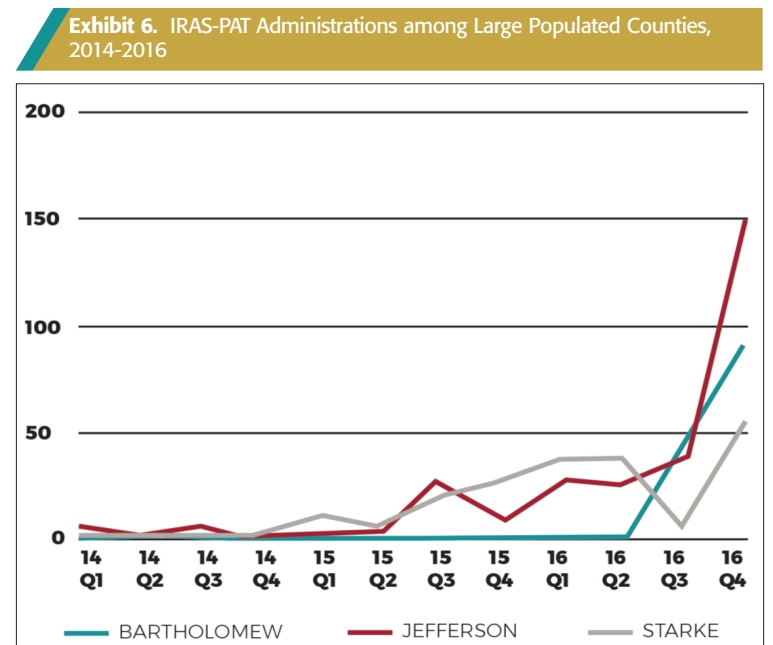
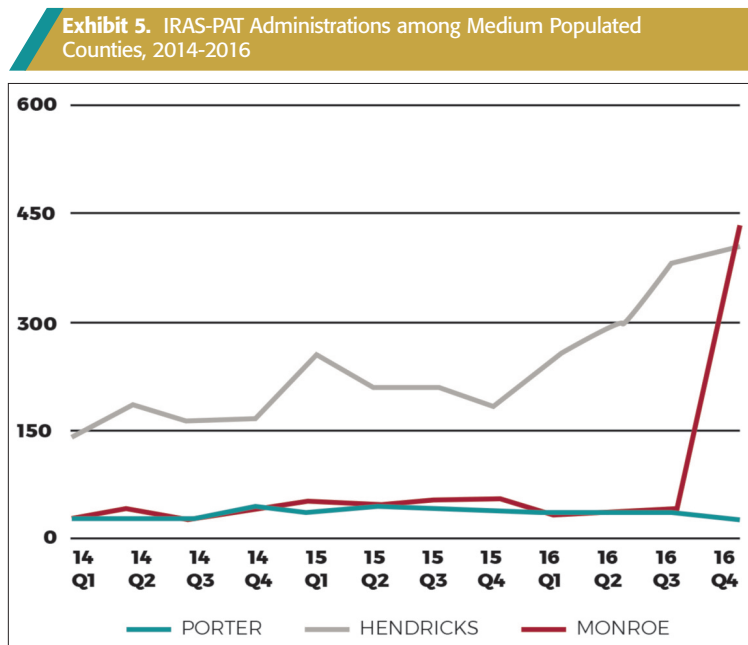
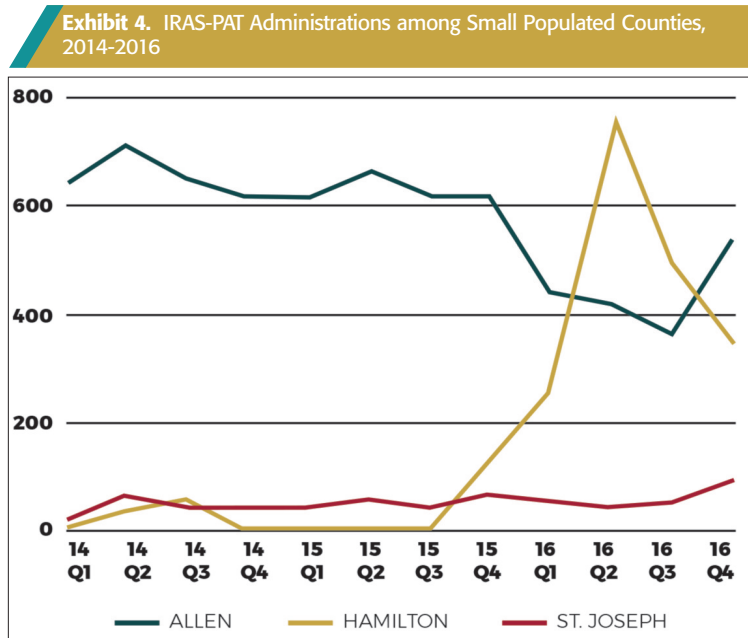
²Tipton County came on as a pilot county relatively late in the process and at the time of data collection had only administered 10 IRAS-PAT instruments and so we do not include them in this analysis.

while Hendricks County has been on a steady increase. There were some notable exceptions to these increases. Allen County had decreases in the number of IRAS-PAT administered throughout 2016 while Hamilton County increased to peak in April 2016 and then decreased. The other notable patterns are St. Joseph and Porter which have remained relatively steady throughout the study period.

The timing of when the IRAS-PAT is administered is also important to understanding whether the instrument is being used to inform pretrial release decisions.³ With the exception of St. Joseph County, all pilot sites reported administering the IRAS-PAT to individuals after jail intake or booking and prior to an initial court appearance. Most of the counties conduct the assessment within 24 hours of an individual's arrest.

The IRAS-PAT is administered by a variety of personnel across the pilot counties, including pretrial service officers, probation officers, and community corrections personnel. Nearly all of the pilot sites administer the tool at the county jail. CCJR researchers and IOCS inquired about the use of other risk assessment tools. Three of the sites—Bartholomew, Hamilton, and Tipton Counties—reported use of the Hawaii's Proxy Scale to assess risk. This instrument consists of three items related to arrestee's age and prior arrests (see Davidson, 2005; Wong, 2009). Based on responses to CCJR's brief online survey of key stakeholders and subsequent interviews, none of the pilot counties administer other assessment tools that would assess mental health and substance use issues at the time that the IRAS-PAT tool is administered. Jefferson County uses the Ontario Domestic Assault Risk Assessment (ODARA) tool for domestic violence cases; this 13-item tool is used to predict the risk of repeat domestic violence victimizations between intimate partners (see Hilton, Harris, Rice, et al., 2004).

With the exception of Porter (which was awaiting judicial approval to use the IRAS-PAT in decisions), all pilot counties report that parties present at initial court hearings are provided with pretrial assessment information prior to or during court appearances. In four of the pilot sites (Jefferson, Monroe, Starke, and Tipton Counties), pretrial services personnel attend initial court hearings and are



³We include a discussion of the main findings in the text; however, readers can refer to Appendix B and Appendix C for a breakdown of when and how counties are using the IRAS-PAT.

available to provide input if required. Additionally, most of the counties have developed guidelines or matrices that consider IRAS-PAT risk levels (along with pending charges) for pretrial release decisions. Four counties—Hendricks, Jefferson, St. Joseph, and Starke—report that these guidelines are under development. The pilot sites that report having pretrial release guidelines that take into account IRAS-PAT risk levels, also report that guidelines for levels of pretrial monitoring, supervision and/or conditions that consider risk assessment levels also are in place.

Emerging themes from stakeholder interviews

Interviews enabled researchers to incorporate the perspectives of a cross section of individuals from a variety of backgrounds working in local pretrial environments. This summary presents highlights of the information gathered from stakeholders in each of the pilot counties. Stakeholders provided valuable information on their current practices in the provision of pretrial services, administration of the IRAS-PAT, needs and resource allocation in service provision, data sharing policies and procedures, and potential obstacles and incentives to sustaining the program long-term. In synthesizing the information gathered during interviews with stakeholders, researchers observed a number of common themes emerging across counties.

BENEFITS TO IRAS-PAT PILOT PROGRAM PARTICIPATION

- Most counties reported that a packet of information including IRAS-PAT results, criminal history, and other information is provided to judges, prosecutors, and defense attorneys prior to the initial hearing, and judges generally follow the recommendations related to release and supervision decisions (taking into account IRAS-PAT assigned risk levels) included in the packet.
- Most stakeholders conveyed that the pretrial recommendations are very helpful at initial hearings. These are most often based on a combination of IRAS-PAT scores, criminal history summaries, nature of current charges, prior FTAs, and supervision officers' recommendations regarding bond and supervision.
- Pilot counties also reported they have established local teams, representing a cross section of practitioners, committed to the pretrial risk assessment process, use of the IRAS-PAT instrument, and the provision of pretrial services. The creation of these teams has facilitated improved collaboration and sharing of information across departments and stakeholder groups, as well as a renewed commitment to program improvements that support evidence-based pretrial release decisions.

CONCERNS RELATED TO USE OF IRAS-PAT

- Some stakeholders reported concerns related to the lack of consensus regarding commitment to use of the IRAS-PAT in making pretrial release decisions. It was reported that, in most cases where notable concerns exist, judges and prosecutors tend to be more skeptical about use of the IRAS-PAT.

- Some of those interviewed perceive that IRAS-PAT scores and assigned risk levels are not always aligned with knowledge of defendants' records; and do not believe that the tool is as comprehensive and thorough as it could be in addressing arrestee risk factors.
- A few stakeholders expressed concerns about the self-reported nature of the information gathered through the IRAS-PAT (e.g., *an individual with a serious substance abuse problem most likely will not admit to being an addict in a criminal justice system setting*).
- Most counties expressed concerns regarding the lack of resources needed to 1) administer the IRAS-PAT to current local target populations, 2) collect data needed to assess program practices and outcomes, both locally and at the state level, and, 3) expand use of the instrument to a wider population in the future. Inadequate resources was broadly identified as the greatest obstacle to sustaining the IRAS-PAT program long-term.
- Some stakeholders who were interviewed stated that implementation of IRAS-PAT has been time-consuming and logistically difficult to get pretrial services officers to buy into. Additionally, as noted previously, many counties indicated the complexity of the data collection process and the lack of integration across local data systems has led to challenges with sharing information with local teams, the state EBDM, and researchers tasked with evaluation of the program.

PRELIMINARY ANALYSIS OF IRAS-PAT DATA

Early in the planning process, CCJR researchers worked closely with IOCS to determine the use of existing data systems in combination with the IRAS-PAT data in INcite. As discussed further below, the research team had a difficult time linking the INcite data to existing data systems (i.e., state-level court data and county-level jail data). However, because the INcite data are able to accurately and consistently capture the results of IRAS-PAT's administered we begin with analysis of these data. As noted above, the INcite data on the IRAS-PAT ranged from January 1, 2014 through December 31, 2016. There were 15,850 cases initially; however, 1290 had a duplicate name and year of birth. Therefore, for the purposes of this analysis we looked at the first IRAS-PAT administered among 14,560 cases. Exhibit 7 illustrates the sociodemographic data among the IRAS-PAT cases; the average age was 33.4 years old; 72.3% were male; 68.8% were white, 25.7% were Black or African American, and 5.5% were from another race/ethnicity category; and 44.2% were charged with a felony offense.

The IRAS-PAT is scored from 0 to 9. Among the full sample (N=14,560) the average score was 3.23 (SD=1.87) and as shown in Exhibit 8, 38.6% were scored as Low risk, 49.3% Moderate risk, and 12.1% High risk. Exhibit 9 provides descriptive statistics for each of the items scored for the IRAS-PAT. Among those who completed the IRAS-PAT most were arrested before the age of 33 (89.2%), did not have any FTA warrants in the 24 months prior (83.1%), and did not have three or more prior jail incarcerations (70.5%). Nearly two-thirds were employed (47.8% full-time and 15.6% part-time) and lived at the same residence for the past six months (66.6%), while 56.1% reported illegal drug use in the past months and 16.2% reported a severe drug use problem..

Next, we looked at the sociodemographic data by IRAS-PAT risk category. As shown in Exhibit 10, the characteristics were fairly similar among the three categories. The low risk tended to be older (36.1 years) compared to the moderate (31.7 years) and high (31.8 years) risk groups. The high risk group was more likely to be female (31.2%) and White (76.9%) than those who were low and moderate risk. Notably, the offense type did vary according to risk categorization as over half (55.2%) of those who were categorized as low risk were charged with a misdemeanor, followed by 39.0% moderate risk cases, and 30.1% of high risk cases.

Finally, we examined how the IRAS-PAT scores varied across the counties. Recall, pilot counties were empowered to screen all arrestees or identify select arrestee

populations to screen. Exhibit 11 shows the breakdown of risk categorization for each county and also displays a horizontal line to show the average for each of the categorizations. There is significant variability among the counties in terms of

Exhibit 7. Sociodemographic Characteristics for IRAS-PAT Cases, 2014-2015

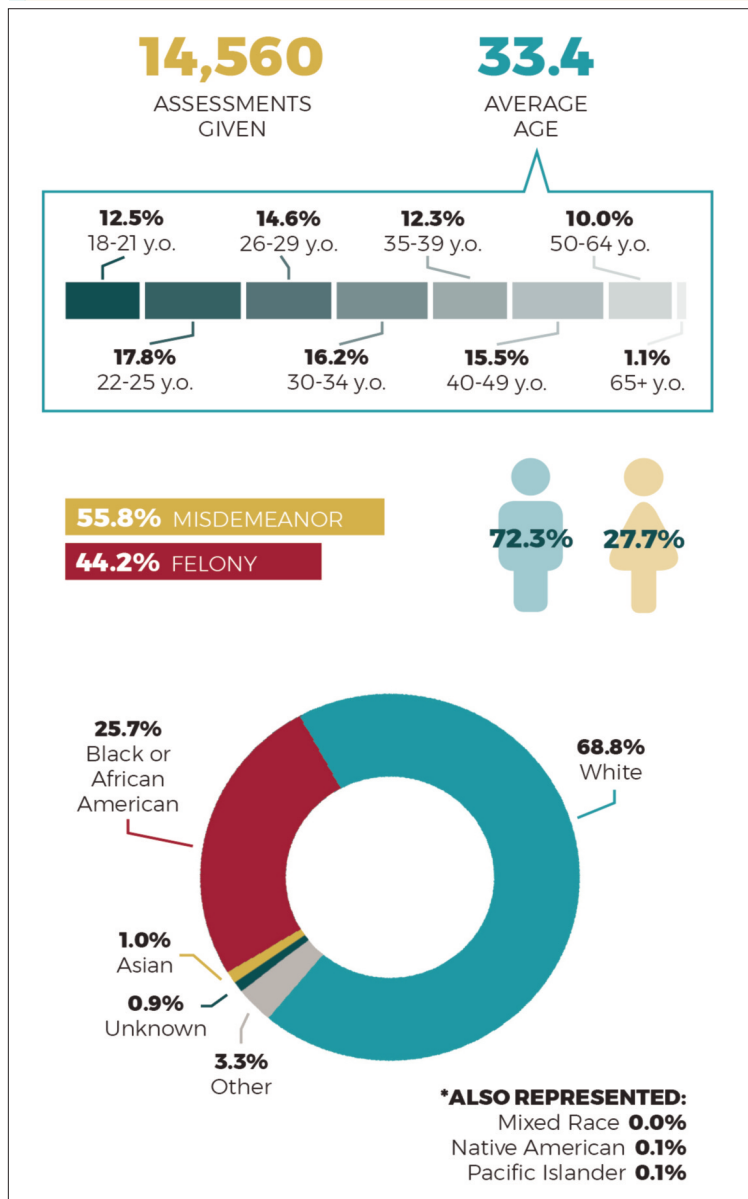


Exhibit 8. IRAS-PAT Risk Categories

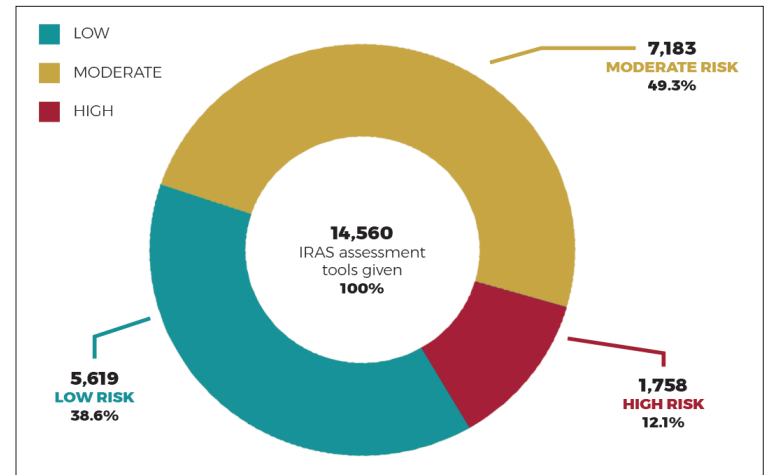


Exhibit 9. Responses to IRAS-PAT Items

	Count	Percentage
Age at First Arrest		
33+	1,568	10.8
Under 33	12,992	89.2
Number of FTA Warrants Past 24 Months		
None	12,094	83.1
One Warrant for FTA	1,724	11.8
Two or More FTA Warrants	742	5.1
Three or More Prior Jail Incarcerations		
No	10,266	70.5
Yes	4,294	29.5
Employed at the Time of Arrest		
Yes, Full-Time	6,966	47.8
Yes, Part-Time	2,275	15.6
Not Employed	5,319	36.5
Residential Stability		
Lived at Current Residence Past 6 Months	9,700	66.6
Not Lived at Same Residence	4,860	33.4
Illegal Drug Use During Past 6 Months		
No	8,172	56.1
Yes	6,388	43.9
Severe Drug Use Problem		
No	12,196	83.8
Yes	2,364	16.2

risk categorization as some counties. To examine this further Exhibit 12 shows the individual responses to each of the IRAS-PAT items by county and county size. It is important to note that these differences should not be seen as reflecting differences in the risk level of the county-level jail population but are more likely the result of variation in the county target population. For example, while a large county overall, Allen County has a narrow target population (e.g., non-violent F5/F6 arrestees) while Bartholomew County, a smaller county, has a much different target population which largely consists of those arrestees with warrants issues or charges filed. Thus, the variation in risk is likely to do differences in implementation—such as the target population the county selected and the timing of risk assessment administration—rather than overall risk within the counties arrestee population.

LINKING IRAS-PAT TO EXISTING DATA SOURCES

The final component in our evaluation of the pretrial pilot project was to link the INcite data, where information about the IRAS-PAT is contained, to court and jail data. Doing so would allow us to examine a variety of research questions relevant to the implementation, assessment, and impact of the IRAS-PAT tool and decisions regarding the IRAS-PAT score; for example:

- The time between risk assessment outcome and release from jail
- Length of detention by risk assessment outcome
- Risk assessment outcomes and court decisions
- The success rate of defendants by risk assessment outcome

In Indiana, a majority of counties use the Odyssey Case Management System (Odyssey) which is a fully integrated web-based case management system designed specifically for statewide deployment. With the exception of Jefferson County, all of the counties in the current evaluation use Odyssey, and we were able to successfully acquire these data. However, identifying and acquiring jail data was much more

problematic as each of the counties use a different jail data management system and they are unable to export data extracts from these systems.⁴ Appendix D summarizes the status of local data collection efforts including local data systems currently in use, the mode of data provision, and whether or not historical jail data and/or quarterly post-pilot implementation data has been provided. During the stakeholder interview process, many counties noted challenges with data collection and the lack of integration across local data systems. *In order to sustain the pilot program and provide outcome based analysis and validation of the IRAS-PAT a more systematic approach to local data collection efforts will be necessary.*

Exhibit 10. Sociodemographic Characteristics by IRAS-PAT Risk Categories

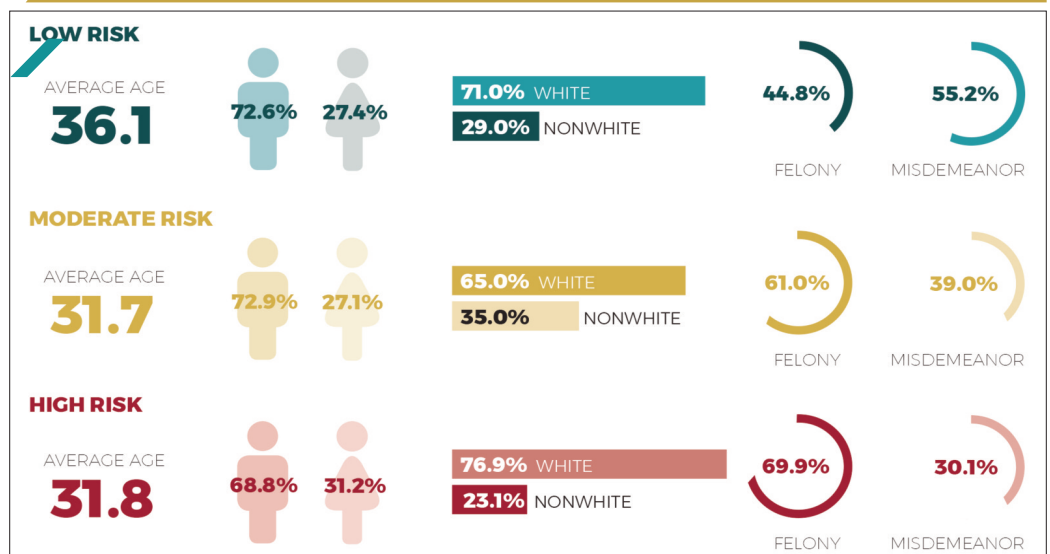
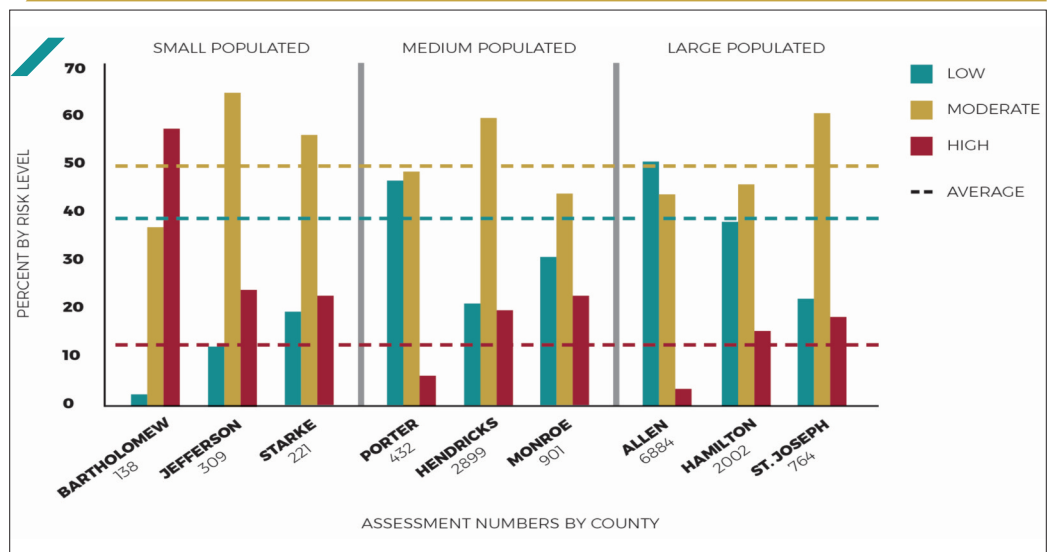


Exhibit 11. IRAS-PAT Risk Categories by County



⁴Having jail data is crucial to the analysis and validation of a risk assessment and would allow researchers to determine repeated periods of incarceration following risk assessment but more importantly they allows researchers to determine when an individual is as risk for pretrial misconduct. In this type of analysis, court data that do not contain release dates simply do not suffice. For example, if persons who are high risk remain in jail, but we do not know that they remain in jail or when they are released from jail, using court data to measure pretrial misconduct would artificially deflate failure rates for the high risk group as they would not have been released and at risk for pretrial misconduct.

Not only are these data necessary for pilot research, these collections will allow counties to self-assess their own progress and population trends as evidence-based pretrial release is scaled to statewide implementation. Thus, it is the primary aim of Phase 2 of the evaluation of the IRAS-PAT pilot program implementation to link INCite data to local jail data for the purposes of validating the IRAS-PAT at the county-level.

LINKING IRAS-PAT TO ODYSSEY DATA: BOND SET AND ORDER FOR RELEASE

While jail data were not available the Odyssey court data were accessible. The research team identified several issues when attempting to merge the Odyssey data to INCite data.⁵ However, we were able to link 79.5% (n=11,572) of the full sample of (N=14,560) IRAS-PAT cases to the Odyssey data. The proportion of matches by risk categorization among this subgroup is similar to the full sample with 39.3% low risk, 49.1% moderate risk, and 11.6% high risk.

Without jail data we do not know if or when the individuals assessed with the IRAS-PAT were released from incarceration. Therefore, we focused instead on court metrics for which we have data and that we might expect to be associated with risk categories. Specifically, we merged the IRAS-PAT data to the 'Bond Set – Released OR' data. In doing so, we found 1,338 cases where the administration of the IRAS-PAT preceded the decision of the court to set a bond and 603 cases where the administration of the IRAS-PAT preceded an order for release.⁶

Exhibit 13 shows the results among those cases where a bond was set (n=1338) and indicates that 50.1% of the cases are low risk, 45.7% moderate risk, and 4.2% high risk. **By risk distribution it is clear that few high risk arrestees had a bond set.** Looking at the sociodemographic characteristics of this group (Exhibit 14) reveals an average age of 34.8 years, 77.7% male, and 61.6% White.

Turning to the order for release group (n=603) we see that the largest portion among the risk categorizations is the moderate risk group (see Exhibit 15); 59.5% of those with an order for release were coded as moderate risk, 30.7% low risk, and 9.8% high risk. Exhibit 16 shows that average is 32.5 years old, with 73.1% male, 60.7% White, and 46.8% charged with a felony.

Exhibit 12. Responses to IRAS-PAT Items by County

	Small Populated Counties			Medium Populated Counties			Large Populated Counties		
	Bartholomew	Jefferson	Starke	Porter	Hendricks	Monroe	Allen	Hamilton	St. Joseph
Age at First Arrest									
33 or older	2.2	4.9	13.6	13.7	10.3	7.3	11.3	13.6	5.6
Under 33	97.8	95.1	86.4	86.3	89.7	92.7	88.7	86.4	94.4
Number of FTA Warrants Past 24 Months									
None	13.0	78.3	78.7	86.8	66.9	82.8	93.1	76.3	85.6
One Warrant for FTA	27.5	16.8	11.3	10.6	22.2	10.9	6.1	15.9	10.2
Two or More FTA Warrants	59.4	4.9	10.0	2.5	10.9	6.3	0.8	7.8	4.2
Three or More Prior Jail Incarcerations									
No	64.5	59.5	58.4	72.7	49.3	73.8	80.0	73.7	61.5
Yes	35.5	40.5	41.6	27.3	50.7	26.2	20.0	26.3	38.5
Employed at the Time of Arrest									
Yes, Full-Time	25.4	38.2	41.2	57.6	29.2	41.6	56.3	53.9	38.2
Yes, Part-Time	10.1	13.6	10.4	18.1	20.3	14.8	15.0	13.7	11.9
Not Employed	64.5	48.2	48.4	24.3	50.5	43.6	28.7	32.4	49.9
Residential Stability									
Lived at Current Residence Past 6 Months	47.1	53.4	65.2	75.9	61.0	62.0	70.7	67.5	58.4
Not Lived at Same Residence	52.9	46.6	34.8	24.1	39.0	38.0	29.3	32.5	41.6
Illegal Drug Use During Past 6 Months									
No	38.4	35.0	38.0	57.6	56.3	38.7	62.8	49.4	50.5
Yes	61.6	65.0	62.0	42.4	43.7	61.3	37.2	50.6	49.5
Severe Drug Use Problem									
No	71.0	47.2	49.8	85.2	84.4	61.6	94.5	72.1	67.7
Yes	29.0	52.8	50.2	14.8	15.6	38.4	5.5	27.9	32.3

⁵There are numerous Odyssey datasets for court related events (i.e., bonds, FTAs, order for release, dispositions, charges, etc.) and each of these datasets uses a CaseID number as a unique identifier of the court case. However, INCite does not use this CaseID. We were able to develop a work around for this as one of the Odyssey datasets called Parites has identifiable information (first name, last name, and year of birth) for the persons attached to each of the CaseID numbers. Here the issue is that there can be multiple CaseID numbers for that person if they had multiple court cases during the study period. Thus, in order to connect the IRAS-PAT data to the Odyssey-Parties we had to use name and year of birth, as well as the court date closest to the IRAS-PAT administration data, to merge these data and obtain a CaseID that could then be matched to the relevant Odyssey Court data files.

⁶It is also worth noting that among these cases 91.4% (n=1774) were from Allen County; however, for this analysis we looked at all of the cases with a match.

Finally, to explore these two outcomes we conducted a series of proportionality tests to examine whether there were significant differences between those arrestees who had a bond set and those with an order for release.⁷ Exhibit 17 shows the factors that were examined in this first analysis. To interpret this table one should consider that we are looking across each of the factors to determine how cases in this factor differed between having a bond set and an order for release. For example, the results suggest that those persons who were given an order for release were significantly younger (32.5 years vs.

34.8 years), more likely to be female (35.2% vs. 29.8%) than male, and more likely to have a felony charge (51.0% vs. 23.1%) than a misdemeanor. There were no statistically significant differences across race-ethnicity categories. For the IRAS-PAT risk categorization those who were low risk were less likely to have had an order for release than a bond (21.6% vs. 78.4%) as were those who were moderate risk (37.0% vs. 63.0%); however, those who were high risk were slightly more likely to have had an order for release (51.3% vs. 48.7%).

To further examine the differences in the IRAS-PAT we looked across outcomes by each of the IRAS-PAT factors. Exhibit 18 shows the differences in these factors between those who had a bond set and those who had an order for release; there were statistically significant differences across each of the factors. Those who had an age of first arrest under 33 were significantly more likely to have been given an order for release than those who were first arrested at 33 or older (32.2% vs. 19.4%). Those who had no prior FTAs in the past 24 months were less likely to have had an order for release than a bond set (29.5% vs 70.7%) and those who two or more FTAs in the past 24 months were slightly more likely to have had an

Exhibit 13. IRAS-PAT Risk Categories where Bond was Set

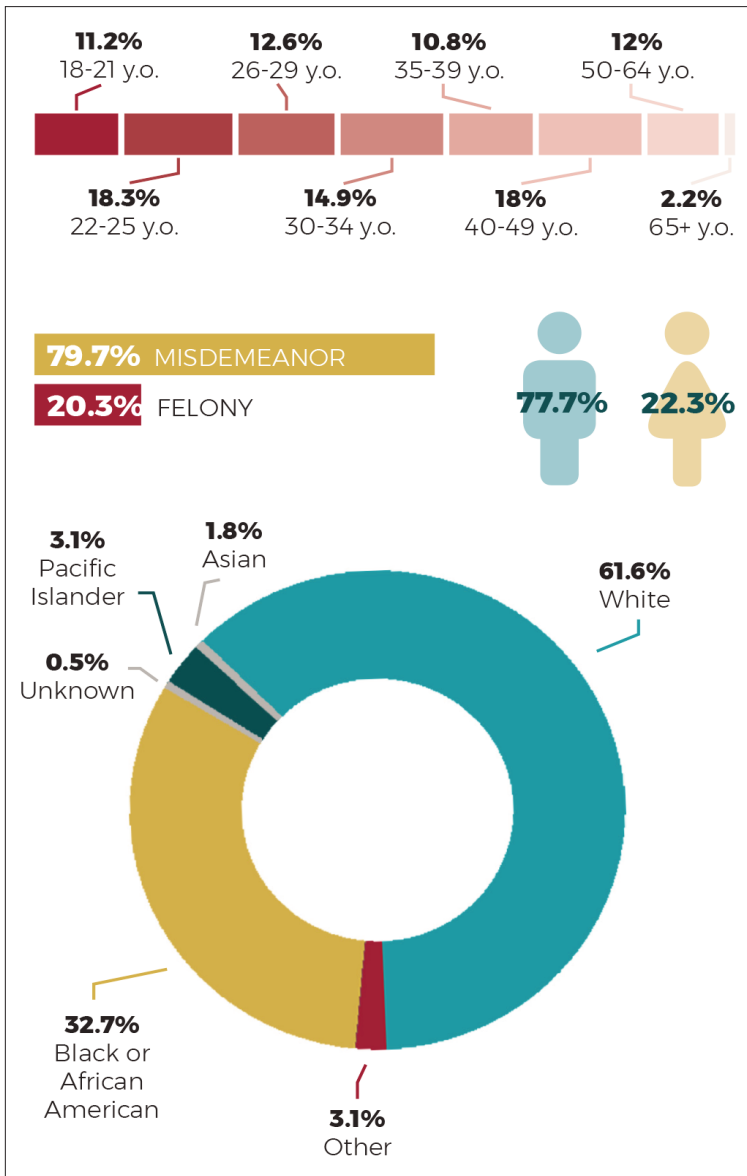
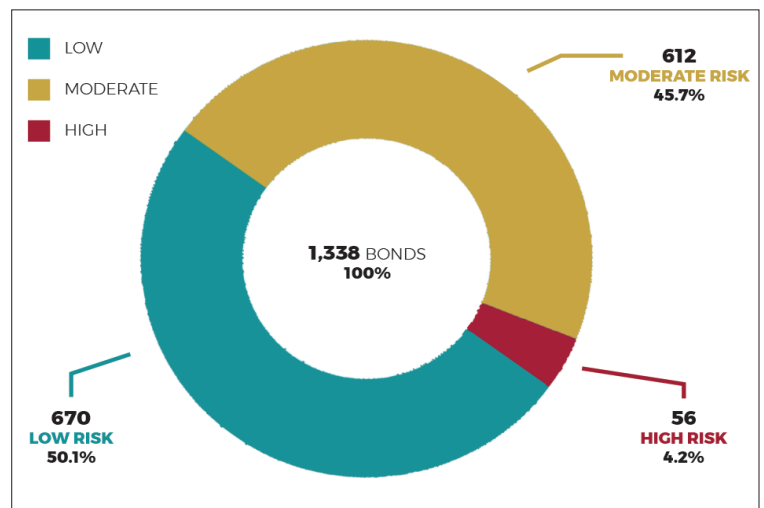


Exhibit 14. Sociodemographic Characteristics for IRAS-PAT Cases where Bond was Set



⁷It is important to note that we are only looking at the likelihood of these two events occurring as we do not have the necessary data to determine what happened post IRAS-PAT admission among the other cases.

Exhibit 15. IRAS-PAT Risk Categories with an Order for Release

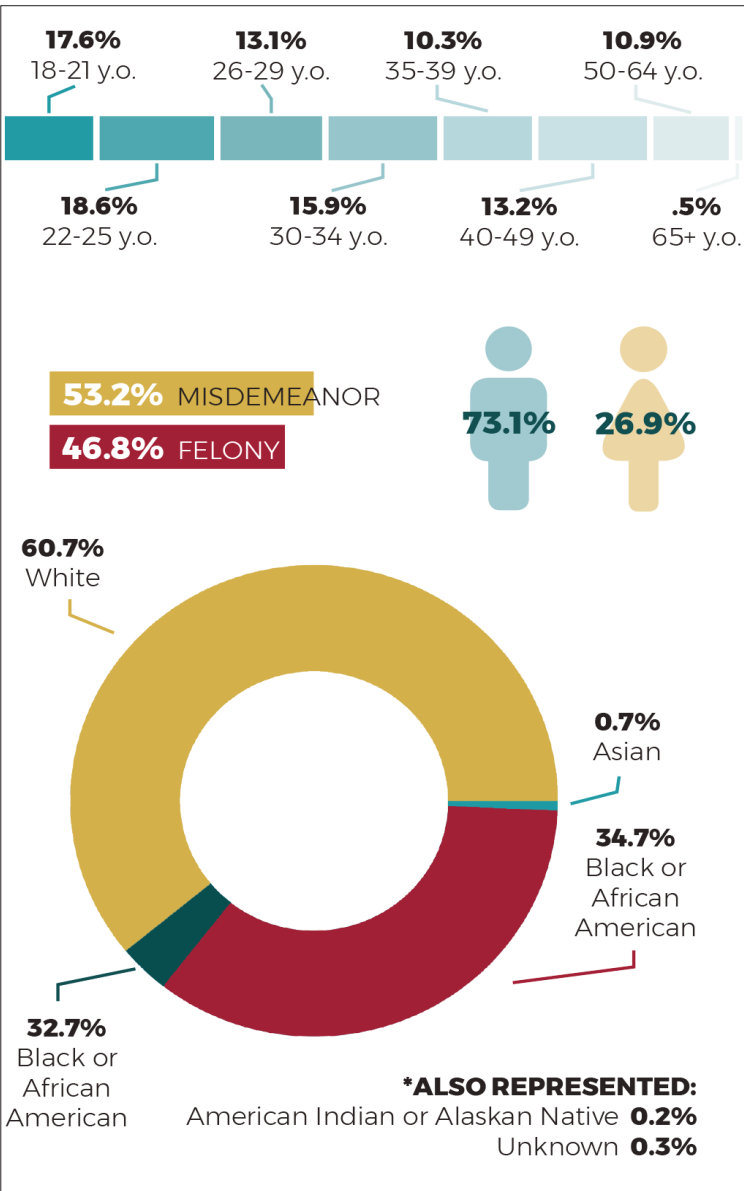
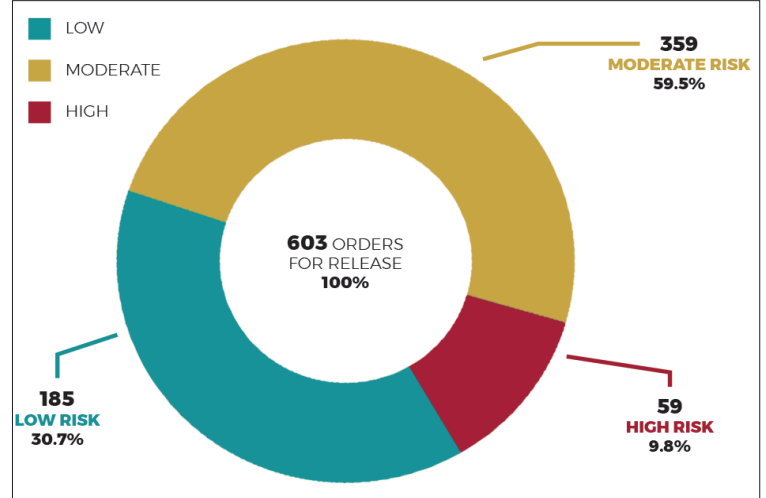


Exhibit 16. Sociodemographic Characteristics for IRAS-PAT Cases with an Order for Release



order for release than a bond set (54.5% vs. 45.5%). Those who had three or more prior jail incarcerations were more likely to have had an order for release than those without (37.2% vs. 29.3%) and those who employed full time were least likely to have had an order for release, followed by those employed part time, and then those who were not employed. Persons who lived at the same residence for the past six months were less likely than those who had not lived at the same residence to have had an order for release (29.3% vs. 34.6%). Finally, those who reported illegal drug use in the past six months and those who indicated having a severe drug use problem were both more likely to have had an order for release than those without reported drug use.

⁷It is important to note that we are only looking at the likelihood of these two events occurring as we do not have the necessary data to determine what happened post IRAS-PAT admission among the other cases.

Exhibit 17. Differences in Sociodemographic Factors by Outcome: Bond Set and Order for Release

	BOND	ORDER FOR RELEASE
AVERAGE AGE	34.8	32.5
SEX		
MALE	70.2%	29.8%
FEMALE	64.8%	35.2%
RACE/ETHNICITY		
WHITE	69.2%	30.8%
NON-WHITE	68.4%	31.6%
OFFENSE TYPE		
FELONY	49.0	51%
MISDEMEANOR	76.9%	23.1%
IRAS CATEGORY		
LOW	78.4%	21.6%
MODERATE	63%	37%
HIGH	48.7%	51.3%

Exhibit 18. Differences IRAS-PAT Factors by Outcome: Bond Set and Order for Release

	BOND	ORDER FOR RELEASE
AVERAGE FIRST ARREST		
33+	80.6%	19.4%
Under 33	67.8%	32.2%
NUMBER OF FTA WARRANTS PAST 24 MONTHS		
0	70.5%	29.5%
1 Warrant for FTA	52.6%	47.4%
2+ FTA Warrants	45.5%	54.5%
3+ PRIOR JAIL INCARCERATIONS		
No	70.7%	29.3%
Yes	62.8%	37.2%
EMPLOYED AT TIME OF ARREST		
Yes, Full Time	74.7%	25.3%
Yes, Part Time	69.8%	30.2%
Not Employed	59.3%	40.7%
RESIDENTIAL STABILITY		
Lived at current resident past 6 months	70.7%	29.3%
Not lived at same residence	65.4%	34.6%
ILLEGAL DRUG USE DURING PAST 6 MONTHS		
No	74.1%	25.9%
Yes	61.9%	38.1%
SEVERE DRUG USE PROBLEM		
No	71.1%	28.9%
Yes	43.7%	56.3%

CONCLUSIONS AND RECOMMENDED NEXT STEPS

There are several general findings that can be gleaned from this initial study. First, this study suggests that Indiana is successfully moving towards implementing the IRAS-PAT, an instrument that is consistent in terms of core elements with other instruments across the nation and which extant research shows is predictive of pretrial misconduct (Bechtel et al. 2016; Desmarais et al. 2016). In general, more arrestees across Indiana are being assessed for pretrial risk than before.

Second, this study identified a number of barriers that have occurred in the implementation of the IRAS-PAT. Specifically our interviews with key stakeholders in the pilot counties suggest that the lack of consensus and commitment to the IRAS-PAT—particularly in terms of its use in making pretrial release decisions—and concern around the validity and predictive ability of the instrument were barriers. Also notable were concerns around the time and resources needed to administer the IRAS-PAT and an inability to integrate existing data systems to examine outcomes associated with risk. However, it is important to note that despite these barriers this study found that pilot counties are increasingly administering the IRAS-PAT and often report doing so among all arrestees.

Third, in examining data on the IRAS-PAT instruments that have been administered we found that the overall risk categorization is consistent with national trends as the majority of arrestees are moderate and low risk; there are few differences by sociodemographic characteristics and risk categorization; yet there is variability in risk categorization by county. However, as noted above, these differences are more likely do to variation in the implementation plan of the county, such as who the IRAS-PAT was administered to and when it was administered in the arrest process, rather than variation in risk by county. Given that pilot counties were each able to develop their own implementation plan, this will require further research within each county to disentangle.

Finally, to explore these two outcomes we conducted a series of proportion tests to examine court outcomes of bond and order for release which suggest that the risk categorizations from the IRAS-PAT are not being considered in these decisions. Our results that younger females and felony offenders were more likely to have had an order for release than a bond. Moreover, the individual risk factors do not correspond to expected release decisions as those with prior FTAs and incarcerations, as well as a history of drug use, were more likely to have had an order for release than a bond. It is also important to note that additional data and analyses are needed to fully examine these outcomes and others as we are

only able to link up 13% of the IRAS-PAT cases to court outcome data. Moreover, perhaps one of the most important findings from this study, was our ability to identify issues that currently exist in regards to systematic and available statewide data elements. Specifically the lack of readily available jail data at the county and state level will constrain future evaluation research and the ability of local counties to self-assess pretrial operations.

Next Steps: Validation by County and Increased Efforts toward Implementation

Risk assessment tools consist of a number of different items empirically associated with social behavior and the literature clearly shows that some tools are more accurate than others. However, less than half of court jurisdictions employing pretrial risk assessments have conducted research or evaluations to assess the accuracy of their tools (Pretrial Justice Institute, 2010). This is an important next step for Indiana. Accuracy here has two meanings. First, assessment tools should produce consistent results upon repeated application to similar defendants by similar assessors. Not only should the tool be sound, the method of administering the assessment must also be systematic. Second, assessment tools should successfully describe, quantify, or predict the metric the tool was designed to measure. Generally speaking, this is the meaning of accuracy most describe when considering the value of any risk assessment tool.

In order to rigorously examine and ultimately validate the IRAS-PAT among the pilot counties we recommend two key steps to assure that data are systematically and consistently collected. First, all relevant Odyssey data metrics—such bond set, FTA, order for release, etc.—should be fully operationalized and defined by IOCS and county court personnel should be retrained on the correct meaning of these concepts and how to interface and collect these metrics consistently. Second, and most importantly, a plan needs to be developed to collect similar jail data metrics in a consistent way across each of the counties. At a minimum researchers need information that can link up INcite data to local jail data but also necessary are individual-level metrics on the arrest and release data for all persons who enter the jail and are eligible to have the IRAS-PAT administered on them.

Finally, while the results are preliminary, we suggest that further efforts are necessary to help implement the IRAS-PAT into the pretrial decision making process. Ideally this would entail having the IRAS-PAT risk categories built into release decisions.

Appendix A. Expectations of Indiana EBDM & Pretrial Pilot Sites

Developed by the Indiana EBDM State Policy Team

1. Guided by a collaborative team process, Indiana pretrial pilot sites will develop and implement pretrial pilot projects within the context of the National Institute of Corrections Evidence Based Decision Making (EBDM) Framework.
2. The following stakeholders will be invited to become members of the local collaborative team:
 - a. Law Enforcement Officials
 - b. Pretrial Officials
 - c. Victim Service Providers
 - d. Prosecutors
 - e. Defense Attorneys
 - f. Jail Administrators
 - g. Court Administrators
 - h. Judges (all criminal court judges are strongly encouraged to actively participate)
 - i. Probation/Parole/Community Corrections Officials
 - j. City/County Managers/Commissioners/County Councils
 - k. Behavioral Health and Human Service Representatives
 - l. Local teams are encouraged to invite faith based organizations, and/or other key community stakeholders.

In selecting stakeholder representation and collaborative team members, each team should ensure the representation is also diverse in nature (e.g. minority representation, gender diversity, etc.)
3. The team will work together collaboratively on all aspects of the development and implementation of the pretrial pilot project.
4. The team will work collaboratively with their local counterparts, the EBDM State Policy Team, and their assigned technical assistance provider(s) in the development, implementation, and enhancement of their pretrial pilot projects.
5. The team is encouraged to discuss, agree upon, and document a set of principles to guide their pretrial work. The following guiding principles have been developed by the EBDM State Policy Team:
 - a. Indiana's pretrial system should strive to achieve the "3 M's":
 - i. Maximize public safety
 - ii. Maximize court appearance
 - iii. Maximize pretrial release

- b. Indiana's pretrial system should:
 - i. Be fair; a pretrial system that is fair is not based on ability to pay, but instead is based on the assessment of objective factors relevant to public safety and court appearance
 - ii. Reduce harm; a pretrial system that reduces harm protects the public from those who pose a danger to the community, while reducing the detention of those whose risk to public safety may actually be increased as a result of pretrial detention
 - iii. Be informed; a pretrial system that is informed is guided by social science research along with comprehensive case-specific information
 - iv. Be parsimonious¹; a pretrial system that is parsimonious reserves expensive jail resources for those who pose a danger to public safety and utilizes non-detention based interventions (e.g., mental health/substance abuse services, pretrial supervision) for those who can be safely managed in the community
6. The team will participate in the cross-site efforts to collect and analyze data in order to establish baseline information about pre-pilot pretrial practices and their impact and the impact of the pilot projects.
7. Pretrial pilot sites are encouraged to review their bond schedule(s) and agree upon a single bond schedule for use within the county. When developing local bond schedules, sites should be mindful that the purpose of bond is to ensure appearance, not to collect fines, costs, and fees.
8. Pretrial pilot sites will operate a risk-informed pretrial system. All pilot sites will use the Indiana Risk Assessment System – Pretrial Assessment Tool (IRAS-PAT). Pilot sites may use additional assessment tools and information as they determine appropriate (e.g., criminal history, supplemental tools to assess violence, substance abuse and mental health assessment information, a secondary risk assessment tool). Sites must establish a policy and procedure that identifies when the assessment is administered and who or what agency administers the assessment.
9. Pretrial pilot sites will develop and implement processes to verify the accuracy of the information obtained to score the risk assessment (e.g., NCIC records check, collateral contacts, etc.), to document the verification sources, and to report whether data has been verified.
10. Assessors will be credentialed in the administration and scoring of the IRAS-PAT as well as any other tools used to assess pretrial risk. Assessors will also participate in periodic training and recertification activities pursuant to the Indiana Risk Assessment Policy.

¹To be parsimonious is to use resources as effectively as possible.

Appendix A. (continued)

11. Pretrial pilot sites will develop and implement a local quality assurance protocol to assure the integrity of the administration, scoring, and use of the risk assessment tool(s).
12. Pretrial pilot sites will utilize a common pretrial assessment report form. This form will be developed by the EBDM State Policy Team, with input from representatives from the pilot sites². Initially the form will be developed in “paper and pencil” format. Ultimately the form will be developed in INcite to enable local and cross-site data collection and analysis.
13. Pretrial pilot sites will develop and implement a court reminder system. The method used (e.g., phone calls, robo-calls, etc.) will be locally determined.
14. Pretrial pilot sites will develop and implement a “look-back” process to identify defendants who remain in detention past the point at which release was expected to have occurred.
15. Pretrial pilot sites will develop and implement a differential supervision approach for those defendants on pretrial release. The EBDM State Policy Team will develop a model that can be tailored to meet local pilot sites’ needs and resource capacity³.
16. Pretrial pilot sites will develop and implement a structured method to respond to pretrial misconduct (i.e., rule infractions, FTA, new arrests). The EBDM State Policy Team will develop a model that can be tailored to meet local pilot sites’ needs and resource capacity⁴.
17. For arrestees who remain in custody, pretrial pilot sites will establish a speedy, meaningful first appearance during which all parties (court, prosecution, defense counsel) are present and the pretrial report is reviewed.
18. Pretrial pilot sites will work collaboratively with their state partners to educate colleagues and the broader community on the goals and values of Indiana’s pretrial justice system.
19. Each of the pilot sites will develop a written protocol to document adherence to these principles.
20. Each of the pilot sites will establish a process for reviewing critical incidents (as defined by the pilot site) to determine any need to adjust local pretrial release policies and procedures.

²Draft to be developed by DATE TBD.

³Draft to be developed by the EBDM State Policy Team.

⁴Draft to be developed by the EBDM State Policy Team.

Appendix B. IRAS-PAT Administration

Pilot County	Pilot program start date	Target population	Timeframe for administering tool		Location tool administered	Tool administered by:	Other risk assessment tools used pretrial	Other assessment tools used pretrial
Allen	15-Mar-16	Non-violent F5/F6 warrantless arrestees with a prior felony conviction and felony Habitual Traffic Violators. Participants are identified by the Prosecutor's Office.	After jail intake/booking but prior to initial court appearance on "pilot population" and Post-initial hearing on "non-pilot population"	Within 24 hours on "pilot population," unless arrest occurs weekend; post-initial hearing on "non-pilot population who post bond"	County jail	Pretrial service officers	P-RAS	None
Bartholomew	15-Sep-16	All pretrial arrestees except for IDOC holds, probation violators, parole violators, out-of-county warrants, and ICE holds.	At jail intake/booking as well as after jail intake/booking but prior to initial court appearance	Within 24 hours of arrest	County jail	Court services staff	Hawaii Proxy	None
Hamilton	1-Jun-16	New arrestees	At jail intake/booking as well as after jail intake/booking but prior to initial court appearance	Within 8 hours of arrest	County jail	Probation officers, jail and community corrections staff	Hawaii Proxy	None
Hendricks	1-Jan-16	Any individual arrested and place in jail	After jail intake/booking but prior to initial court appearance	Within 24 hours of arrest	County jail	Probation officers	None	None
Jefferson	1-Oct-16	Pretrial defendants	After jail intake/booking but prior to initial court appearance	Within 24 hours of arrest during week; within 72 hours of arrest on weekends	County jail	Community Corrections staff - pretrial services coordinator and pretrial case manager	None	ODARA for domestic violence cases
Monroe	1-Oct-16	Any individual arrested and place in jail	After jail intake/booking but prior to initial court appearance	If arrestee is released pursuant to bond schedule, individual signs promise to appear for pretrial intake and assessment on the next business day. Ineligible for monetary bond or unable to post bond, are assessed within one business day of arrest	Jail for defendants who do not post bail; Probation Office for defendants who post bail	Probation officers	None	None
Porter	1-Mar-17	Arrestees charged with felony		Within 24 hours of arrest	County jail	Community Corrections staff	None	Domestic violence assessment
St. Joseph	1-Jul-16	Felony arrestees; currently use a presumptive ROR list for misdemeanor offenses unless override by prosecutor or courts	After initial court appearance	Conducted as ordered by court for those unable to post bond on felony cases	Defendants interviewed at the county jail if still in custody; at probation department if released	Probation officers	None	ODARA for domestic violence cases
Starke	1-Jan-16	Arrestees charged with felony	After jail intake/booking but prior to initial court appearance	Within 48 hours of felony arrests	County jail	Pretrial services officer, probation staff	None	None
Tipton	1-Oct-16	All arrestees	After jail intake/booking but prior to initial court appearance	Within 72 hours of arrest; If eligible to be released, individual signs form that he/she will contact community corrections office within 24 hours	Community Corrections	Community Corrections staff	Hawaii Proxy	None

Appendix C. IRAS-PAT Results Usage in Pretrial Release and Supervision Decisionbs

Pilot County	Parties present at initial court hearing	Are parties provided pretrial assessment information prior to or during initial court appearance?	Are pretrial services staff present at initial court hearing?	Guidelines/matrix to guide pretrial release decisions	Jurisdiction provide pretrial supervision	Who is supervised	Guidelines/matrix for establishing levels of pretrial monitoring, supervision and/or conditions
Allen	Magistrate/Court Commissioner, prosecutor, public defender/defense attorney	Yes, when requested by the court; parties receive assessment report (including criminal history and FTA information) prior to hearing	Yes	Low or medium risk - defendant is released OR with standard conditions of supervision/ If HIGH risk - defendant is held with bond and can adhere to existing bond schedule	Yes	Low, medium, high and other specific charge types regardless of risk level	Yes
Bartholomew	Judge, Magistrate/ Court Commissioner	Yes, arrestee not ROR will have a report completed by the Pretrial Officers that contains risk information and recommendation for detention/release	No	Pretrial officers use matrix to determine if individual should be released immediately or held over for court	Yes	Medium and low risk pretrial releases and other specific charge types regardless of risk level	Yes
Hamilton	Judge, Magistrate/Court Commissioner, prosecutor, public defender/defense attorney	Yes, assessment report emailed to court and parties	No	Incorporated into local rule and used throughout pretrial process	Yes	Low, medium and high risk pretrial releasees	Yes
Hendricks	Magistrate/Court Commissioner, prosecutor, public defender/defense attorney	Yes, intake report and risk assessment results distributed at initial hearing	No	Under development	Under development	Under development	Under development
Jefferson	Judge, pretrial staff, prosecutor, public defender/defense attorney	Yes, court and parties also receive copy of assessment	Yes	Under development	Yes	Low, medium, high and other specific charge types regardless of risk level	Yes
Monroe	Judge, pretrial staff, prosecutor, public defender/defense attorney	Yes, pretrial staff provide pretrial release recommendations to parties prior to initial hearing	Yes	Matrix considers IRAS-PAT risk level and pending charges to guide release information.	Yes	Low, medium, high and other specific charge types regardless of risk level	Yes
Porter							Awaiting judicial approval
St. Joseph	NA - IRAS-PAT administered after initial hearing	NA - assessment report provided to court when ordered	No	Under development	Yes	As ordered by the court	Under development
Starke	Judge, Magistrate/Court Commissioner, pretrial staff, prosecutor, public defender/defense attorney	Yes, results of assessment are incorporated into bond report provided to all parties	Yes	Under development	Yes	All pretrial releasees	Under development
Tipton	Judge, prosecutor, public defender/defense attorney	Yes, risk level is made available at court appearance and report includes criminal history and performance under supervision	Yes	Matrix considers IRAS-PAT risk level and pending charges to guide release information.	Yes	Low, medium, high and other specific charge types regardless of risk level	Yes

Appendix D. IRAS-PAT Data Collection and Evaluation

Pilot County	Data systems used	Historical jail data received	Qtrly post-pilot implementation data received	Mode of data provision
Allen	Odyssey, INcite, IDACS, Pretrial CMS (CAD), Justice Exchange - Appriss, Law enforcement database (Spillman)	No	No	Jail data exported as PDF, not suitable for analysis in current form
Bartholomew	Courts: JTS w/change to Odyssey in 2016, Justice Exchange – Appriss, Incite, Sheriff/Jail/Police: OSSl, Court Services: PBS/Informer	Yes	Yes (Q1, Q2)	Separate pretrial data spreadsheet
Hamilton	Odyssey, New World, IDACS	No	No	na
Hendricks	Odyssey, INcite, PCMS, doxPOP, NCIC, IDACS	Yes	Yes	IU CCJR web-based data entry tool
Jefferson	Court Management and CMS systems - PBS, Justice Exchange - Appriss	No	Yes (Q1, Q2)	Separate pretrial data spreadsheet
Monroe	Odyssey, Quest CMS, Justice Exchange - Appriss	Yes	No	Extract data directly from jail system
Porter	Odyssey, Justice Exchange – Appriss, Other Google	No	No	na
St. Joseph	Odyssey, Supervision CMS - DataEase and Odyssey, CISCO, Informer for GPS clientele	Yes	No	Separate pretrial data spreadsheet
Starke	Court Management System: Odyssey, Supervision CMS: Odyssey, Justice Exchange - Appriss	Yes	Yes	IU CCJR web-based data entry tool
Tipton	Odyssey, PBS, Jail Data System - Sunguard live June 1st	Yes	No	Extract data directly from jail system

REFERENCES

*Indicates Recommended Resources

- American Bar Association. (2007). *ABA Standards for criminal justice: Pretrial release* (3rd ed.). Washington, DC: American Bar Association.
- Bechtel, K., Holsinger, A. M., Lowenkamp, C. T., & Warren, M. J. (2016). A meta-analytic review of pretrial research: Risk assessment, bond type, and interventions. *American Journal of Criminal Justice*. DOI: 10.1007/x12103-016-9367-1.
- BKD. (2016). *Jail capacity data analytics: Strategic plan for the city of Indianapolis – Marion County*. Kansas City, MO: BKD.
- *Clark, J. & Henry, D. A. (2001). *Pretrial service programming at the start of the 21st century: A survey of pretrial service programs*. Washington DC: US Department of Justice, Office of Justice Programs, National Institute of Justice.
- *Coopridge, K. (2009). Pretrial risk assessment and case classification: A case study. *Federal Probation*, 73, 12-15.
- Coopridge, K. W., Gray, R., & Dunne, J. (2003). Pretrial services in Lake County, Illinois – Patterns of change over time, 1986-2000. *Federal Probation*, 67(3), 33-41.
- Davidson, J. (2005). *Screening for risk of re-offending: Hawaii's proxy scale and level of service inventory-revised*. Honolulu, HI: State of Hawaii, Interagency Council on Intermediate Sanctions.
- Desmarais, S. L., Johnson, K. L., & Singh, J. P. (2016). Performance of recidivism risk assessment instruments in U.S. correctional settings. *Psychological Services*, 13(3), 206-222.
- Gottfredson, S. D. & Gottfredson, D. M. (1986). Tools for structuring court discretion; What do they work for and why don't they work better? *Criminal Justice Policy Review*, 1(3), 268-285.
- Governor's Commission to Reform Maryland's Pretrial System. (2014). *Governor's Commission to reform Maryland's Pretrial System: Final report*. Annapolis, MD: Office of the Governor of Maryland.
- Gupta, A., Hansman, C., & Frenchman, E. (2016). The heavy costs of high bail: Evidence from judge randomization. *The Journal of Legal Studies*, 45(2), 471-505.
- Heaton, P. S., Mayson, S. G., & Stevenson, M. (2017). The downstream consequences of misdemeanor pretrial detention. *Stanford Law Review*, 69, 711-794.
- Hedlund, J., Cox, S. M., Hines, M., Carollo, J., & Dwyer, L. (2005). *Development and validation of an assessment for pretrial conditional release*. New Britain, CT: Central Connecticut State University, Department of Criminology and Criminal Justice.
- Hedlund, J., Hines, M., & Carollo, J. (2007). *Expanded validation of a decision aid for pretrial conditional release*. New Britain, CT: Central Connecticut State University, Department of Criminology and Criminal Justice.
- Hilton, N. Z., Harris, G. T., Rice, M. E., Lang, C., Cormier, C. A., & Lines, K. J. (2004). A brief actuarial assessment for the prediction of wife assault recidivism: The Ontario Domestic Assault Risk Assessment. *Psychological Assessment*, 16(3), 267-275.
- Jones, P. R. & Goldkamp, J. S. (1991). The bail guidelines experiment in Dade County, Miami: A case study in the development and implementation of a policy innovation. *Justice System Journal*, 14/15(3/4), 445-476.
- Lotze, E., Clark, J., Henry, D. A., & Juskiewicz, J. (1999). *The pretrial services reference book: History, challenges, programming*. Washington, DC: Pretrial Services Resource Center.
- Lowenkamp, C. T. & Bechtel, K. (2009). *Meeting pretrial objectives: A validation of the Summit County pretrial risk assessment instrument (SCPRAI)*. Cincinnati, OH: University of Cincinnati, Center for Criminal Justice Research.
- Lowenkamp, C. T., VanNostrand, M., & Holsinger, A. (2013b). *Investigating the impact of pretrial detention on sentencing outcomes*. Houston, TX: Laura and John Arnold Foundation.
- Lowenkamp, C. T. & Wetzel, J. (2009). The development of an actuarial risk assessment instrument for US Pretrial Services. *Federal Probation*, 73(2), 33-36.
- Mamalian, C.A. (2011). *The state of the science of pretrial risk assessment*. Washington, DC: US Department of Justice, Office of Justice Programs, Bureau of Justice Assistance.
- Minton, T. D. & Zeng, Z. (2015). *Jail inmates at midyear 2014*. Washington, DC: US Department of Justice, Office of Justice Programs, Bureau of Justice Statistics.
- *Myburgh, J., Camman, C., & Wormith, J. S. (2015). *Review of pretrial risk assessment and factors predicting pretrial release failure*. Saskatoon, SK: University of Saskatchewan, Centre for Forensic Behavioural Science and Justice Studies.
- *National Association of Pretrial Services Agencies. (2004). *Standards on pretrial release* (3rd ed.). Washington, DC: National Association of Pretrial Services Agencies.
- Ortiz, N. R. (2015). *County jails at a crossroads: An examination of the jail population and pretrial release*. Washington, DC: National Association of Counties.
- Phillips, M. T. (2004). *Release and bail decisions in New York City: Research brief*. New York, NY: Criminal Justice Agency, Inc.
- Prell, L. (2008). *Validation of the Fifth Judicial District Pretrial Release Point Schedule on Polk County defendants*. Des Moines, IA: Iowa Department of Corrections.
- *Pretrial Justice Institute. (2010). *Pretrial justice in America: A survey of county pretrial release policies, practices and outcomes*. Rockville, MD: Pretrial Justice Institute.
- Reaves, B. A. (2013). *Felony defendants in large urban counties, 2009*. Washington, DC: US Department of Justice, Office of Justice Programs, Bureau of Justice Statistics.
- Stevenson, M. (2016). *Distortion of justice: How the inability to pay bail affects case outcomes*. Philadelphia, PA: University of Pennsylvania Law School.
- Tsarkov, A. (2017). *Report to the Governor and the General Assembly on pretrial release and detention in Connecticut*. New Britain, CT: Connecticut Sentencing Commission.
- Winterfield, L., Coggeshall, M., & Harrell, A. (2003). *Development of an empirically-based risk assessment instrument: Final report*. Washington, DC: Urban Institute.
- Wong, T. (2009). *Validation of the state of Hawaii LSI-R proxy*. Honolulu, HI: State of Hawaii, Interagency Council on Intermediate Sanctions.

Process Evaluation of the IRAS-PAT Pilot Program Implementation

Report to the Indiana Office of Court Services

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Development of the
Nevada Pretrial Risk Assessment System
Final Report

Prepared by

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June 2016

Introduction

This report summarizes how the Nevada Pretrial Risk Assessment (NPR) was developed. It provides a description of the procedures and research methods (including sampling process, data collection and analysis) that were used to create a validated instrument for Nevada's criminal courts. It should be emphasized that further testing and analysis will be required as the NPR is used on a pilot basis for Clark, Washoe and White Pine counties over the next 12 months.

This study was supported by the U.S. Department of Justice, Office of Justice Programs, which provides technical assistance to state and local criminal agencies through its Diagnostic Center program. This technical assistance effort was coordinated by Angela Jackson-Castain who provided all of the administrative and management for the project.

Development of the Proto-type Instrument

Under the leadership of Associate Chief Justice James W. Hardesty, a Committee to Study Evidence-Based Pretrial Release in Nevada was convened in 2015. The purpose of the Committee was to study the current pretrial release system and to examine alternatives and improvements to that system through evidence-based practices and current risk assessment tools. As part of its work, the Committee held several meetings during which it receive information on a variety of pretrial risk instruments that have been implemented in numerous jurisdictions. These reviews included in formation on the Arnold Foundation, COMPAS, and Ohio Risk Assessment System (ORAS).

It was decided that it would be preferable to develop a customized pretrial risk instrument that incorporated all of the positive attributes of these risk instruments but had the advantage of being tested and normed on defendants being released in Nevada.

The first step was to create a proto-type instrument that was presented to the Committee in February 2016. Referred to as the Nevada Pretrial Risk (NPR) instrument, Committee members were briefed on its design and were asked to offer constructive recommendations to modify the proposed NPR or other factors that should be considered. The initial NPR instrument also included information on other potential risk factors that could be tested as part of the validation effort.

The following nine items were selected to be on the prototype instrument:

1. Existing pending criminal case at time of current offense;
2. Age at first arrest (adult or juvenile);
3. Prior misdemeanor arrests;

4. Prior felony or gross misdemeanor arrests;
5. Prior arrests for violent crimes;
6. Prior FTA's past two years;
7. Current employment status;
8. Current residency; and,
9. Indications of substance abuse.

The weights for each of the nine scoring items and the overall risk scale were based on prior studies of other similar risk instruments. In particular the ORAS was relied upon as several of the NPR factors were based on that system. However, it was expected that both the weights and scale would be modified after the data were collected and analyzed.

By the close of February 2016 the prototype instrument was completed and was ready to be pilot tested on a representative sample of released defendants.

Sampling Process

The next task was to create a sample of defendants who had been released from custody in the three target counties. The plan was to have the prototype instrument completed on each cases that was sampled. In doing so, the following goals of the pilot test would be completed:

1. Description of the types of people currently being released in pretrial status in terms of their demographics, offense, and criminal history;
2. The methods of release and time in custody prior to release;
3. Re-arrest and Failure to Appear (FTA) rates;
4. Testing of the prototype instrument in terms of its validity; and,
5. Methods for improving the NPR predictive qualities.

Four separate samples of cases were created. In Clark county, two random samples were created for defendants released from either the Clark County Detention Center or the Las Vegas City Jail in 2014.¹ A third random sample was created for people released from the Washoe County Detention facility in 2014. Finally, a fourth sample that consisted of all defendants also released in 2014 from White Pine County. Because the number of people released from that county was so small there was no need to actually sample the cases.

There were a total of 1,160 cases originally sampled from the data files received from the four jurisdictions. Of that number 1,057 (91%) were finally captured and used for analysis. Virtually all of the 101 deleted cases presented jail releases that were not pretrial releases (e.g., credit for time served, transferred to state prison,

¹ The SPSS random number generator was used to select samples that reached a specific threshold sufficient for statistical analysis within each jurisdiction.

etc.). Statistical tests were performed to ensure that both the original and final samples were comparable to the original universe of pretrial releases for all four sites.

Table 1. Sample and Final Sample Sizes

County	2014 Pretrial Releases	Original Sample	Final Sample
Clark			
Detention Center	7,172	416	406
Municipal Jail	5,419	259	179
Washoe	5,982	421	410
White Pine	63	63	62
Total	18,637	1,160	1,057

Data Collection

Once the samples were created, the names and identifiers of the sampled cases were forwarded to designated criminal court staff (typically pretrial service agency staff) with instructions on how to complete the prototype form. There were several conference calls between these staff to address questions on how to collect and record data on the form. The forms were sent to the consultants on a regular basis and double-checked for accuracy. The data were hand entered into a spreadsheet and then converted to an SPSS data file for statistical analysis.

Table 2 summarizes the key attributes of the sampled cases by the four jurisdictions. There are both similarities and differences among the four sites. Across the sites, the vast majority are males who reside in Nevada. Regarding race and ethnicity, Washoe County had predominantly white defendants while Clark County had higher proportions of Black and Hispanic defendants. The dominant forms of release were Own Recognizance and Surety Bond. The average and median bail amounts ranged from \$3,251 (Clark Muni) to \$19,122 (Clark Detention Center). Many of the defendants had prior misdemeanor, gross misdemeanor and felony arrest histories.

Analysis

The two key dependent variables that were recorded on each sampled case were 1) whether the released defendant was rearrested for a new crime and 2) whether there was a bench warrant issued for failing to appear (FTA) for any scheduled court hearing.

Table 2. Key Attributes of the Pretrial Releases by Jurisdiction

Attribute	Clark	Clark Muni	Washoe	White Pines	Total
Releases	406	179	410	62	1,057
Gender					
Male	77%	73%	85%	77%	80%
Female	23%	27%	15%	23%	20%
Race					
White	46%	40%	66%	NA	50%
Black	30%	30%	11%	NA	21%
Hispanic	16%	26%	18%	NA	18%
Asian	6%	3%	1%	NA	3%
Other	2%	1%	4%	NA	8%
Method of Release					
Cash Bail	3%	10%	9%	10%	7%
Surety Bond	37%	23%	36%	63%	35%
OR	46%	31%	55%	26%	46%
Other	14%	36%	0%	1%	12%
Nevada Resident	78%	74%	86%	81%	81%
LOS Prior Release	15	8	12	5	12
Ave. Bail	\$19,122	\$3,251	\$8,043	\$12,563	\$11,674
Median Bail	\$10,000	\$2,115	\$2,500	\$9,000	\$5,000
Ave Prior Misd Arrests	6	3	2	3	4
Ave Prior Fel/GM Arrests	4	1	2	2	3

Validation analysis was designed to determine if the scoring items that were contained on the proto-type NPR instrument were statistically associated with either the rate of re-arrest or FTA.

A “composite” dependent variable that measured whether the person was either re-arrested or had an FTA was also constructed although the FTA is measuring a somewhat different phenomenon (criminal behavior versus non-compliance with a court order).

Table 3 shows the re-arrest, FTA and composite rates for the four jurisdictions. The overall re-arrest rates is 135 with White Pine having the highest rate (23%) and Clark Muni having the lowest (3%). Conversely, Clark Detention Center has the highest FTA rate (28%) followed by White Pine. These two jurisdictions also have the higher composite rate of 37% and 36%. Compared to other jurisdictions, the low re-arrest rates are comparable with the exception of White Pine (23%). Clark Detention Center releases have a higher FTA rate then one would expect. This

higher FTA rate could be a function of the risk levels for Clark Detention Center releases and/or pretrial supervision options and methods.

It should also be noted that 73% of the people who had an FTA warrant issued against them did not have any re-arrests for criminal charges (Table 4). Conversely, of the 135 people who were re-arrested, 62% of them had no FTA warrants issued. As has been noted in the other studies, FTA behavior should be viewed as distinct from re-arrest behavior.

Table 3. Re-Arrest and FTA Rates By Jurisdiction

Attribute	Clark	Clark Muni	Washoe	White Pines	Total
Releases	406	179	410	62	1,057
Re-Arrest	16%	3%	12%	23%	13%
FTA	28%	16%	9%	19%	18%
Arrest or FTA	37%	17%	17%	36%	26%

Table 4. Re-Arrest by FTAs

Re-Arrested	FTA		Total
	No	Yes	
No	784	138 (73%)	922
Yes	84 (62%)	51	135
Total	868	189	1057

The next level of analysis was to test the prototype instrument against the outcome measures of re-arrest, FTA and the composite FTA or Re-arrest rates. It was expected that there would be some tweaking of the proto-type instrument’s nine scoring item’s weights and the overall risk scale. Consequently, a number of statistical runs were completed to find those factors that had the strongest relationship with the dependent variables. While all of the nine scoring items had statistically significant bivariate relationships, there were some subcategories that were not performing well in terms of risk assessment. Consequently, it was necessary to either modify or consolidate certain subcategories. There was also an effort to see if some “non-scoring items” were predictive and should be added to the NPR. This re-assessment process produced the following adjustments to the prototype NPR:

1. Added the factor of possession of valid cell phone number (non-cell phone releases had a higher FTA rate);
2. Consolidated the substance abuse factor by only using prior drug/alcohol related arrests (other measures of drug use were not valid);

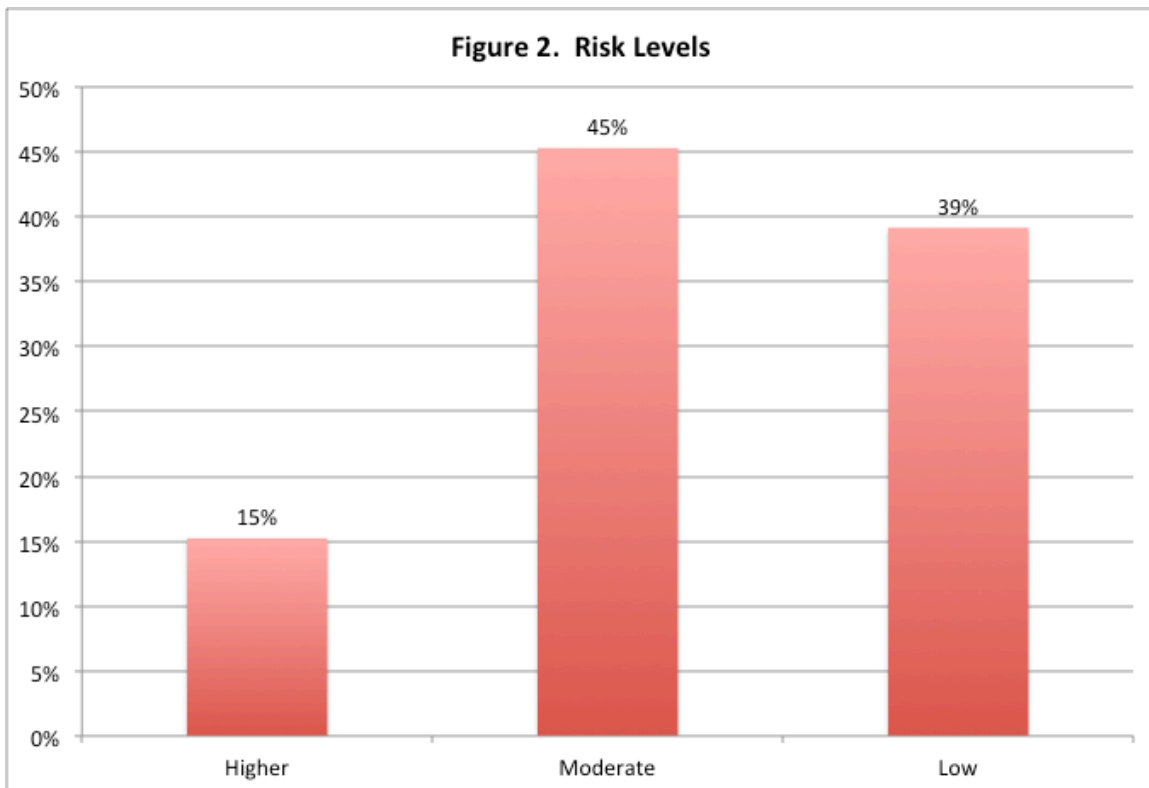
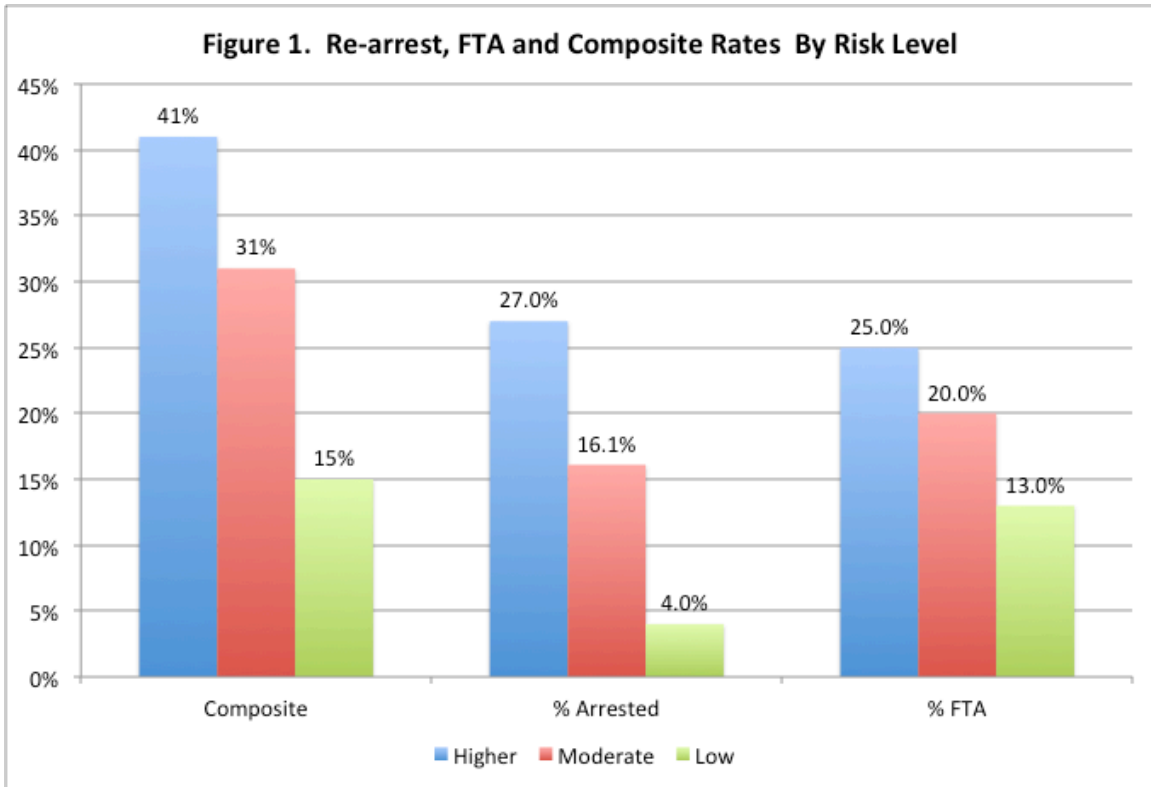
3. Modified the residence factor by adding whether the person was a resident of Nevada (non- residents have a higher FTA rate);
4. Consolidated prior misdemeanor arrest score so that 3 or more receive 2 points (no difference in rates by 3-5 and 6 or more categories);
5. Consolidated prior felony/gross misdemeanor arrests score so that 2 or more are scored as 2 points (no difference in rates by other categories); and,
6. Re-calibrated the overall scale so that it matches the new scoring process.

Based on these changes the overall validity of the instrument (see appendix A for a copy of the modified instrument) is shown in Figures 1 and 2.

In terms of re-arrest rates, the scored low risk group has a very low risk (4%) of being arrested for a new crime until their cases are disposed of. But even the vast majority of the “higher risk” group is also very unlikely (73%) to be re-arrested while awaiting the disposition of their criminal cases. Looking at the composite rates, 85% of low risk people will neither be re-arrested or FTA. Conversely, 59% of the higher risk group will not be re-arrested or FTA. But this group only accounts for 15% of all releases (Figure 2).

Summary

Based on these results, the modified NPR has proven to be a statistically valid pretrial risk instrument that meets industry standards in terms of the factors being used and their overall predictive accuracy. The NPR has been normed on representative samples of the four jurisdictions that were involved in the pilot test. It is now ready to be implemented in the four jurisdictions. Additional training will be required for 1) staff who will be using the instrument to score pretrial defendants and 2) court officials who will be using the results to make pretrial release decisions.



Appendix A

Finalized Nevada Pretrial Risk Instrument

NEVADA PRETRIAL RISK ASSESSMENT (NPR)

Defendant's Name: _____ Assessment Date: ____/____/____
Case #: _____ County: _____ Assessor: _____
Most Serious Charge: _____ Initial Total Bail Set: \$ _____
Verified Cell Phone #: _____ Address: _____ City _____ State _____ Zip _____

SCORING ITEMS

SCORE

1. Does the Defendant Have a Pending Case at Booking?
 - a. Yes - 2 pts.
 - b. No - 0 pts._____
2. Age at First Arrest
 - a. Under age 21 yrs. - 2 pts.
 - b. 22-35 yrs. - 1pt.
 - c. 36 Plus. - 0 pts._____
3. Prior Misdemeanor Arrests.
 - a. Two or less- 0 pts.
 - b. 3 or more - 2 pts._____
4. Prior Felony/Gross Misd Arrests
 - a. None or One - 0 pts.
 - b. 2 or more - 2pts._____
5. Prior Arrests - Violence:
 - a. None - 0 pts.
 - b. 1 or more - 2 pts._____
6. Prior FTAs Past 24 Months
 - a. None - 0 pts.
 - b. 1 FTA Warrant - 1 pt.
 - c. 2 or more FTA Warrants - 2 pts._____
7. Employment Status at Arrest
 - a. Employed or Student or Retired - 0 pts.
 - b. Unemployed - 2 pts._____
8. Residential Status Date of Residency: ____/_____
 - a. Nevada Resident - Living in current residence 6 mos. or longer - 0 pts.
 - b. Nevada Resident - Not lived in same residence 6 mos. or longer - 1 pt.
 - c. Homeless or Non-Nevada Resident- 2pts._____
9. Substance Abuse
 - a. Otherwise - 0 pts.
 - b. Prior multiple arrests for drug possession/alcohol/drunkenness - 2 pts._____
10. Verified Cell Phone
 - a. Yes - 0 pts. (list) _____
 - b. No - 2 pts._____

Total Score: _____

Scored Risk Level: 0-4 pts. LOW 5 -10 pts. MODERATE 11+ pts. HIGHER

Over-Ride? ____ Yes ____ No

Over Ride Reason(s): ____ Mental Health ____ Disability ____ Gang Member ____ Flight Risk

Other Reason: _____

Final Recommended Risk Level; ____ LOW ____ MODERATE ____ HIGHER

PRETRIAL JUSTICE REFORM STUDY

Evaluation of Pretrial
Justice System
Reforms That Use
the Public Safety
Assessment

Effects of New Jersey's
Criminal Justice Reform

1

NEW JERSEY
SERIES

REPORT 1

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Cindy Redcross
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with
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NOVEMBER 2019

On January 1, 2017, the State of New Jersey implemented Criminal Justice Reform (CJR), a sweeping set of changes to its pretrial justice system. With CJR, the state shifted from a system that relied heavily on monetary bail to a system based on defendants' risks of failing to appear for court dates and of being charged with new crimes before their cases were resolved. These risks are assessed using the Public Safety Assessment (PSA), a pretrial risk-assessment tool developed by Arnold Ventures with a team of experts. The PSA uses nine factors from an individual's criminal history to produce two risk scores: one representing the likelihood of a new crime being committed, and another representing the likelihood of a failure to appear for future court hearings. The PSA also notes whether there is an elevated risk of a violent crime. The PSA is used in conjunction with a New Jersey-specific decision-making framework (DMF) that uses an individual's PSA risk score in combination with state statutes and statewide policies to produce a recommendation for release conditions.

The PSA is used at two points in New Jersey's pretrial process: (1) at the time of arrest, when a police officer must decide whether to seek a complaint-warrant (which will mean booking the person into jail) or issue a complaint-summons (in which case the defendant is given a date to appear in court and released); and (2) at the time of the first court appearance, when judges set release conditions for defendants who were booked into jail on complaint-warrants. (The DMF is also used at this second point.) CJR includes a number of other important components: It all but eliminated the use of monetary bail as a release condition, established the possibility of pretrial detention without bail, established a pretrial monitoring program, and instituted speedy-trial laws that impose time limits for case processing.

This report is one of a planned series on the impacts of New Jersey's CJR. It describes the ef-

fects of the reforms on short-term outcomes, including the number of arrest events (where an "arrest event" is defined as all complaints and charges associated with a person on a given arrest date), complaint charging decisions, release conditions, and initial jail bookings. Additional reports in this series will examine CJR's effects on outcomes such as court appearance rates, new arrests, the amount of time defendants are in jail while waiting for their cases to be resolved, and case dispositions (that is, whether defendants were found guilty or not guilty or had their cases dismissed). The effects of the reforms for different subgroups of the pretrial population (for example, those defined by risk levels and race) will also be examined in a subsequent report.

Findings in this report include:

- Fewer arrest events took place following CJR's implementation. There was a reduction in the number of arrest events for the least serious types of charges — namely, nonindictable (misdemeanor) public-order offenses.
- Police officers appear to be issuing complaint-summonses more often and seeking complaint-warrants less often since CJR was implemented.
- Pretrial release conditions imposed on defendants changed dramatically as a result of CJR. A larger proportion of defendants were released without conditions, and rates of initial booking into jail were lower than predicted given pre-CJR trends.
- CJR significantly reduced the length of time defendants spend in jail in the month following arrest.
- CJR had the largest effects on jail bookings in counties that had the highest rates of jail bookings before CJR. ■

OVERVIEW

INTRODUCTION

In most jurisdictions, judges set bail for individuals charged with crimes as a way to ensure that those people will return to future court hearings and will avoid incurring new criminal charges as they wait for their cases to be disposed of (that is, until they are found guilty or not guilty, or have their cases dismissed). In practice, using bail means that people with the financial resources to post bail are released, and those without the financial means are booked into jail. Spending even a few days in jail can have a number of negative consequences: It can cause people to lose employment or housing; it can disrupt their family lives; it can expose them to inmates with criminal histories that in turn put them at a greater risk of committing new crimes when they are released; and it may result in them pleading guilty to crimes they did not commit, since they may face the choice of remaining in jail for weeks or months or pleading guilty and being released.¹ In 2012, 12 percent of the people in New Jersey’s jails were being held solely because they could not pay bail of \$2,500 or less;² meanwhile, individuals who posed greater risks to public safety were released when they could afford to pay.

In recent years reformers have been pushing to change the pretrial system, and in particular to reduce this heavy reliance on money bail. The State of New Jersey undertook groundbreaking and substantial changes to its pretrial justice system under its Criminal Justice Reform (CJR) initiative, which took effect on January 1, 2017.³ Under CJR, the state shifted from a system that relied heavily on money bail as a condition of release to a system that measures defendants’ risks of failing to appear and committing new crimes.⁴ These risks are assessed using the Public Safety Assessment (PSA), a tool developed by Arnold Ventures that uses nine factors from a defendant’s criminal history to produce two risk scores, one representing the likelihood of a person with a similar background being charged with a new crime, and the other representing the likelihood that such a person will fail appear for future court hearings (with higher scores indicating higher likelihoods). The PSA also notes whether there is an elevated risk of a violent crime. The New Jersey Judiciary worked with a team of PSA experts to develop a customized decision-making frame-

1 Lowenkamp, VanNostrand, and Holsinger (2013); Dobbie, Goldin, and Yang (2016); Pager (2003); Moore, Stuewig, and Tangney (2016).

2 VanNostrand (2013).

3 For more background about the motivations for CJR, see Chief Justice of the New Jersey Supreme Court Stuart Rabner’s piece in the *New Jersey Star-Ledger*: Rabner (2017).

4 Rabner (2017).

work (DMF) that produces recommendations for release conditions based on the PSA risk scores and state-specific policies and guidelines.

The PSA is used at two points in New Jersey’s pretrial process: (1) at the time of arrest, when a police officer must decide whether to seek a “complaint-warrant” from a judicial officer (which will mean booking the person into jail) or issue a “complaint-summons” (in which case the defendant is given a date to appear in court and released); and (2) at the time of the first court appearance, when a judge sets release conditions for a defendant who was booked into jail on a complaint-warrant. The PSA is used in conjunction with the DMF to make this decision. The reforms also greatly reduced the use of monetary bail as an initial release condition,⁵ created an option for pretrial detention without bail,⁶ established a pretrial monitoring program, and instituted speedy-trial laws that impose time limits for the processing of certain cases.

With funding from Arnold Ventures, MDRC is conducting an independent study of how CJR was implemented and assessing its effects on case dispositions, new criminal charges, and other important outcomes. This report on the effects of CJR’s shift to a risk-based decision-making framework informed by the PSA is the first in a planned series; it presents early evidence of CJR’s effects on the number of arrests in the state, on the types of charges and complaints issued, on pretrial release conditions, and on initial rates of jail commitment. Additional reports will examine CJR’s effects on defendant and case outcomes (such as failures to appear at court hearings, new arrests during the pretrial period, total days incarcerated in jail, and case dispositions), on racial disparities in outcomes, and for different subgroups of the pretrial population (for example, those defined by risk score and race). Additionally, future reports will examine in greater depth how CJR’s effects differed among counties, which could have broad implications for pretrial policy nationally.

The PSA is used at two points in New Jersey’s pretrial process:

- 1. At the time of arrest**
- 2. At the time of the first court appearance**

-
- 5** While monetary bail is still technically available, it is now used very rarely as a condition for being released initially. The analysis found only three instances where bail was set as an initial release condition in 2017. Since CJR was implemented, bail is more commonly used for responding to violations or failures to appear for scheduled court events.
 - 6** Before CJR, the courts had no way to simply hold someone in custody unless the individual was charged with specific high-level offenses. When the courts wanted to hold someone, they gave that person high monetary bail. With CJR, the statute was changed to allow a prosecutor to request detention if that prosecutor is concerned about new criminal charges or a failure to appear. Throughout this report, this new option for pretrial detention without bail is referred to merely as “pretrial detention.”

BACKGROUND ON CRIMINAL JUSTICE REFORM AND THE PRETRIAL CASE PROCESS

Through CJR, the State of New Jersey shifted from a pretrial justice system that relied on money bail to a fairer, risk-based system in which release conditions are not financially based and cases are processed and disposed of faster. CJR consisted of the following main components: (1) a substantial reduction in the use of money bail; (2) the use of the PSA to assess defendants' risks and the DMF to inform the release conditions needed to manage those risks; (3) the legal ability to detain defendants without bail until their cases are disposed of (pretrial detention); (4) the creation of a pretrial monitoring program in which defendants check in with court staff members at regular intervals; and (5) speedy-trial laws that limit the time prosecutors have to reach major milestones such as indictment and case disposition for defendants in jail, and on the time courts have to schedule a first appearance hearing and make a release decision following an initial jail booking. New Jersey's goals for CJR were to improve fairness throughout its pretrial system while protecting public safety and making sure defendants still appear in court.

Figure 1 depicts the steps in the current pretrial process (the process since the implementation of CJR). The process begins with an arrest by a police officer. When a person is arrested and charged in New Jersey, he or she is issued either a complaint-warrant or a complaint-summons. While complaint-warrants are required for some serious criminal charges (such as murder or sexual assault), for most criminal charges either type of complaint can be used. Similarly, both "indictable" and "nonindictable" charges — New Jersey's equivalents of felonies and misdemeanors — may be issued using either type of complaint.⁷

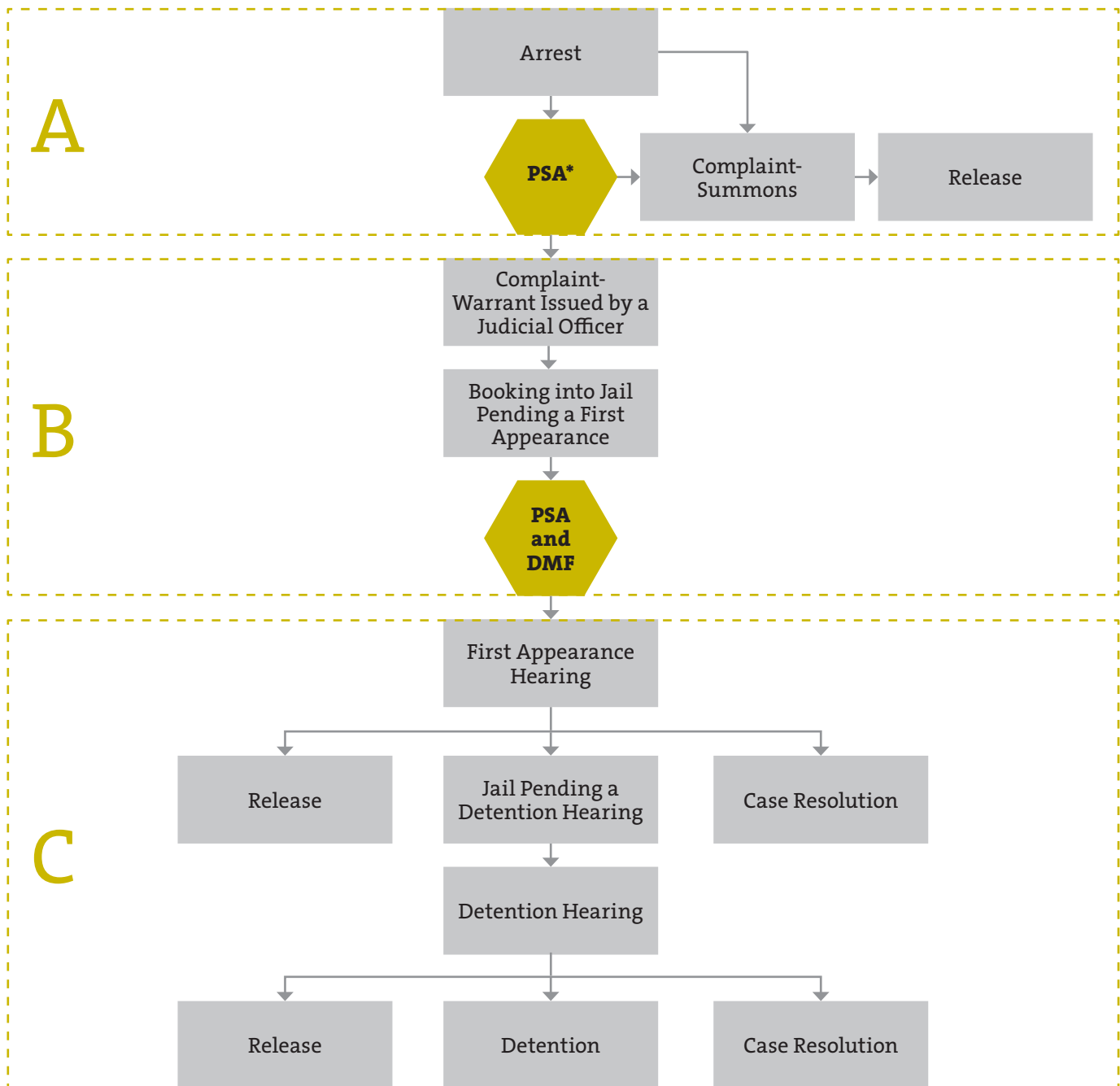
Area A of Figure 1: Complaint Processes

The complaint-summons process. The complaint-summons process has changed little as a result of CJR. If a police officer decides to issue a complaint-summons, he or she can do so without needing the approval or review of a judicial officer. The same was true before CJR.⁸ A defendant who receives

⁷ Nonindictable charges are not technically considered criminal. (New Jersey also has other processes to issue complaints for other, less serious matters, such as traffic offenses, municipal ordinances, and other low-level violations. This report does not touch on these complaints because there is no reason to expect CJR to have affected them. And in fact a sensitivity analysis showed no evidence that CJR did affect those complaints.)

⁸ Typically, the officer brings the defendant to the police station to issue the complaint-summons. The same was true before CJR. Defendants issued complaint-summonses are fingerprinted while at the police station, which was often but not uniformly the case before CJR.

FIGURE 1 New Jersey Pretrial Case Flow Since CJR Was Implemented



*This PSA is referred to as the "preliminary PSA." For defendants issued complaint-warrants, this score is later reviewed and will be regenerated by Pretrial Services before the first appearance hearing, as indicated by the second "PSA" hexagon in the pretrial case flow.

a complaint-summons is released and given a date to appear in court for a hearing. A police officer does not need to obtain a PSA score in order to issue a complaint-summons, although the officer may seek a PSA score if he or she is not sure whether to issue a complaint-summons or pursue a complaint-warrant (see below).

The complaint-warrant process. CJR has changed the procedure for issuing complaint-warrants considerably. Before CJR, if a police officer wanted to seek a complaint-warrant, he or she would fingerprint the individual and call a judicial officer to request a warrant, describing the evidence and the reasons for requesting a warrant over the phone.

Since CJR was implemented, if a police officer wants to pursue a complaint-warrant or is not sure whether to seek a complaint-warrant or issue a complaint-summons, he or she collects fingerprints and generates a PSA report.⁹ The PSA report generated at this step is referred to as the “preliminary PSA” in New Jersey, which distinguishes it from the PSA report generated later in the process (see below). The PSA report provides the officer with a preliminary score. The officer then uses that score and considers whether to issue a complaint-summons or pursue a complaint-warrant based on the charge, the PSA score, and guidelines issued by the state attorney general.¹⁰ If a complaint-warrant is not recommended and the officer decides to issue a complaint-summons, he or she does so following the same complaint-summons process described above. If it is determined that a complaint-warrant may be recommended and the officer decides to pursue one, or if a complaint-summons is recommended but the officer still wants to pursue a warrant, the officer sends the complaint and the preliminary PSA report to a judicial officer for review. This information is typically sent electronically, with prosecutors or supervisory police officers reviewing the information on a computer, tablet, or smartphone before it is sent to the judicial officer. To determine probable cause for issuing a warrant, judicial officers consider the case details, the PSA report, and legal statutes and rules of the

9 At this stage, the PSA uses information from the defendant’s in-state criminal history — which is available from state databases once fingerprints are taken — to calculate a risk score.

10 At the beginning of 2017, the attorney general’s guidelines said that officers may pursue a complaint-warrant when the failure-to-appear score or new-criminal-activity score produced by the PSA was 4 or higher. In May 2017, this threshold was changed to scores of 3 or higher, and the guidelines added that officers may pursue a complaint-warrant if the PSA identifies a risk of a new violent crime. See Porrino (2017).

courts.¹¹ Notably, this process is more formal and time-consuming for police officers than the process they followed before CJR.

If the judicial officer does not find probable cause based on the documents provided and his or her conversation with the police officer (described above), the complaint ends. The same was true before CJR.¹² If the judicial officer does find probable cause, the judicial officer may issue either a complaint-warrant or a complaint-summons. Before CJR, bail was generally set immediately by the judicial officer based on a statewide schedule that listed a range of recommended bail amounts for each criminal charge. Judicial officers were not required to follow the bail schedule and could set bail outside of the recommended ranges or choose to release a defendant on his own recognizance (ROR) without any monetary conditions. Since CJR was implemented, bail is not an option at this stage and if a complaint-warrant is issued, the defendant is held in jail pending a first appearance hearing before a judge, where release conditions are determined (described below).

Area B of Figure 1: The Initial Jail Booking Process for Defendants Issued Complaint-Warrants

CJR affected the initial charging process by requiring that defendants issued complaint-warrants be booked into jail pending a first appearance hearing, with a release decision to be made within 48 hours. Before CJR, bail would be set for these defendants, and if bail was paid immediately, defendants would be released from the police station (without going to jail) pending their court appearances. Defendants who were not able to post bail immediately were booked into jail and remained there until bail was posted, they were released at court hearings, or their cases were disposed of.

As described above, since CJR was implemented, bail is no longer an option; at this stage in the process defendants issued complaint-warrants are booked into jail while they await a first appearance hearing (which must occur within 48 hours). The jurisdiction's Pretrial Services staff reviews the preliminary PSA report produced at the request of the police, and may add missing criminal-history information (for example, information from other states)

11 The rules governing the New Jersey courts include instructions for when a complaint-warrant is required or presumed. For example, a complaint-warrant may be required if there is probable cause to believe that the defendant committed certain serious offenses, such as murder, sexual assault, or robbery. See *New Jersey Courts* (2018).

12 It is unknown how many cases ended without any complaint being filed, since such cases would not appear in the New Jersey arrest data.

or modify erroneous information. Changes in criminal-history information result in an automatic recalculation of the PSA results. Pretrial Services then generates a release recommendation by incorporating the amended PSA report into the decision-making framework that accounts for state-specific policies.¹³ In New Jersey, the DMF generates three possible release recommendations: (1) ROR; (2) release to one of four levels of pretrial monitoring by Pretrial Services;¹⁴ or (3) no release. The PSA results and the recommendation for release conditions are then made available to the presiding judge, prosecutor, and defense attorney ahead of the first appearance hearing.

Area C of Figure 1: Initial Hearings

A defendant booked into jail after being issued a complaint-warrant attends a first appearance hearing. The same was true before CJR, but CJR changed the required time frame and content of this hearing. Before CJR, the first appearance hearing occurred 5.7 days on average after an initial jail booking and consisted of little more than the judge formally reading the charges to the defendant.¹⁵ Although judges could review and change the amount of bail set, they rarely did, according to local court staff members.¹⁶ The case could also be dismissed or the defendant could take a plea deal at this point or at any other point in the pretrial process. In practice, very few cases were disposed of at the first appearance.

13 New Jersey-specific policies about current charges sometimes result in a more restrictive DMF recommendation than what would result from a PSA score alone. For example, some serious charges, such as murder, manslaughter, sexual assault, or carjacking, would almost always result in a DMF recommendation that the person not be released, regardless of the PSA risk score. So would a combination of a charge for a violent crime and a PSA determination that there was a risk of a new violent crime.

14 Within pretrial monitoring, the DMF recommends the level of supervision, referred to as the Pretrial Monitoring Level (PML). A defendant released on his or her own recognizance will have no conditions, no face-to-face contact with a Pretrial Services officer, and no phone contact with the officer. At PML 1, there is monthly phone reporting. At PML 2, defendants must report once a month in person and once a month by telephone, and are subject to some monitored conditions such as a curfew. At PML 3, defendants are monitored in person or by phone every week and are also subject to monitored conditions. Defendants at the next level — PML 3 plus electronic monitoring or home detention — are subject to all the PML 3 conditions and also may be confined to their homes or required to wear GPS monitoring devices. See American Civil Liberties Union, National Association of Criminal Defense Lawyers, and State of New Jersey Office of the Public Defender (2016).

15 Before CJR, there was no requirement that the first appearance hearing take place within 48 hours of jail booking, like there is since CJR was implemented.

16 Court administrators and judges told MDRC that bail was more often reconsidered at bail review hearings. These hearings could be requested after first appearance hearings but were often not scheduled until several weeks later.

Since CJR was implemented, the PSA scores and recommendations for release are read into the record by the judge at the first appearance hearing.¹⁷ As mentioned above, statute requires that the hearing occur within 48 hours after a person is booked into jail. (In practice, among the CJR cases in this study that began after the implementation of CJR, the average was 1.2 days, or about 29 hours.) New Jersey has been able to hold first appearance hearings faster since CJR in part because public defenders have agreed to represent all defendants provisionally at their first appearance hearings, before it has been determined whether they are eligible for public defenders based on their incomes.

At the first appearance hearing, the prosecutor, the defendant's attorney, and the judge are involved in making decisions about release. If the prosecutor files a motion for pretrial detention, the defendant is typically held in jail pending a detention hearing, which must then occur within three business days. Since there are often brief adjournments granted to either the prosecution or the defense, however, in practice detention hearings commonly occur about a week after first appearance hearings.¹⁸ Detention hearings did not exist before CJR (the legal option for preventive detention was a component of CJR). If the prosecutor does not file a detention motion, the judge decides whether to give ROR or to release the defendant on pretrial monitoring, sometimes with other conditions attached.¹⁹ Money bail is technically an option at this point, but since CJR was implemented, it is almost never set as an initial release condition.²⁰

As was the situation before CJR, the judge may also dismiss the case or a defendant may accept a plea deal at any point in the pretrial process. Only a small percentage of cases statewide are disposed of at or before the detention hearing, however.²¹

17 That is, they are stated aloud and recorded in the court records.

18 When a motion for detention is filed, a prosecutor may request an adjournment of up to three additional business days and a defense attorney may request an adjournment of up to five additional business days. Judges, court administrators, prosecutors, and defense attorneys told MDRC in interviews that detention hearings usually occur about a week after first appearance hearings.

19 These other conditions may include electronic monitoring or conditions related to the circumstances of the case, such as no contact with the victim. The court cannot detain a defendant under any circumstances if the prosecutor does not file a motion for detention. The New Jersey Constitution was amended to authorize the courts to deny pretrial release to certain criminal defendants.

20 As mentioned above, it was only set three times for cases initiated on complaint-warrants in 2017, according to data provided to MDRC by the New Jersey Administrative Office of the Courts.

21 Findings regarding case resolutions at the first appearance and detention hearings are presented in greater detail below.

Speedy-Trial Laws

CJR included speedy-trial laws that set clear time limits on the amount of time prosecutors have to reach case-processing milestones such as indictment and case disposition, and on the amount of time courts have to schedule a first appearance hearing following an initial jail booking. If the prosecution fails to meet these deadlines in a case, then the court must release the defendant while the case is awaiting disposition. There is an overall time limit of two years to dispose of a case. Speedy-trial laws did exist before CJR, but they did not set explicit time limits like these.

METHODS AND DATA SOURCES

For the purposes of this analysis, all complaints and charges associated with a person on the same arrest date are considered a single “arrest event.” (For ease of explanation, this report also uses the word “defendant” and “case” interchangeably with “arrest event.”) Each arrest event is only counted once in the analysis, even if it resulted in more than one complaint, complaint type, or charge. Arrest events that resulted in both a complaint-warrant and a complaint-summons are treated as resulting in complaint-warrants, and if multiple charges were filed, then the analysis focuses on the most serious charge.²²

The analysis uses an interrupted time series design to estimate the effects of CJR. The defendants are grouped into monthly cohorts (for example, all defendants whose arrest dates were in January 2017 are included in the January 2017 cohort) to create a time series of monthly averages. Data from the pre-CJR months (January 2009 through June 2016) are used to predict what the monthly averages would have been in the period after CJR was implemented (January 2017 through December 2017) had no changes in policy taken place.²³ The effect of CJR is then estimated by comparing the *actual* monthly averages in the period after CJR was implemented with these predicted averages. In other words, the analysis examines whether the observed values for selected measures in the period after CJR was implemented are different from what

22 Indictable charges are treated as more serious than nonindictable charges. Charges are further ranked by severity using the National Crime Information Center’s system for classifying offense descriptions. See National Institute of Justice (1983).

23 The analysis is intended to use data that were unaffected by CJR to predict what would have happened had CJR not happened at all. Because some aspects of CJR were pilot tested in some counties about six months before they were implemented in the rest of the state, and because training in the changes introduced by CJR also took place during this time, data from July 2016 through December 2016 are excluded from this regression.

would have been expected had pre-CJR trends continued. More detailed information about the statistical methods used in this evaluation is available in a technical working paper.²⁴ Box 1 explains how to read the time-series figures that illustrate the effects in this report.

BOX 1 How to Read the Time-Series Figures

The graphs in this report show outcomes in each month of the years before and after CJR was implemented. The gray-shaded area on the right of each graph, from January 2017 onward, represents the period after CJR was implemented. The black line shows the observed outcome values in each month (as aggregated counts or percentages), while the gray line shows the prediction for outcome values in the absence of CJR based on the data from the pre-CJR period. The difference between the black and gray lines represents the estimated effect of CJR on the outcome measure — the difference CJR made. The blue envelope around the gray line in the period after CJR was implemented represents the 95 percent confidence interval around the predicted value at each point. For any month, if the black line falls outside of the blue envelope, then the effect is considered to be statistically significant. The predicted value, observed value, difference (effect — or *impact*), and percentage change for each graphed outcome are presented in the table below each figure for arrest events in July 2017, six months after the policy was implemented. Six months is a reasonable time to expect to observe the effects of CJR on the immediate outcomes measured in this report. This time frame accounts for several months of start-up after the date CJR was officially launched, yet is close enough to that date that effects on outcomes can still be attributed to CJR. If the effect in that month is statistically significant, an asterisk (*) appears next to the effect number in the table. The effect in the table is estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing the average effect in Months 5 through 7 after CJR was implemented.

The data used in the analysis were provided by the New Jersey Administrative Office of the Courts. The sample covers the eight years before CJR went into effect and one year afterward, and includes all arrest events in New Jersey between January 1, 2009 and December 31, 2017 that resulted in complaint-warrants and complaint-summonses. The total sample size is 1,776,181 arrest events: 574,368 that resulted in complaint-warrants and 1,191,813 that resulted in complaint-summonses (or about 200,000 arrest events per year over the nine-year sample period). For each arrest event, the data include the arrest date, the complaint type, the charges, the municipality, the county, the initial release conditions, and the admission and release dates from county jail. In addition, for complaints issued in the period after CJR was implement-

²⁴ Miratrix (2019).

ed, the data include PSA scores and DMF recommendations. The outcomes presented in this report are based on the 30 days after the arrest event. Future reports will include at least nine months of follow-up data, which will allow for measures of case outcomes such as disposition, court appearance, and new arrests during the pretrial period.²⁵

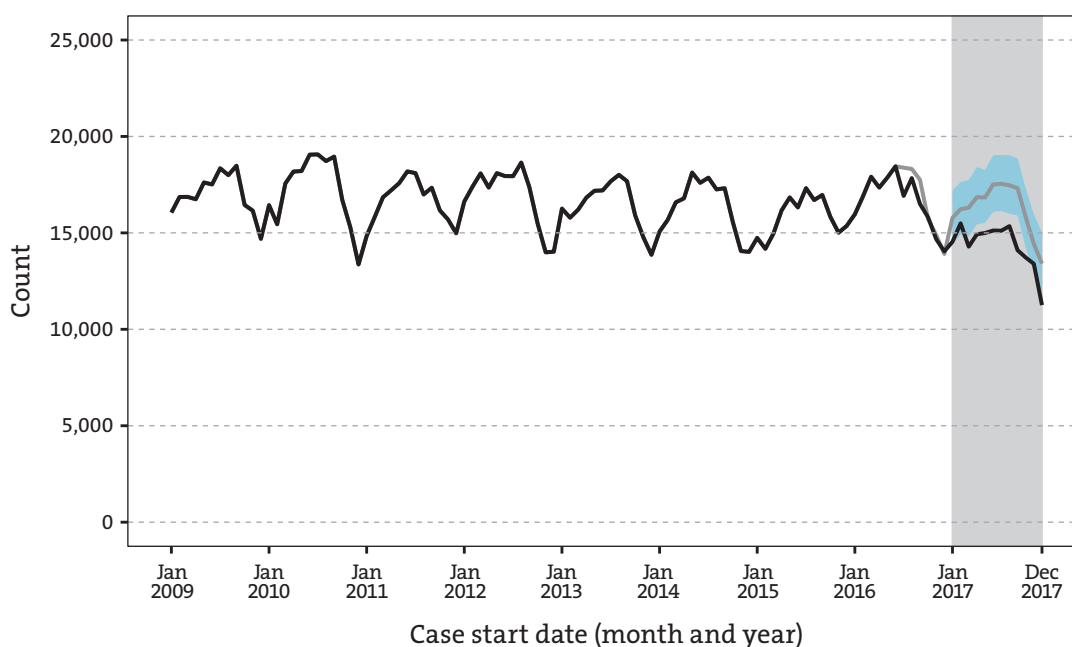
CJR'S EFFECTS ON THE NUMBER AND COMPOSITION OF ARREST EVENTS

Understanding whether CJR led to any changes in the number or characteristics of court cases in New Jersey is central to interpreting effects on outcomes that occur later in the judicial process, such as release conditions and rates of initial jail booking. For example, one might expect to see more restrictive release conditions if the cases entering the courts had more serious charges, on average, after CJR was implemented. Since CJR involved changes to the process police officers followed when making arrests, it could have affected the types of arrest events or cases. This section examines how these outcomes changed with the implementation of CJR.

Figure 2 shows effects on the total number of arrest events by month. The gray shaded area on the right, from January 2017 to December 2017, represents the period after CJR was implemented. The black line shows the actual number of arrest events in each month, while the gray line shows what the number was predicted to have been in the absence of CJR, based on the pre-CJR trend. The difference between those two lines represents the estimated effect of CJR. The blue envelope around the predicted values in the period after CJR was implemented indicates the uncertainty, or confidence interval, of the predicted trend. If the black line falls outside of the blue envelope, then the effect is statistically significant. See Box 1 for more information on how to read the time-series figures.

25 At the time this report was written, the New Jersey Administrative Office of the Courts was in the process of expanding the amount of data available for the evaluation. Specifically, future data will include additional court and jail outcomes and criminal-history details for the sample analyzed in this report. The future data are not anticipated to affect the number or composition of the arrest events or outcomes presented in this report. Although the results presented in this analysis are unlikely to change with the new data, they should be considered preliminary. Any updates to the analysis will be posted as they are available.

FIGURE 2 Effects on the Total Number of Arrest Events



Number of Arrest Events in July 2017

Arrest Events	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Total arrest events	17,444	15,264	-2,180*	-12.5

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for arrest events occurring in Month 6 using an asterisk (*) next to the difference in the table below the graph. The effect in the table is estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing the average effect in Months 5 through 7.

- **CJR was associated with a significant reduction in the total number of arrest events in the year following implementation.**

As shown in Figure 2, the number of arrest events was lower than the predicted trend in the year after CJR was implemented.²⁶ The largest reductions occurred during the summer months when arrests typically peak. For example, the predicted number of arrests in July 2017 was estimated to be 17,444 and the actual number of arrest events was 15,264 — more than 2,000 fewer than

²⁶ Only one arrest event is counted per defendant per date. See the Methods and Data Sources section for more information on the unit of analysis.

predicted. The actual number of arrests remained significantly below the predicted number through the end of the year.

It is also worth noting that here and elsewhere in this report, the interrupted time series analysis cannot establish with complete certainty that CJR was the only contributor to the results observed. It is possible that other policy changes (such as a reduction in the use of stop-and-frisk police practices, as was happening in Newark and surrounding Essex County around the time of CJR) also played a role. However, the stable patterns observed in the large amount of pre-CJR data available — and the fact that those patterns remained very stable even though other, similar policy changes occurred throughout the years before CJR — increases the likelihood that the changes detected truly are related to CJR.

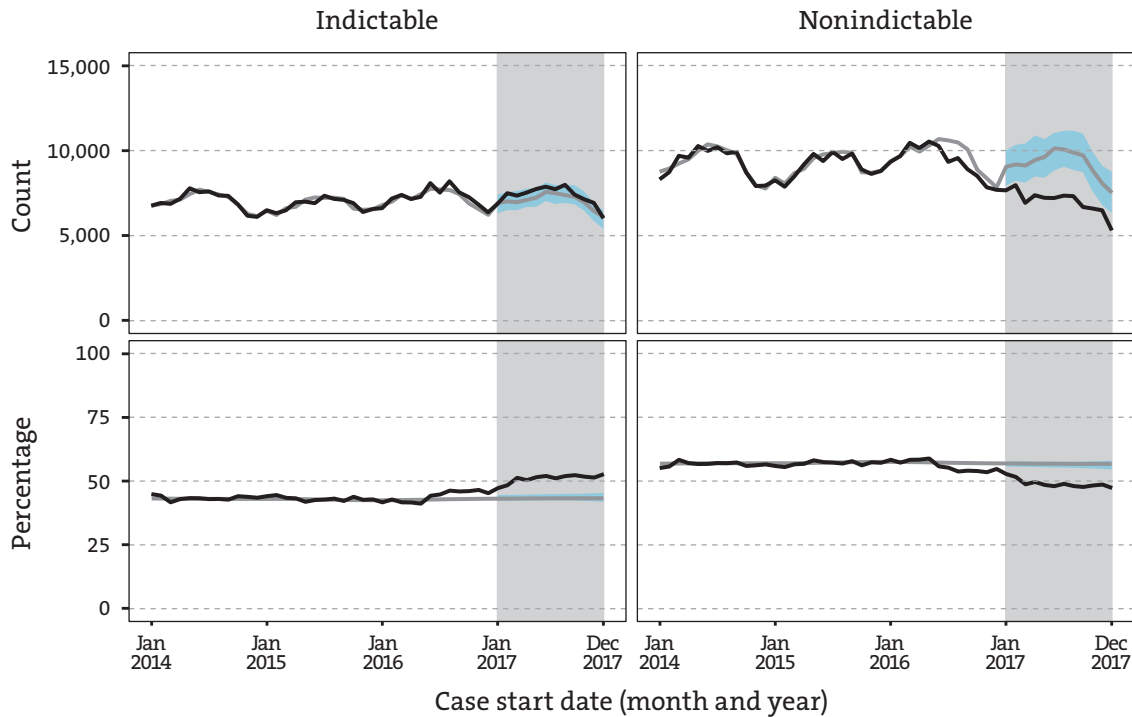
- **The reduction in the total number of arrests events largely reflects a reduction in arrest events involving less serious charges. This reduction in arrests for less serious charges meant that the cases that reached the courts involved more serious charges, on average, after CJR was implemented.**

As shown in the top panel of Figure 3, there were significantly fewer nonindictable (misdemeanor) arrest events after CJR was implemented than predicted by the pre-CJR trend, amounting to about a 25 percent reduction (or more) in April through December of 2017. The least serious types of nonindictable charges accounted for the bulk of the decline — specifically, charges for nonindictable public-order crimes such as loitering, gambling, or obscenity, which are typically issued on complaint-summons (see Appendix Figure A.1).²⁷ CJR did not lead to any significant change in the number of arrest events with indictable charges, however, which indicates that the reduction in the total number of arrest events was largely caused by police officers making fewer arrests for lower-level charges.

In the graphs in Figure 3 showing effects on nonindictable charges, it appears that changes in arrest events began several months before January 2017. These changes were probably due to the preparations and training for CJR that were happening throughout the state during those final months of 2016. Many of the court staff members, judges, and other stakeholders that MDRC interviewed described CJR as requiring a culture change that involved train-

²⁷ Charges were classified by their offense descriptions into four categories — violent, drug, property, and public order — using the National Crime Information Center system mentioned above.

FIGURE 3 Effects on the Number and Percentage of Arrest Events, by Charge Class



Charges Among July 2017 Cases

Type of Charge in the Case	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Indictable (count)	7,513	7,855	342	4.6
Nonindictable (count)	10,076	7,409	-2,667*	-26.5
Indictable (percentage)	43.6	51.3	7.6*	17.4
Nonindictable (percentage)	56.4	48.7	-7.6*	-13.5

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the difference in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through 2016, however.

ing judges and staff members and obtaining their support for the reforms during the months leading up to the launch.²⁸

²⁸ As mentioned above, because this gradual change was in progress during that time, the research team excluded the six months before January 2017 from the pre-CJR data used to predict what would have happened in the absence of CJR.

(continued)

Since the number of arrest events with nonindictable charges declined while the number of arrest events with indictable charges remained constant, the cases entering the courts involved more serious charges, on average, after CJR was implemented. The bottom panel of Figure 3 shows that cases involving indictable charges were a greater percentage of all cases in the period after CJR was implemented than was predicted by the pre-CJR trend. There was no change relative to the predicted trend in the *number* of cases involving indictable charges.

Additional information about the characteristics of defendants and cases in the period after CJR was implemented is shown in Appendix Table A.1. Defendants in the period after CJR was implemented were more likely to have past criminal histories than was predicted based on the pre-CJR trend, were more likely to have had convictions for violent crimes and sentences to incarceration, and were more likely to be classified as high-risk by the PSA. On average, among cases involving nonindictable charges there were fewer charges after CJR was implemented for public-order offenses and somewhat more charges for drug-related offenses. There were few significant differences in the types of indictable charges after CJR was implemented.

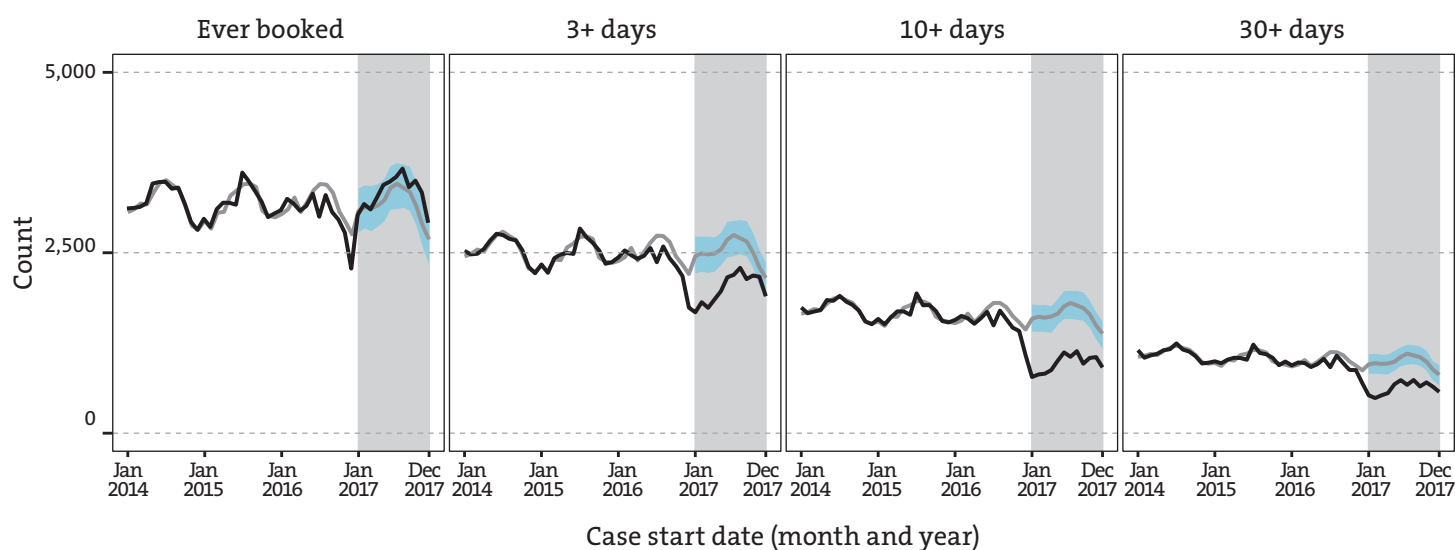
In short, given changes in the types of arrest events, the cases that reached the courts involved more serious charges (indictable offenses) after CJR was implemented, and the defendants were generally higher-risk. These changes appear to be an effect of CJR, and therefore the analyses later in this report that try to isolate how CJR affected court practices must account for them.

CJR'S EFFECT ON INITIAL JAIL STAYS AMONG ALL DEFENDANTS

Figure 4 shows CJR's overall effects on initial jail stays among all defendants, including those who were issued complaint-summons. Including cases issued on complaint-summons allows for an assessment of the overall effect

Also as described above, the City of Newark in Essex County underwent a series of changes in police practices related to arrests that could have contributed to the overall decline in arrest events observed statewide in this analysis. After a complaint was filed by the U.S. Department of Justice claiming that the Newark police department's "stop-and-frisk" practices violated the U.S. Constitution and federal law, the city entered into a consent decree with the Department. The city agreed to implement changes, subject to federal monitoring, that would effectively reduce its use of stop-and-frisk. A sensitivity analysis that removed Essex County showed results that were qualitatively similar: The reduction in arrest events that began before January 2017 was somewhat less pronounced statewide without Essex County included, but followed largely the same pattern.

FIGURE 4 Effects on Lengths of Initial Jail Stays Among All Defendants



Jail Stays Among July 2017 Cases

Jail Stay	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Ever booked	3,445	3,573	129	3.7
Held 3+ days	2,743	2,303	-440*	-16.0
Held 10+ days	1,804	1,150	-653*	-36.2
Held 30+ days	1,106	744	-362*	-32.8

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the differences in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

of CJR that takes into account the fact that there were fewer arrest events overall, which itself could affect jail stays. In other words, this analysis reports the overall effect of CJR on jail bookings but does not attempt to isolate whether the reduction in jail stays is due to CJR policies or the fact that there were fewer arrest events. The leftmost panel of the figure shows that CJR had little effect on the total number of defendants initially booked into jail (“ever booked”). Recall that since CJR was implemented, all defendants issued complaint-warrants must be booked into jail pending a first appearance hearing, with no

option to post bail and avoid jail. Posting bail was an option before CJR. The right three panels of the figure show that the number of defendants held in jail for 3 or more days, 10 or more days, and 30 or more days were all significantly less than predicted, with reductions of about a third or more for the latter two categories. These findings indicate that among all defendants, CJR appears to have led to faster release from jail: Since CJR had no effect on the number of defendants initially booked but did reduce the number of defendants held in jail for three days or longer, it must have increased the number of defendants who were released after only one or two days. CJR led to these faster releases despite the new requirement that all defendants issued complaint-warrants be booked into jail, which is a particularly notable achievement.

CJR'S EFFECT ON POLICE DECISIONS ABOUT WHETHER TO ISSUE COMPLAINT-WARRANTS OR COMPLAINT-SUMMONSES

This section explores whether CJR affected police decisions about whether to pursue complaint-warrants or issue complaint-summonses. Complaint-warrants carry the possibility of pretrial detention — and since CJR was implemented, they always result in an initial jail booking pending a first appearance hearing — while complaint-summonses always result in an immediate release with a date to return to court. One might anticipate that CJR could have affected the decision about whether to pursue a complaint-warrant or issue a complaint-summons because of the use of the PSA to inform that decision, the new procedures and oversight required to pursue a complaint-warrant, or the broad cultural shifts occurring across the judiciary and the courts.

As described above, CJR led to significant changes in the number and composition of cases in the system: It reduced the number of arrest events involving less serious (nonindictable) charges while having no effect on the number of arrest events with more serious (indictable) charges. These changes in policing that occurred at the same time as CJR make it challenging to interpret effects on additional outcome measures because it is difficult to parse whether any observed effects on other outcomes, such as detention, are because of the bail and court policies associated with CJR or are because of the changes in policing (which resulted in a mix of cases with more serious charges and higher-risk defendants, on average, after CJR was implemented — see Appendix A). The remainder of the analyses in this report therefore focus only on

arrest events for indictable charges. As has already been seen, this number remained relatively constant, indicating it was not affected by CJR.²⁹

- **CJR appears to have led to an increase in the proportion of complaints issued on summonses and a corresponding decrease in the proportion issued on warrants.**

Figure 5 shows the proportions of arrest events with indictable charges that were initiated through complaint-warrants and complaint-summonses. The proportion where complaint-warrants were issued declined relative to the predicted trend after CJR was implemented. Conversely, the proportion where complaint-summonses were issued was significantly higher than predicted.³⁰ This pair of findings appears to indicate that police officers issued complaint-summonses after CJR was implemented in some cases where they would have pursued complaint-warrants before CJR. The same pattern was generally observed among the full set of arrest events (that is, among cases with both indictable and nonindictable charges; see Appendix Figure A.2).

- **The initial effects of CJR on complaint decisions appear to dissipate among cases initiated during the second half of the year following the launch of CJR.**

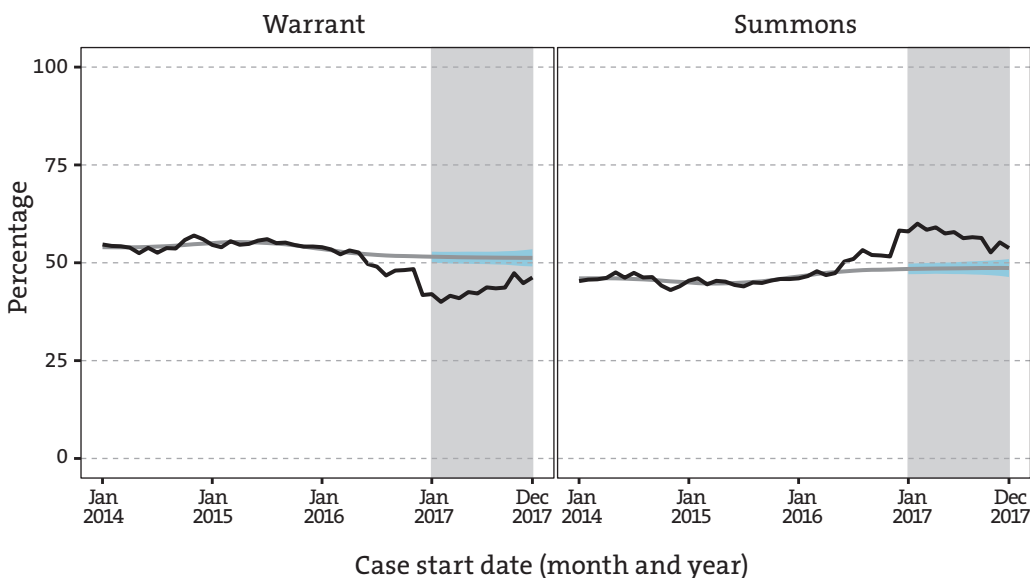
Notably, the effects on complaint decisions shrink during the latter half of 2017, with the proportion of indictable charges issued on complaint-warrants moving toward pre-CJR levels between July and December 2017 (conversely, the proportion of charges issued on complaint-summonses decreased during this period). This change in the trend midway through the year may be due to a modification to the attorney general's guidelines made in May 2017 that lowered the PSA scores at which a complaint-warrant is recommended.³¹ It will

²⁹ The types of offenses among defendants with indictable charges were largely unaffected by CJR (shown in Appendix B). In the latter half of 2017, there was a steady uptick in the proportion of indictable cases with violent charges. A sensitivity test was conducted to determine whether this small increase in the proportion of cases with violent charges was leading to a spurious effect on outcomes such as initial detention. The results of the sensitivity analysis are shown in Appendix B and indicate that this small increase in the proportion of indictable violent offense charges does not skew the observed effects of CJR presented in the remainder of this report.

³⁰ Figure 5 also shows that changes in the proportions of arrest events issued on complaint-warrants and complaint-summonses began to occur several months before January 2017, probably because of the preparations and training for CJR mentioned above. The 2016 changes in Essex County policing practices, also mentioned above, also probably contributed to these late-2016 changes. A sensitivity analysis that removed Essex County showed results that were qualitatively similar to the results including all counties.

³¹ Porrino (2017). Recall that the PSA score is used to inform a police officer's decision about whether to pursue a complaint-warrant or issue a complaint-summons. As mentioned above, the revised attorney general guidelines reduced the threshold for issuing a complaint-warrant from a PSA score of 4 to a score of 3 in mid-2017.

FIGURE 5 Effects on Complaint Types Among Cases with Indictable Charges



Complaint Type Among July 2017 Cases with Indictable Charges

Complaint Type	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Warrant	51.3	43.3	-8.0*	-15.6
Summons	48.6	56.7	8.0*	16.5

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the difference in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

Arrest events can be initiated only on a complaint-warrant or a complaint-summons in this sample, so the two measures are exhaustive and mutually exclusive. Any slight differences in effects between the two measures are solely due to the predictive modeling approach used in this analysis.

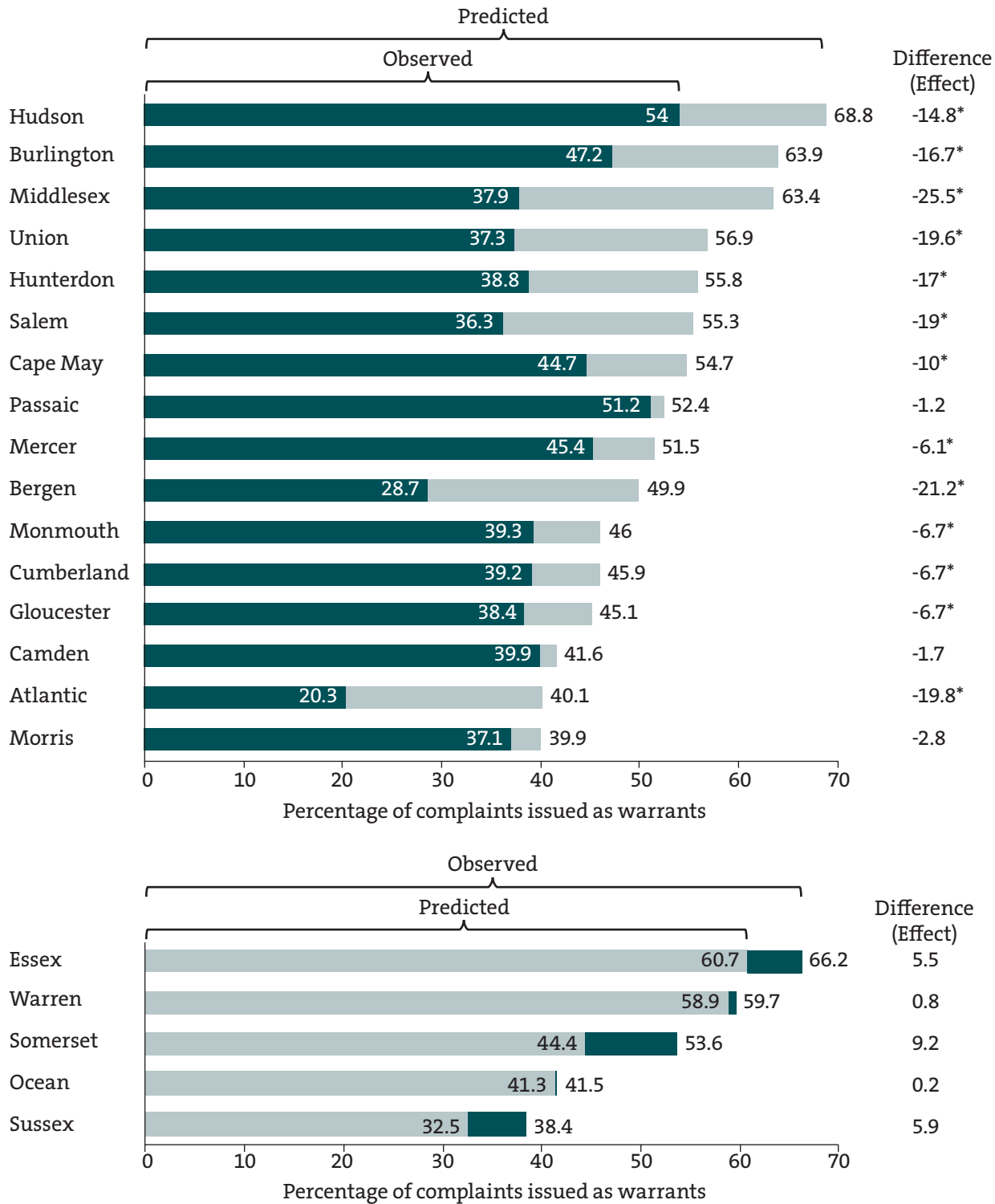
The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

be important to explore how this trend evolves with additional follow-up, because it has implications for how the effects of CJR can be sustained over time.

- **An analysis by county found that the decrease from the predicted trend in the proportion of charges issued on complaint-warrants occurred in most counties.**

Figure 6 shows the effects of CJR on the decision to issue charges on a complaint-warrant or complaint-summons, by county. Each county is shown in the figure. The top portion of the figure shows the counties that experienced decreases from their predicted trends in the percentage of arrest events

FIGURE 6 Effects on Complaint-Warrants Among Defendants Arrested on Indictable Charges, by County



SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range; statistical significance is indicated using an asterisk (*).

The predicted and observed percentages were calculated by aggregating the results of monthly interrupted time series analyses for 2017 into averages for the year.

involving complaint-warrants.³² The five counties shown in the bottom panel of the figure experienced slight increases from their predicted trends in the percentage of indictable charges issued on complaint-warrants. None of those small increases are statistically significant.

The figure shows that most counties in New Jersey (13 of 21) experienced statistically significant reductions in the percentages of arrest events for indictable charges involving complaint-warrants, compared with the prediction. In other words, these counties experienced a substantial shift from complaint-warrants (and potential jail commitments) to complaint-summonses and immediate releases (since a smaller percentage of complaint-warrants meant a larger percentage of complaint-summonses). In sum, in most counties, CJR led to a greater use of complaint-summonses rather than complaint-warrants. Future reports will further explore the differences in effects by county.

CJR'S EFFECTS ON PRETRIAL RELEASE CONDITIONS

As illustrated in Figure 1, once a defendant is issued a complaint-warrant, he or she is booked into jail and scheduled for a first appearance hearing, where a decision is made about the conditions under which the defendant may be released while waiting for the case to be disposed of. CJR made sweeping changes to the menu of possible pretrial release conditions and to the process for determining release conditions in a given case. As described in detail above, a system based mainly on money bail was replaced with a system that includes a pretrial monitoring program and the possibility of preventive detention. This section examines the effects of CJR on pretrial release conditions (among arrest events involving indictable charges, for reasons explained in the previous section).

- **CJR resulted in a higher proportion of defendants being released without conditions following the first appearance hearing.**

The effects of CJR on release conditions for defendants arrested on indictable charges are summarized in Table 1. The first column of numbers in the table shows predictions based on trends for all of 2017. The second column shows the actual percentage assigned each release condition during that year.³³ The

³² These percentages were calculated by aggregating the results of monthly interrupted time series analyses for 2017 into averages for the year.

³³ These percentages were calculated by aggregating the results of monthly interrupted time series analyses into averages for the year.

**TABLE 1 Average Effects on Release Conditions
Among Defendants Arrested on Indictable Charges**

Release Condition (%)	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Release condition as of the first appearance hearing				
Released	77.9	82.2	4.3	5.5
Without conditions	53.5	62.7	9.2*	17.2
With conditions	24.5	19.5	-5.0*	-20.4
Not released	21.9	17.3	-4.6*	-21.0
Case resolved	0.6	0.5	-0.1	-16.7
Release condition as of the detention hearing ^a				
Released	78.0	90.7	12.7*	16.3
Not released/detained	21.9	7.3	-14.6*	-66.7
Case resolved ^b	0.6	2.0	1.4*	233.3

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range; statistical significance is indicated using an asterisk (*).

The predicted and observed percentages were calculated by aggregating the results of monthly interrupted time series analyses for 2017 into an average for the year. Only January-October 2017 are included from the period after CJR was implemented due to data-availability limitations.

Outcomes do not always sum to 100 and there may be small differences in effects for categorical measures due to the predictive modeling approach used in this analysis.

All complaint-summons are included in "released/released without conditions" in both panels. For complaint-warrants in the period after CJR was implemented, ROR = "released without conditions," pretrial monitoring = "released with conditions," and detention motions and preventive detention = "not released/detained." For complaint-warrants in the pre-CJR period, at the first appearance hearing defendants might be given ROR ("released without conditions"), released on bail ("released with conditions"), or not released because they did not post bail ("not released/detained").

^aSince there was no detention hearing before CJR, the predicted number is based on defendants' pre-CJR statuses as of the first appearance hearing, and the observed number is based on their statuses after CJR was implemented as of the detention hearing.

^bFor the period after CJR was implemented, cases are counted as resolved if they were resolved at the first appearance hearing or within 10 days after arrest.

difference between these columns represents the estimated effect of CJR. The top panel of the table shows release conditions as of the first appearance hearing, while the bottom panel shows release conditions as of the detention hearing. It is important to note that people issued complaint-summons are included in the "released without conditions" category.³⁴

34 See the notes below Table 1 for more detail regarding this analysis. See Appendix Table A.2 for more detailed information about release conditions for the full sample in both periods (that is, among cases with both indictable and nonindictable charges). The patterns of effects for the full sample are generally similar to those described here for the sample of arrest events with indictable charges, although the percentages themselves vary somewhat.

The top panel of Table 1 shows that CJR led to a significant increase of about 9 percentage points over the predicted trend in the percentage of defendants released without conditions, either because they were charged on complaint-summonses or because they were released on their own recognizance at a hearing (though the vast majority were released on complaint-summonses). Even though CJR introduced pretrial monitoring and pretrial detention motions at the first appearance hearing, fewer defendants were released with conditions or held in jail by the time of the first appearance hearing than was predicted based on the pre-CJR trends. These changes indicate that pretrial monitoring and pretrial detention motions were used with a smaller percentage of defendants than would have been assigned bail had CJR not occurred. In particular, a smaller percentage of defendants were held in jail because of detention motions than would have been held in jail because they did not post bail.

- **CJR reduced the proportion of defendants held in jail after the final release condition was set.**

CJR was expected to reduce the number of defendants being held in jail because they were unable to pay monetary bail. However, CJR also introduced pretrial detention motions, which could have the opposite effect, causing more people to be detained with no possibility of bailing out. To shed light on how CJR affected release conditions, the bottom panel of Table 1 shows the release conditions set as of the detention hearing among defendants arrested on indictable charges. These “final” release conditions are the ones that will apply to defendants as long as their cases are open.³⁵ The table shows that after CJR was implemented, just 7 percent of defendants were detained as their final release condition, compared with a predicted rate of 22 percent. (The vast majority were released by the time of the first appearance hearing and did not have detention hearings.) This effect is the equivalent of a 67 percent reduction in the proportion of defendants detained while their cases are being adjudicated. As discussed previously, the percentage of cases disposed of at this point through dismissals or plea deals is very small, but it appears to be higher than predicted after CJR was implemented. A full analysis of CJR’s effects on case disposition is planned for a future report.

³⁵ For many defendants, the final release condition is set when a police officer decides to issue a complaint-summons, or at the first appearance hearing. For defendants who are detained following the first appearance hearing, the final release condition is set at the detention hearing. The release condition can change if a defendant incurs a new charge or misses a court hearing.

Figure 7 shows CJR’s effects on the percentage of defendants who were booked into jail as of the detention hearing, by county (among defendants arrested on indictable charges). As the figure shows, all but one county in New Jersey experienced significant reductions in the percentage of defendants who were booked into jail, compared with what was predicted had CJR not occurred. Larger reductions were generally observed among counties with higher predicted jail-booking rates, that is among counties with the highest rates of jail booking before CJR (for example, Hudson, Warren, Essex, Burlington, and Union), with some exceptions.

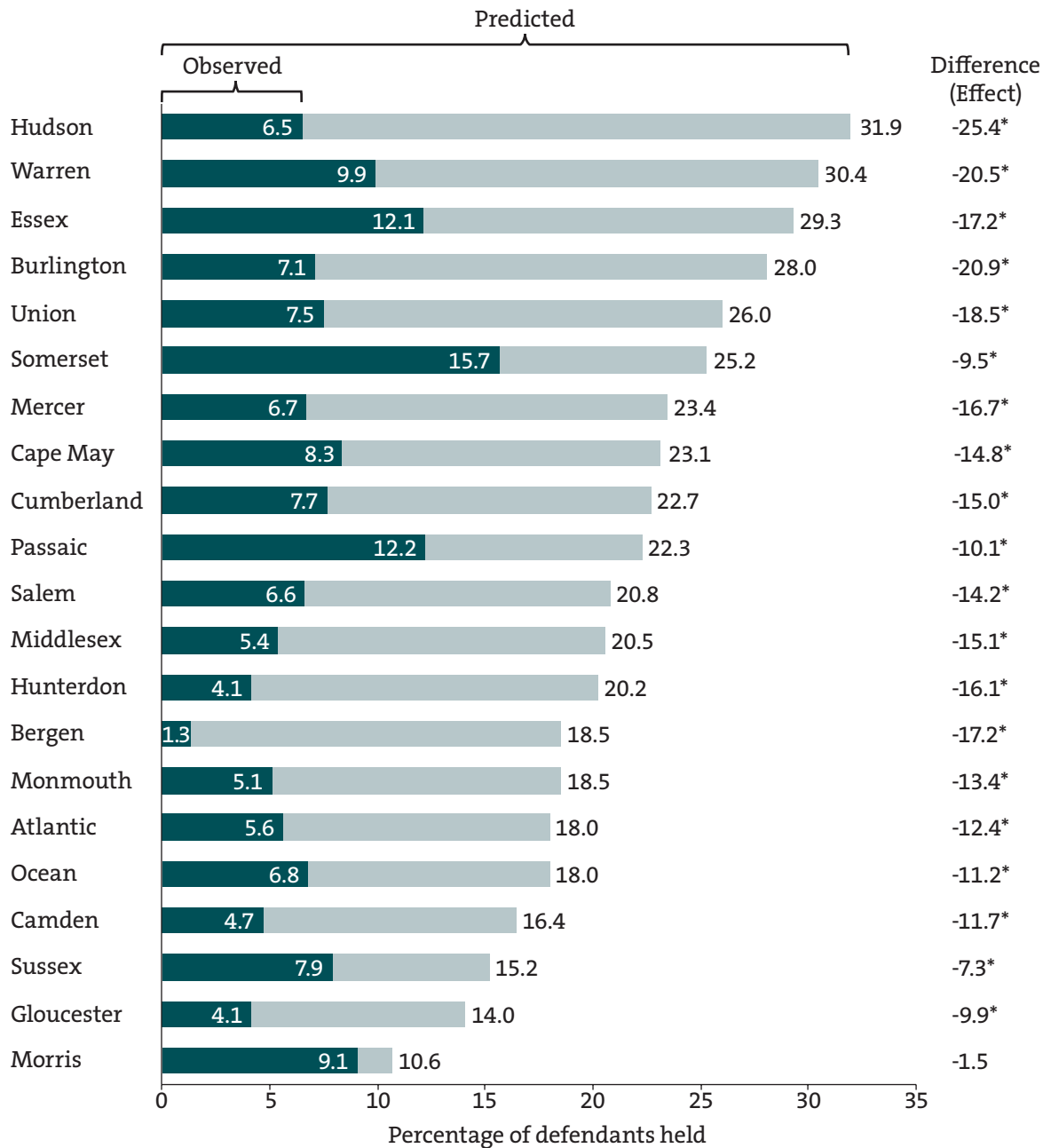
Appendix Figure A.3 shows the “initial” release conditions for defendants after CJR was implemented (defined here as release conditions as of the first appearance hearing), by county. Counties differed somewhat in their use of various initial release conditions after CJR was implemented. County differences in initial release conditions may reflect differences across counties in the severity of the charges on cases in the courts, in the types of defendants in the justice system, or in the ways the counties implemented CJR.

CJR’S EFFECTS ON INITIAL JAIL STAYS

This section examines CJR’s effects on jail stays within the first 30 days after arrest. Figure 8 shows effects on the percentage of arrest events involving indictable charges in which the defendant was initially booked in jail, and the percentages detained for at least 3 days, for at least 10 days, and for at least 30 days.³⁶ These measures are not mutually exclusive; for example, all defendants with an initial detention of at least 10 days are also included as having been detained for at least 3 days.

36 The jail data do not include information about the exact times that an individual was booked into and out of jail. These measures are based on calendar dates. If an individual was booked into and out of jail on the same calendar day, he is coded as having been detained for one day. If he was released the day after he was initially booked, he is coded as having been detained for two days. As explained above, this analysis focuses on defendants with indictable charges so that any observed effects can be attributed with greater confidence to CJR policy changes after the point of arrest rather than to the changing composition of defendants and charges attributed to changing law enforcement patterns. See above for a discussion of CJR’s effects on initial detention among all defendants (including those charged with nonindictable offenses).

FIGURE 7 Effects on Jail Bookings as of the Detention Hearing Among Defendants Arrested on Indictable Charges, by County

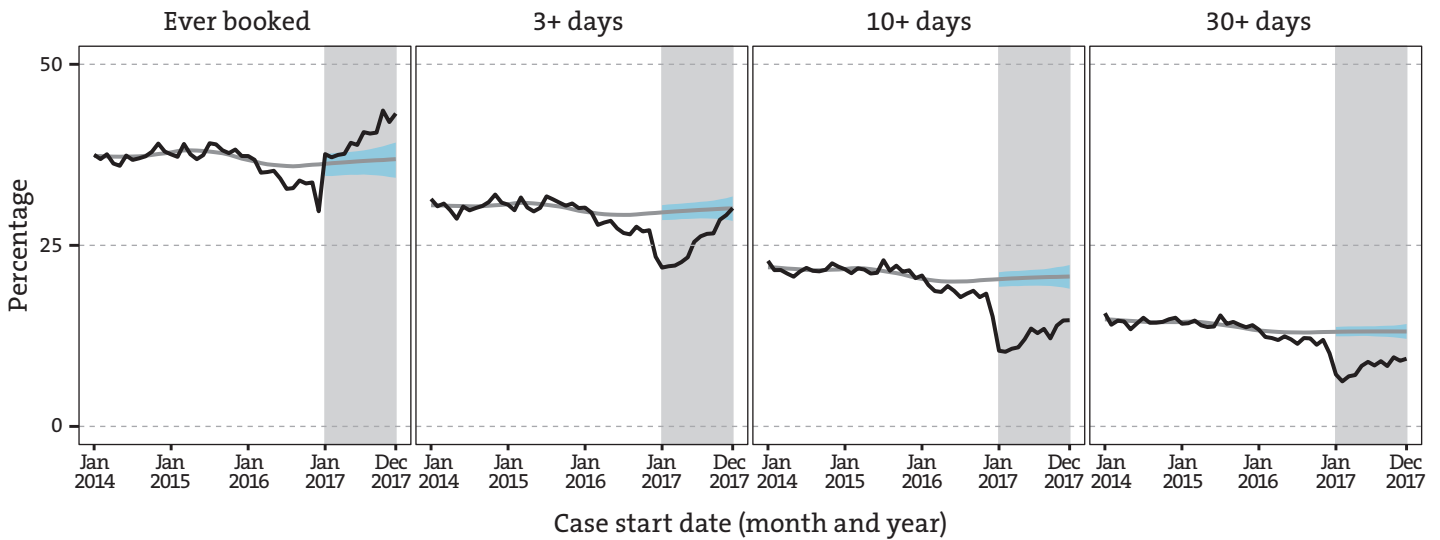


SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or impact, is the observed outcome minus the predicted outcome. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range; statistical significance is indicated using an asterisk (*).

The predicted and observed percentages were calculated by aggregating the results of monthly interrupted time series analyses for 2017 into averages for the year.

FIGURE 8 Effects on Lengths of Initial Jail Stays Among Defendants Arrested on Indictable Charges



Jail Stays Among Defendants with Indictable Charges in July 2017

Jail Stay	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Ever booked	36.7	39.3	2.6*	7.1
Held 3+ days	29.9	25.7	-4.2*	-14.0
Held 10+ days	20.6	13.0	-7.6*	-36.9
Held 30+ days	13.1	8.5	-4.6*	-35.0

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the differences in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

- **CJR led to an increase in the proportion of defendants who were initially booked into jail, but significantly reduced the amount of time that defendants were held in jail in the 30 days following arrest.**

The leftmost panel in Figure 8 shows a gradual climb in the rates of initial jail booking beginning in January 2017, when CJR went into effect. This increase is not particularly surprising since CJR eliminated the option to post bail for defendants issued complaint-warrants, requiring instead that all those issued complaint-warrants be booked into jail pending a first appearance hearing

(which had to occur within 48 hours). The reduction described previously in the total number of defendants issued complaint-warrants tempered the increase observed here somewhat. In other words, the percentage of defendants initially booked would have been even higher had complaint-warrants been issued at the same rate they were before CJR. The gradual increase in the percentage booked into jail midway through the year after CJR went into effect is probably related to a similarly observed increase in the percentage of complaint-warrants issued for indictable cases over the same period (see Figure 5 above).³⁷ The increase shown in the figure became statistically significant starting in June 2017 and continued to rise through the end of the year.³⁸ It will be important to obtain additional follow-up data that allow for a more complete assessment of these effects.

While CJR led to an initial reduction in the proportion of defendants held for 3 or more days, the figure shows that this effect began to recede in mid-2017 and was no longer significant by the end of the year. CJR's near-elimination of bail combined with the option for pretrial detention motions — and a mid-2017 expansion of this option — probably contributed to this pattern of effects. Specifically, the attorney general issued revised guidelines in May 2017 that lowered the PSA score threshold where it was recommended that a defendant be held. Before this directive, the recommended threshold for a recommendation to issue a complaint-warrant (thus holding a defendant) was a PSA score of 4 or higher; the directive revised that threshold to a PSA score of 3 or higher. At the same time, the judiciary added certain charges, such as firearm offenses, to the list of those where the DMF automatically recommends no release at the initial appearance hearing.³⁹ These changes may explain why the pattern of effects on this measure appears to reverse in mid-2017.

As shown in the right two panels of the figure, CJR led to sustained reductions in the percentage of defendants held in jail longer than 10 days. Both the percentage held for 10 or more days and the percentage held for 30 or more days were about a third lower than predicted. In other words, while the percentage

37 The proportion of indictable cases initiated on complaint-warrants began climbing back to pre-CJR levels in mid-2017, possibly due to changes in mid-2017 that lowered the PSA score threshold at which a complaint-warrant was recommended. Porrino (2017).

38 The reason that there was no effect on the *number* of all defendants ever booked into jail yet a positive effect on the *percentage* of defendants with indictable charges ever booked (as well as the percentage of all cases — see Appendix Figure A.5) is related to the changing number and share of complaint-warrants. A greater proportion of defendants were initially booked into jail due to CJR's requirement that all those issued complaint-warrants be initially booked, but this increase in the proportion of defendants initially booked was counteracted by a reduction in the proportion of defendants issued complaint-warrants, yielding no net effect on the total number of defendants initially booked.

39 Porrino (2017).

of defendants with indictable charges who were initially booked into jail increased, releases came faster and individuals spent substantially less time in jail during the pretrial period, after CJR went into effect.⁴⁰ The same pattern was generally observed across the counties. Since this analysis was limited to defendants with indictable charges, the number of whom was unaffected by the overall decline in arrest events, the faster releases from jail appear to be a result of changes to the pretrial processes in the courts.

CONCURRENCE BETWEEN RELEASE CONDITIONS AND THE RECOMMENDATIONS OF THE DMF

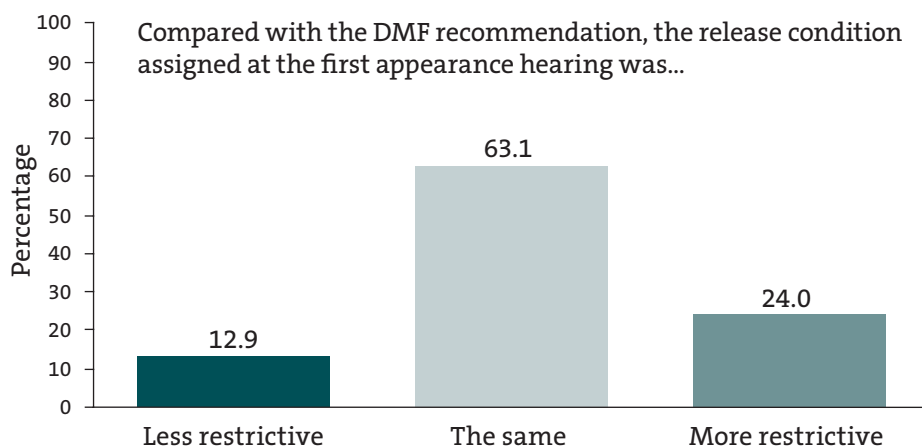
The results presented in the previous section show that the broad set of policy changes implemented under CJR led to shifts in the conditions of pretrial release in New Jersey. This section focuses more specifically on the role of the PSA and DMF in the period after CJR was implemented by examining the extent to which the release conditions after CJR was implemented corresponded with the recommendations of the DMF developed by the judiciary (referred to as “concurrency”). The analysis is limited to defendants issued complaint-warrants with indictable charges in the period after CJR was implemented, and focuses on the outcome of the first appearance hearing, at which point in the process the PSA score and DMF recommendation are available. Future reports from this evaluation will examine the overall alignment of defendants’ assessed risk levels with the release conditions they received.

A defendant can be issued one of three broad categories of release conditions — ROR with or without conditions, release to pretrial monitoring, or no release. The DMF recommends one of these possible release conditions.⁴¹ Figure 9 shows the proportion of defendants for which the release condition assigned at the first appearance hearing matched the recommendation of the DMF and among those for whom the condition did not match the recommendation, whether the actual condition was more restrictive than recommended (for ex-

40 Since there was a small increase in the percentage of defendants with indictable violent charges after CJR was implemented, a sensitivity test was conducted on lengths of initial jail stays that excluded those with violent charges from the analysis of defendants with indictable charges. The general trends for this subset were similar to those observed among all defendants with indictable charges, but the rates of the initial jail-stay outcomes were a little lower across the board. As a result, there was less of an effect on the percentage initially booked into jail and greater reductions in the percentages held for 3 or more, 10 or more, and 30 or more days. See Appendix B for more details.

41 There are different levels within pretrial monitoring that have been collapsed for this analysis. Release to pretrial monitoring at any level is considered to correspond with any DMF-recommended level of pretrial monitoring.

FIGURE 9 Concurrence Among Defendants Arrested on Complaint-Warrants with Indictable Charges



SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: Only January-October 2017 are included due to data-availability limitations. This figure excludes 202 cases (fewer than 1 percent of the total) that were resolved at the first appearance hearing.

To illustrate the meanings of the categories above, the “less restrictive” category would include an instance where pretrial monitoring was given when no release was recommended, the “same” category would include an instance where pretrial monitoring was given when pretrial monitoring was recommended, and the “more restrictive” category would include an instance where pretrial monitoring was given when ROR was recommended.

ample, a detention motion when the DMF recommended pretrial monitoring) or less restrictive.

- **The initial release conditions matched the DMF recommendations most of the time. When an actual release condition did not match the recommendation, it was often because the prosecutor decided to request a detention hearing.**

In almost two-thirds of cases (63 percent), the release conditions resulting from first appearance hearings matched the DMF recommendations. Release conditions were more restrictive than the DMF recommendations in about one-quarter of cases (24 percent) and less restrictive in about 13 percent of cases.

When there were deviations from the DMF recommendations, it was most often because prosecutors decided to move for detention at the first appearance hearing: Among the instances in which the release conditions did not match the recommendations, in more than one-third the prosecutor moved for detention when it was not recommended by the DMF, and in about one-third the

prosecutor did not move for detention when the DMF did recommend it (not shown in the figure). Most of the remaining nonmatching situations (fewer than one-third) were those in which the DMF recommended ROR but the defendant was released with pretrial monitoring.

These results speak to the important role prosecutors play in determining whether someone will be detained in New Jersey since CJR was implemented. The concurrence findings also suggest that sometimes a defendant who is placed on pretrial monitoring would have been released without conditions before CJR. This trend may be related to the fact that in 2017, judges could not attach conditions such as “no contact with the victim” to an ROR. Starting in 2018, judges can now attach certain conditions to an ROR, which may mean that judges’ decisions currently concur more with the DMF when ROR is recommended than was the case in the time period included in this analysis.

Appendix Figure A.4 shows concurrence rates by county. In most counties release conditions concurred with DMF recommendations most of the time — between about 50 percent and 80 percent of the time — with one exception. These relatively high concurrence rates in most counties suggest that at least some of the variation across counties in release conditions seen earlier — particularly for defendants issued complaint-warrants — may reflect county differences in case and defendant characteristics (in addition to county differences in CJR implementation). For example, some counties may have had more detention motions because larger proportions of their defendants were assessed as being high-risk.

SUMMARY OF FINDINGS

CJR led to large-scale changes in New Jersey’s arrest and pretrial processes, which resulted in dramatic effects on arrest events, on the use of complaint-summonses and complaint-warrants, on release conditions, and on initial jail stays. The effect on arrest events was unexpected: CJR led to a decrease in the total number of arrest events, which was largely the result of a reduction in arrests for the least serious types of charges (nonindictable public-order offenses). Among arrest events involving the most serious types of charges (indictable offenses), the number of which was not affected by CJR, a greater percentage of defendants than predicted received complaint-summonses (which guarantee immediate release) and a smaller percentage received complaint-warrants (which guarantee at least some jail detention, since after CJR individuals can no longer pay bail to be released before the first

CJR led to large-scale changes in New Jersey’s arrest and pretrial processes, which resulted in dramatic effects on arrest events, on the use of complaint-summonses and complaint-warrants, on release conditions, and on initial jail stays.

appearance hearing). These patterns occurred across most counties, which strengthens confidence that statewide findings can be attributed to CJR (since they are not due to a few larger counties implementing other, simultaneous policy changes).

As expected, CJR led to significant changes in the release conditions given to defendants. In particular, a larger proportion of defendants were released without conditions after CJR was implemented, mostly because police officers shifted to complaint-summonses. Bail was virtually eliminated, with pretrial monitoring and detention motions often used for those arrested on complaint-warrants. Yet even with the option of pretrial detention motions, the proportions of defendants held in jail at the time of the first appearance hearing and detention hearing were significantly lower than predicted based on pre-CJR trends. This finding means that lower percentages of defendants were given pretrial detention at these stages than would have been held before CJR because they did not pay bail. The release conditions given by judges after CJR was implemented usually concurred with DMF recommendations at the first appearance hearing, and this finding was generally observed across the counties, with some variation. When the release conditions differed from the recommendations, it was often because prosecutors moved for pretrial detention when the DMF recommendation was for release or because prosecutors did not move for pretrial detention when it was recommended.

For defendants with indictable charges, CJR increased the percentage who were initially booked into jail, because CJR required that those defendants be held pending a first appearance hearing with no option to bail out. However, CJR reduced the percentages detained for 10 or more and 30 or more days. Since this effect occurred among defendants with indictable charges (which appear to be largely unaffected by the decline in overall arrests), the shorter stays in jail appear to be the result of changes in the courts' pretrial processes. This pattern of findings was generally observed across counties and the reduction in length of jail stays was also observed among the full sample of defendants. In short, CJR led to fewer individuals spending long amounts of time in jail after they were arrested even though it required that all those issued complaint-warrants be booked into jail initially.

POLICY IMPLICATIONS

With CJR, New Jersey changed the pretrial process at multiple points and affected the decisions of multiple actors, including police officers, prosecutors, public defenders, and judges. As a result, there were large effects on the number and composition of arrest events and charges, on the release conditions imposed on defendants awaiting trial, and on the lengths of initial jail stays. The net result was a much smaller number of people in jail awaiting trial. These results provide important lessons for other jurisdictions looking to make similar changes.

While New Jersey did not explicitly aim to reduce arrests, CJR appears to have had the effect of reducing the total number of arrests for the least serious types of offenses. This effect may have been the result of a number of factors: broader culture changes that accompanied the reforms, changes in the process required for issuing complaint-warrants (such as the use of the PSA), new paperwork requirements, and greater oversight of police complaint charging decisions. The effect on the types of complaints issued once charges were initiated on an arrest (that is, police officers' use of complaint-summons in lieu of complaint-warrants) may have been because the use of the PSA informed that decision or because of the changes to the complaint charging process.

While the changes in the number of people arrested are large, this analysis is able to isolate those effects from the effects that occurred within the courts. The analysis presented in this report offers compelling evidence that changes in the policies and practices of the courts, and not just changes in policing, affected release conditions and reduced the length of time defendants spent in jail awaiting trial. That is, the effects on release conditions and initial jail stays were due to changes in the pretrial process *after* the point of arrest: the revised procedures for issuing complaints, the virtual elimination of bail, the first appearance hearing process, revised release conditions (including pretrial detention motions), and the use of the PSA and DMF to inform release conditions. These results suggest that jurisdictions could reduce pretrial jail stays, even if there were no changes to policing and even with the option for pretrial detention motions. Future reports that are planned from this evaluation will assess whether the reforms affected court appearance rates and new criminal charges, both of which are of concern as more defendants are released.

CJR's effects on initial jail bookings are important for jurisdictions to consider when they contemplate reducing or eliminating money bail. The in-

The analysis presented in this report offers compelling evidence that changes in the policies and practices of the courts, and not just changes in policing, affected release conditions and reduced the length of time defendants spent in jail awaiting trial.

crease after CJR was implemented in the proportion of defendants initially booked into jail means that some defendants were booked into jail after CJR was implemented who would not have been before CJR. On the other hand, the system since the implementation of CJR is more equitable since jail commitment is no longer based on one's ability to afford bail, and ultimately the system after CJR was implemented resulted in less jail time for those who were booked. It will also be important to continue to examine the effects on cases that were initiated after December 2017 (and to look at case and crime outcomes that occur beyond the 30-day follow-up period of this report, particularly given the steady climb in jail detention and detention for 3 or more days that was observed over the course of 2017).

Lastly, readers should bear in mind that this report is the first in a series that has been planned on the effects of New Jersey's Criminal Justice Reform. The findings in this report show that CJR appears to have been successful in nearly eliminating money bail, releasing more defendants on complaint-summons and without conditions even in the presence of a new pretrial monitoring program. It also reduced jail stays despite the option for preventive detention. However, it remains to be seen whether these promising changes had any effect on defendants' rates of failing to appear at court hearings, new criminal activity, or case dispositions. Subsequent reports will present findings on these topics, and will also examine the effects of CJR on racial disparities and further explore the role of risk-based decision making in achieving the effects.

APPENDIX TABLE A.1 Defendant and Crime Characteristics

Characteristic (%)	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Defendant characteristics (complaint-warrant arrest events only)				
Race ^a				
Black	42.9	47.9	5.0*	11.7
Not black	53.6	51.2	-2.4*	-4.5
Female	19.9	15.4	-4.5*	-22.6
Less than 23 years old	16.9	16.9	0.0	0.0
Criminal history				
Prior conviction	57.3	68.0	10.7*	18.7
Prior violent conviction	23.5	29.5	6.0*	25.5
Prior violent indictable conviction	14.8	19.5	4.7*	31.8
Failure to appear in the past 2 years	31.3	44.8	13.5*	43.1
Failure to appear more than 2 years ago	44.0	52.5	8.5*	19.3
Prior sentence to incarceration	35.9	45.6	9.7*	27.0
Risk level ^b				
Low	34.1	21.8	-12.3*	-36.1
Medium	32.5	29.8	-2.7*	-8.3
High	33.5	48.4	14.9*	44.5
Crime characteristics (complaint-warrant and complaint-summons arrest events)				
Charge class				
Indictable	43.2	51.3	8.1*	18.8
Nonindictable	56.6	48.7	-7.9*	-14.0
Charge category				
Violent	19.6	19.2	-0.4	-2.0
Drug	36.1	41.8	5.7*	15.8
Property	19.6	21.8	2.2*	11.2
Public order	24.4	16.7	-7.7*	-31.6

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range; statistical significance is indicated using an asterisk (*).

Outcomes do not always sum to 100 and there may be small differences in effects for categorical measures due to the predictive modeling approach used in this analysis.

^aRace information was missing for a small percentage of individuals.

^b"Risk level" was assessed by applying the PSA algorithm and grouping based on the resulting failure-to-appear and new-criminal-activity scores: "high risk" = a 5 or 6 on either score, "medium risk" = a 3 or 4 on either score but nothing higher, "low risk" = a 1 or 2 on either score but nothing higher.

APPENDIX TABLE A.2 Descriptive Breakdown of
Release Conditions Among All Defendants

Release Condition (%)	Before CJR	After CJR Was Implemented
Release condition as of the first appearance hearing		
Released	87.1	91.0
Without conditions	71.0	79.1
Summons	66.4	76.7
ROR	4.6	2.4
With conditions	16.1	11.9
Posted bail	16.1	--
Pretrial monitoring	--	11.9
Not released	11.3	8.7
Did not post bail	11.3	--
Detention motion	--	8.7
Case resolved	1.6	0.3
Release condition as of the detention hearing ^a		
Released	87.1	95.2
Not released/detained	11.3	3.7
Case resolved ^b	1.6	1.1

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

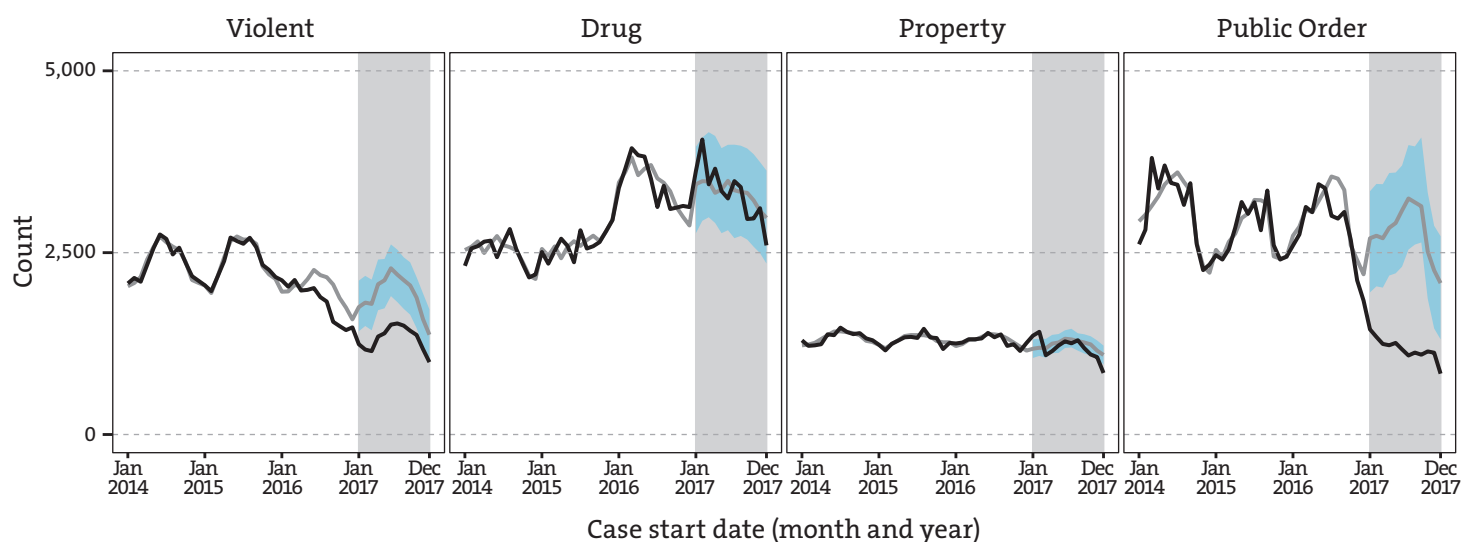
NOTES: The pre-CJR analysis includes January 2009 through June 2016; July-December 2016 are excluded since this was a transition period leading up to implementation of CJR. Only January-October 2017 are included in the analysis of the period after CJR was implemented due to data-availability limitations.

All summons complaints are coded as "summons" and "released without conditions" in the first panel and as "released" in the second panel.

^aSince there was no detention hearing before CJR, the pre-CJR numbers reflect defendants' statuses as of the first appearance hearing. The numbers after CJR was implemented reflect their statuses as of the detention hearing.

^bFor the period after CJR was implemented, "case resolved" means cases were resolved by the first appearance hearing or within 10 days after the arrest.

APPENDIX FIGURE A.1 Effects on the Number of Cases with Nonindictable Charges, by Crime Type



Number of Cases with Nonindictable Charges in July 2017, by Crime Type

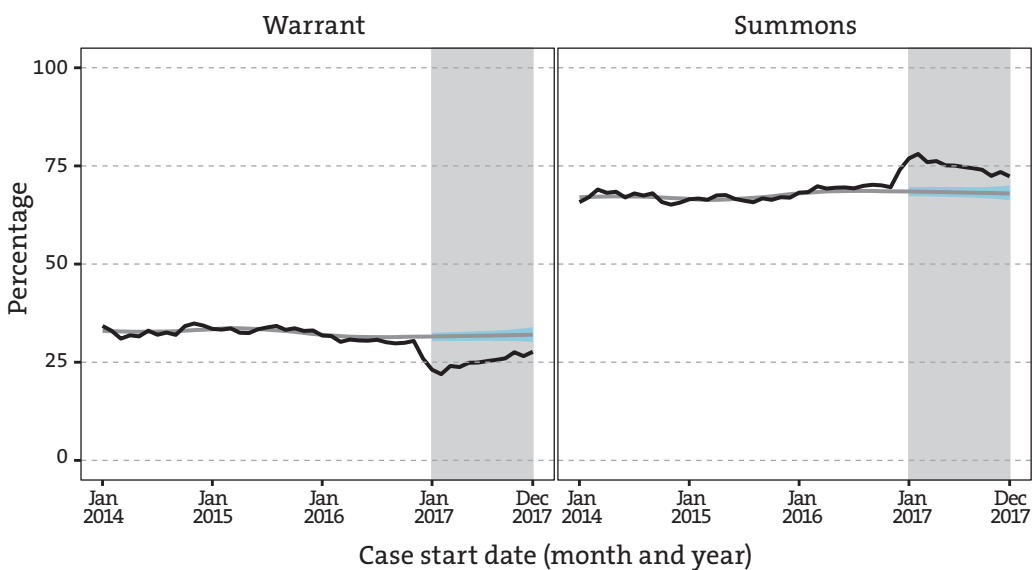
Crime Type	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Violent	2,195	1,537	-657*	-29.9
Drug	3,365	3,248	-117	-3.5
Property	1,308	1,244	-64	-4.9
Public order	3,231	1,378	-1,853*	-57.3

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the difference in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

APPENDIX FIGURE A.2 Effects on Complaint Types Among All Cases



Complaint Type Among All July 2017 Cases

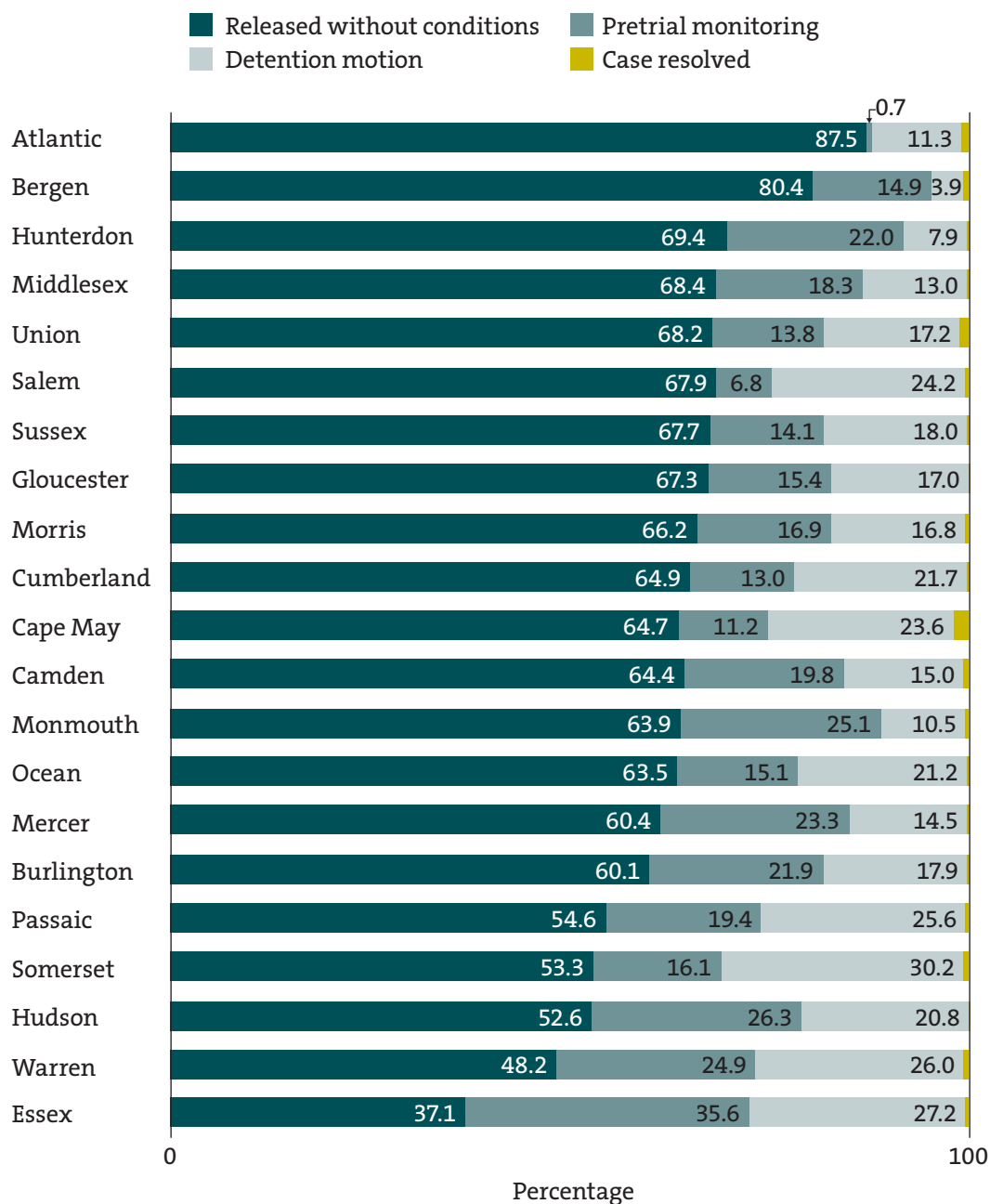
Complaint Type	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Warrant	31.8	25.6	-6.2*	-19.5
Summons	68.2	74.4	6.2*	9.1

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the difference in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

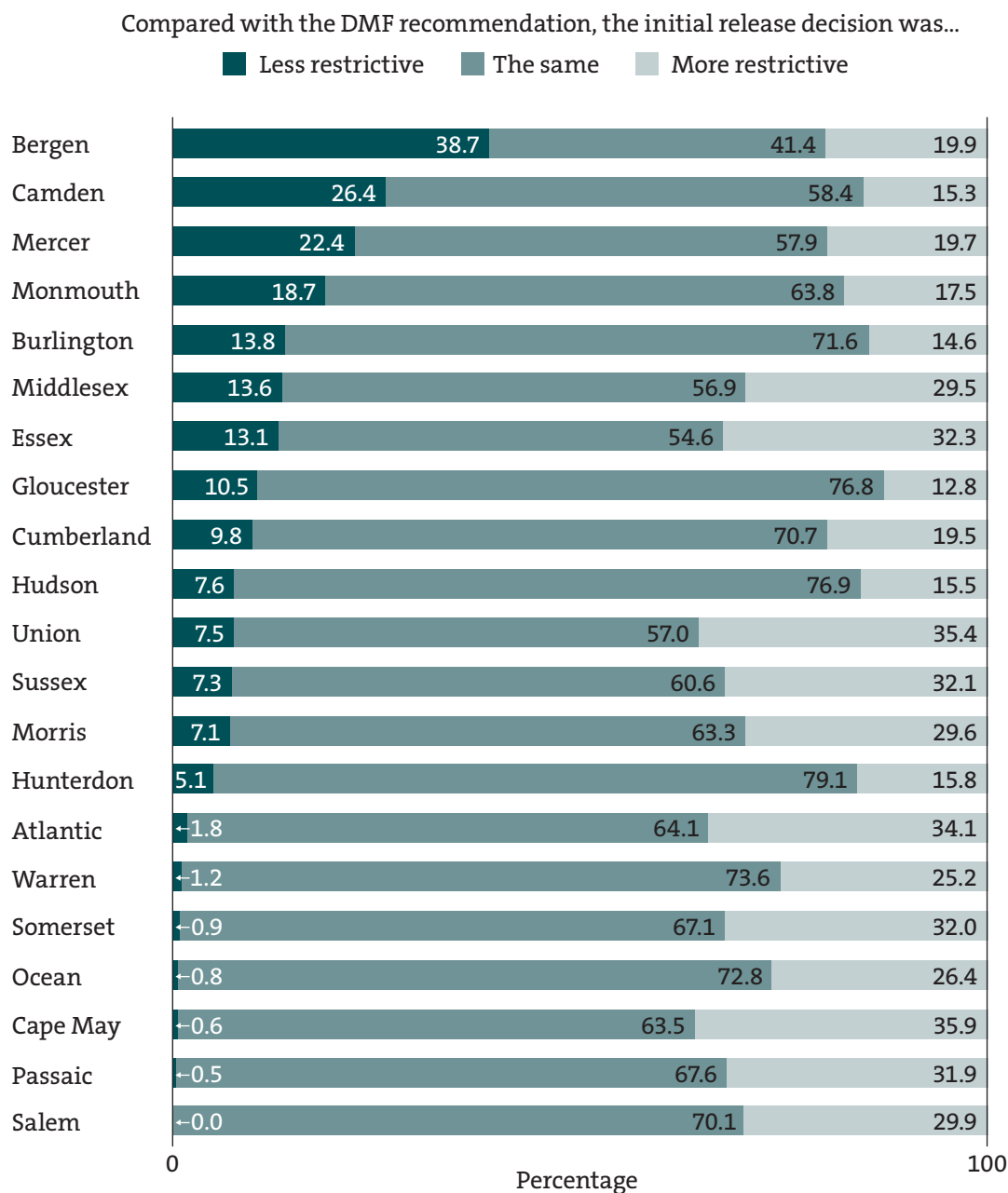
The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

APPENDIX FIGURE A.3 Initial Release Conditions by County After CJR Was Implemented, Among Defendants Arrested on Indictable Charges



SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

APPENDIX FIGURE A.4 Concurrence Among Defendants Arrested on Complaint-Warrants with Indictable Charges, by County

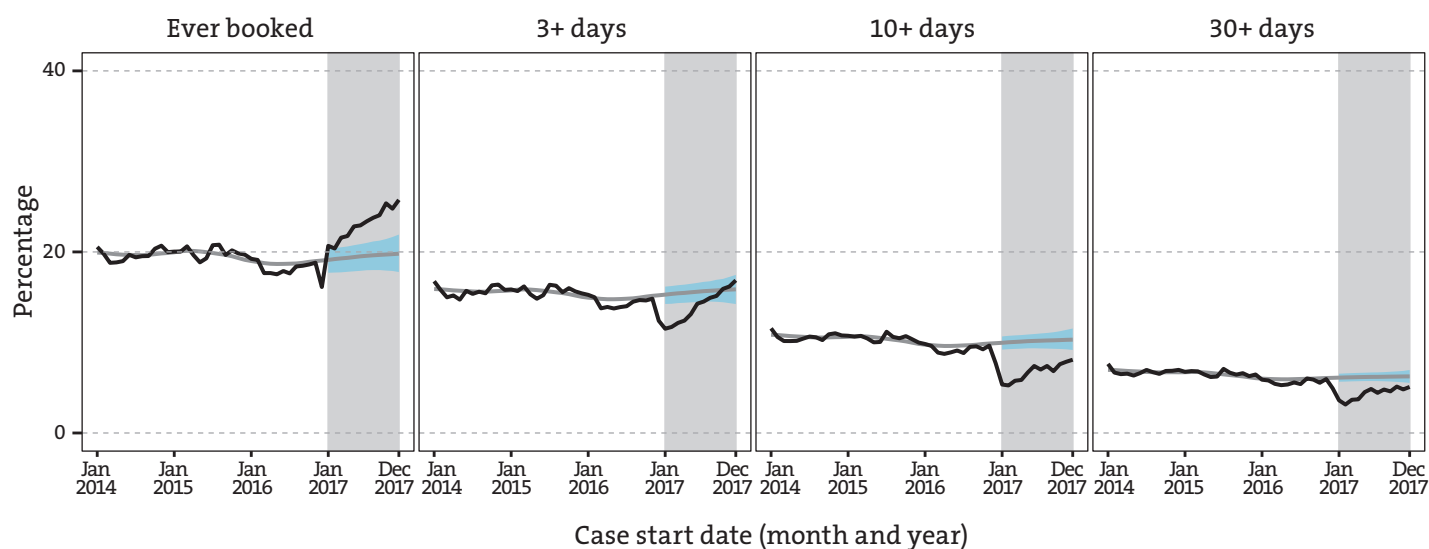


SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: Only January-October 2017 are included due to data-availability limitations.

The figure excludes a small number of cases that were resolved at the first appearance hearing.

APPENDIX FIGURE A.5 Effects on Lengths of Initial Jail Stays Among All Defendants



Jail Stays Among All Defendants with Cases Started in July 2017

Jail Stay	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Ever booked	19.6	22.8	3.2*	16.3
Held 3+ days	15.6	14.3	-1.3*	-8.3
Held 10+ days	10.2	7.1	-3.2*	-31.3
Held 30+ days	6.2	4.5	-1.7*	-27.3

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

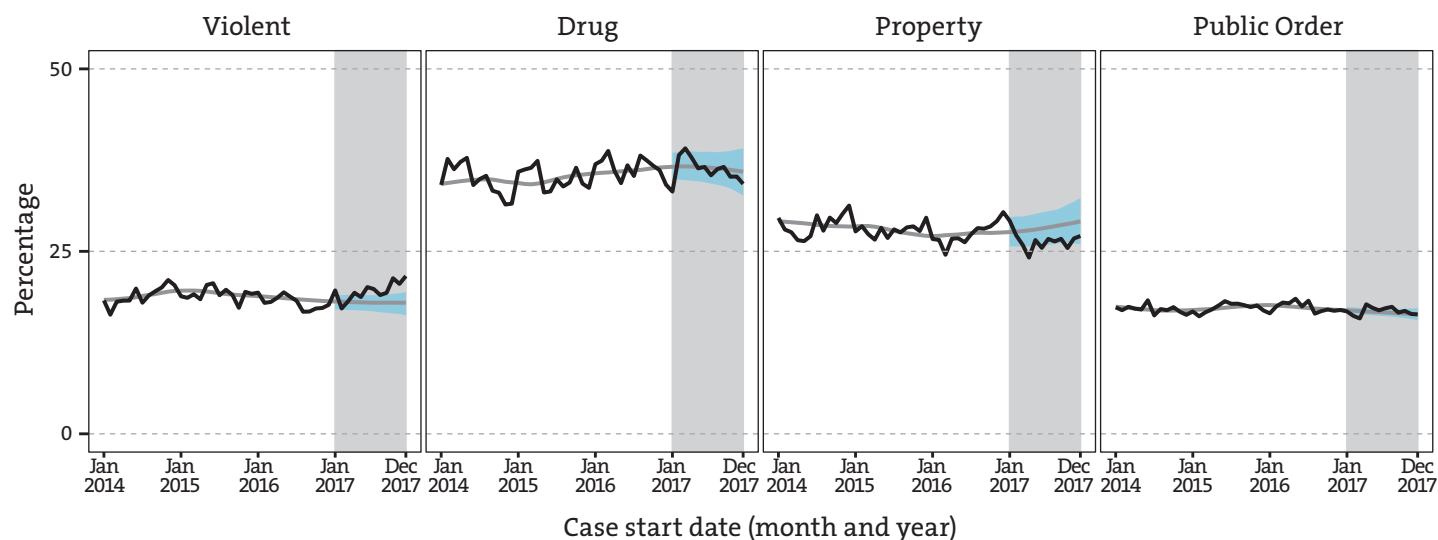
NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is also indicated for Month 6 arrest events using an asterisk (*) next to the differences in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 in order to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

SENSITIVITY TEST FOR EFFECTS ON LENGTHS OF INITIAL JAIL STAYS AMONG DEFENDANTS ARRESTED ON INDICTABLE CHARGES

Among cases with indictable charges, CJR resulted in a small increase in the percentage that involved charges for violent crimes (see Appendix Figure B.1). A sensitivity test was therefore conducted for the effects presented in the body text on lengths of initial jail stays among all defendants with indictable charges. The sensitivity test included only nonviolent indictable cases. The purpose was to assess whether the general patterns in effects on initial jail stays described in the text were still present, and to what extent they could be attributed to the change in case composition. As shown in Appendix Figure B.2, the sensitivity test revealed that the small increase in arrest events involving indictable charges for violent crimes largely explains the increase in the proportion of defendants with indictable charges who were ever booked into jail. However, the increase in arrest events involving indictable charges for violent crimes does not explain the reductions in the proportions of defendants with indictable charges who were initially held for 3 or more, 10 or more, and 30 or more days. Therefore, this analysis confirms that CJR's changes to the pretrial process after the point of arrest probably sped defendants' release from jail by reducing the proportion of cases in which defendants were held for longer periods.

APPENDIX FIGURE B.1 Effects on the Percentages of Crime Types
Among Cases Involving Indictable Charges



Number of Cases by Crime Type

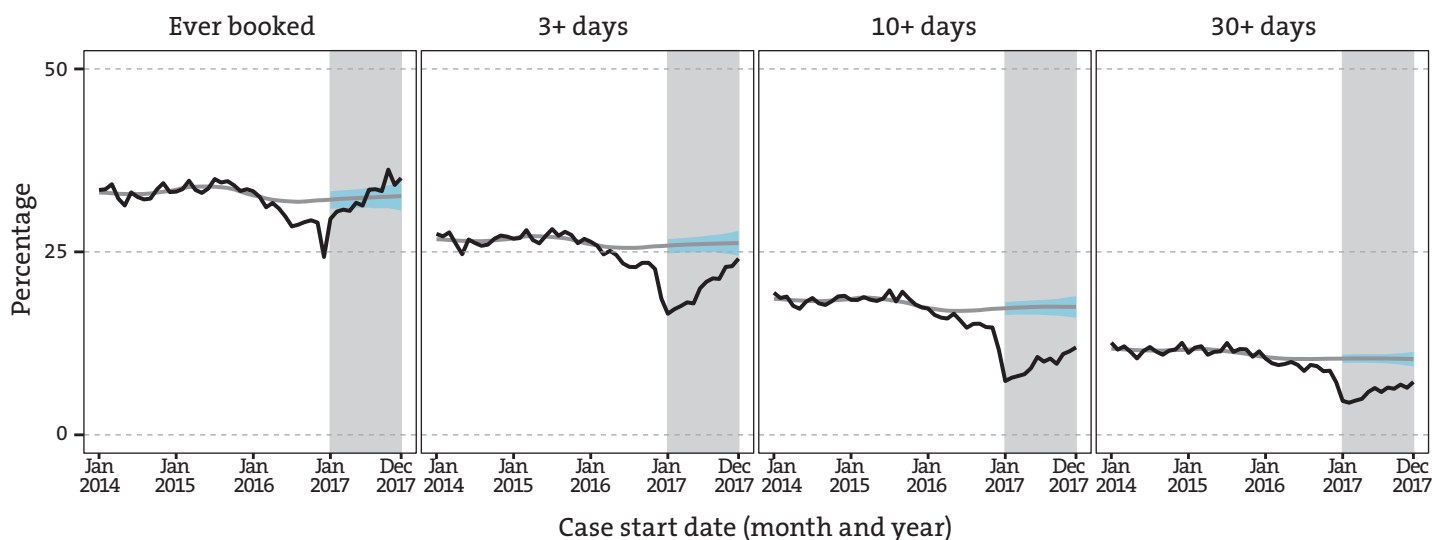
Crime Type	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Violent	17.9	19.4	1.5*	8.4
Drug	36.4	36.1	-0.4	-1.1
Property	28.2	26.7	-1.5	-5.3
Public order	16.6	16.8	0.2	1.2

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the differences in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

APPENDIX FIGURE B.2 Effects on Lengths of Initial Jail Stays Among Defendants Arrested on Nonviolent Indictable Charges



Jail Stays Among Defendants Arrested on Nonviolent Indictable Charges with Cases Started in July 2017

Jail Stay	Predicted Outcome	Observed Outcome	Difference (Effect)	Percentage Change
Ever booked	32.5	32.1	-0.4	-1.2
Held 3+ days	26.1	20.4	-5.7*	-21.8
Held 10+ days	17.5	10.1	-7.4*	-42.3
Held 30+ days	10.4	6.1	-4.3*	-41.2

SOURCE: MDRC calculations based on data provided by the New Jersey Administrative Office of the Courts.

NOTES: The *difference*, or effect, is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value. The difference is *statistically significant* if the observed outcome falls outside of the predicted confidence interval range indicated by the blue envelope in the graph; statistical significance is indicated for Month 6 arrest events using an asterisk (*) next to the differences in the table below the graph. The effects in the table are estimated with smoothing in order to increase power. As a result, the numbers in the table can be thought of as representing average effects in Months 5 through 7.

The graphs only show January 2014 through December 2017 to make the effects after CJR was implemented more visible. The predictive models were fit to data from January 2009 through June 2016, however.

American Civil Liberties Union, National Association of Criminal Defense Lawyers, and State of New Jersey Office of the Public Defender. 2016. *The New Jersey Pretrial Justice Manual*. Washington, DC: National Association of Criminal Defense Lawyers.

Dobbie, Will, Jacob Goldin, and Crystal Yang. 2016. "The Effects of Pre-Trial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges." *American Economic Review* 108, 2: 201-240.

Lowenkamp, Christopher, Marie VanNostrand, and Alexander Holsinger. 2013. "The Hidden Costs of Pretrial Detention." Website: https://craftmediabucket.s3.amazonaws.com/uploads/PDFs/LJAF_Report_hidden-costs_FNL.pdf.

Miratrix, Luke. 2019. "Technical Paper for the Public Safety Assessment Impact Evaluation in Mecklenburg County, N.C." Unpublished paper. New York: MDRC.

Moore, Kelly, Jeffery Stuewig, and June Tangney. 2016. "The Effect of Stigma on Criminal Offenders' Functioning: A Longitudinal Mediation Model." *Deviant Behavior* 37, 2: 196-218.

National Institute of Justice. 1983. *National Crime Information Center (NCIC) Code Manual*. Washington, DC: U.S. Department of Justice, National Institute of Justice.

New Jersey Courts. 2018. "Rules Governing the Courts of the State of New Jersey." Website: www.njcourts.gov/attorneys/rules.html.

Pager, Devah. 2003. "The Mark of a Criminal Record." *American Journal of Sociology* 108, 9: 37-75.

Porrino, Christopher. 2017. "Attorney General Law Enforcement Directive No. 2016-6 v2.0: Modification of Directive Establishing Interim Policies, Practices, and Procedures to Implement Criminal Justice Reform Pursuant to P.L. 2014, c. 31." Website: https://www.state.nj.us/oag/dcj/agguide/directives/ag-directive-2016-6_v2-0.pdf.

Rabner, Stuart. 2017. "Chief Justice: Bail Reform Puts N.J. at the Forefront of Fairness." *New Jersey Star-Ledger* January 9, 2017.

VanNostrand, Marie. 2013. "New Jersey Jail Population Analysis: Identifying Opportunities to Safely and Responsibly Reduce the Jail Population." Website: www.drugpolicy.org/sites/default/files/New_Jersey_Jail_Population_Analysis_March_2013.pdf.

REFERENCES

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PRETRIAL SERVICES

This division of the court utilizes a validated risk assessment called the Summit County Pretrial Risk Assessment Instrument (SCPRAI). The instrument is administered to those booked into the Summit County Jail and charged with a felony.

The Pretrial Services Staff consists of one supervisor, seven officers and one support staff specialist. Pretrial performs two primary functions:

1. Make bond recommendations to the Judges in the Court of Common Pleas, as well as Akron Municipal Court, for any individual making an initial or attorney appearance on a Felony Charge. Bond recommendations are made after the offenders are interviewed and specific information, such as criminal record, home address, and employment, are investigated and verified.
2. Help alleviate jail overcrowding. This is accomplished through bond recommendations and supervision which mitigates the likelihood of a defendant's re-arrest while released on bond.
3. Pretrial Services may be contacted at 330-643-2245.

In order to mitigate failure to appear for court and/or re-arrest pending trial, supervision may be assigned based on the defendant's level of risk determined by SCPRAI. There are three levels of supervision Minimum, Medium, and Maximum. Supervision of those pending trial may include random drug/alcohol testing, reporting, and referrals to appropriate community agencies. These referrals are intended to initiate rehabilitative efforts.

In the event a defendant is placed on supervision as a Condition of Release, they are to report to Oriana House, Inc., Pretrial Supervision at 750 West Market Street, Akron, Ohio.

Probation Assessments

The establishment of the Probation Assessment Unit was part of a larger strategic initiative of implementing evidence-based practices for community control. The Summit County Adult Probation Department utilizes the validated Ohio Risk Assessment System Instrument. This instrument is administered in order to identify the risks and needs of the probationer when they are placed on community control. The instrument serves as the foundation for the case plan, which will appropriately target resources. "Research has demonstrated that evidence-based interventions directed towards offenders with a moderate to high risk of committing new crimes will result in better outcomes for both offenders and the community"¹

¹ *Putting Public Safety First: 13 Strategies for Successful Supervision and Reentry.* PEW Center. No. 7. December 2008.

Summit County Pre-Trial Services

Mission

The Summit County Pretrial program operates under the American Bar Association (ABA) standard that the law favors the release of defendants pending the adjudication of charges. The purpose of the program is to ensure due process to individuals accused of crimes, uphold the integrity of the court by assuring the appearance of defendants for all court proceedings, and protect the public. Pretrial Service's main function is to provide objective information to the Courts to assist in the decision of bail and to provide supervision and services to pretrial defendants.

History

The current Summit County Jail was built in 1990 and expanded in 1995. Since its opening, it has battled chronic overcrowding issues. As a result, three system assessments were completed between 1989 and 2000. The first was completed by the Bureau of Justice Assistance in 1989; the second was done by the National Institute of Corrections in 1999. The third assessment was conducted by the Institute for Law and Policy Planning (ILPP) and included a systems-based strategic plan to overhaul the Summit County Justice System.

All three assessments showed that the Summit County Pretrial Program needed restructuring. During the time of the assessments, the Summit County Jail had an inmate population that largely consisted of un-sentenced offenders. In the initial assessment by the Bureau of Justice Assistance, it was observed that 90% of the jail population was pre-trial defendants. In 2000, the ILPP study indicated that:

“Although Summit County does not suffer from a lack of programs and services, it does suffer from inadequate coordination and a failure to screen offenders at the earliest stages of arrest, booking and pretrial release. The county jail population is mainly pretrial (80%), and the system lacks any adequate pretrial program, screening system, or mechanism to objectively release offenders. The County can never fully realize a well integrated criminal justice system is such an important component of the system remains neglected”.

In addition, the research showed that compounding the problem was the length of stay for pretrial inmates. Accused misdemeanants spent an average of two weeks pending adjudication, while accused felons waited nearly 2 months for disposition.

Since the ILPP report was presented, stakeholders in the Summit County Justice System began to address Pretrial issues under the Summit County Criminal Justice Advisory Board (SCCJAB), which is used to identify and resolve interagency problems within the justice system, and to create a process for effective future planning.

A subcommittee was formed to address the need to overhaul the current Pretrial program. As a foundation for the new Pretrial Program, SCCJAB sought a validated instrument to screen individuals booked into the jail on felonies. In addition, the board wanted an instrument that could be revalidated over time to ensure that tool was accurately assessing the risk of pretrial misconduct over time. The ABA and National Association of Pretrial Services urge the use of using objective criteria to assess a defendant's risk of failing to appear for court appearances and of being arrested for new offenses pending trial.

After the subcommittee reviewed the current pretrial tool and determined it was too subjective and not validated, they began to research other pretrial programs within the country. The subcommittee favored the Virginia Pretrial Risk Assessment Instrument (VPRAI) and decided to use it for a model for Summit County. The model was modified to meet the specific needs of Summit County and named the Summit County Pretrial Risk Assessment (SCPRAI). Summit County was the first jurisdiction in the United States to validate this modified instrument. In 2006, the risk assessment was implemented as part of a criminal justice reengineering project. The risk assessment includes the following indicators: whether the current charge is a felony, pending charges at the time of arrest, violent criminal history, outstanding warrants, adult criminal history, history of failing to appear, length of residence, employment history, and drug use history. When scored, each of the 9 indicators is given one point with the exception of failure to appear, which is given two points, for a total of 10 points.

The defendants can then be classified into risk categories based on their scores. The levels of risk are as follows: low, below average, average, above average, and high. Each of these levels is broken down into a grid based on the type of charges. The grid subdivisions are: nonviolent-without presumption of prison, nonviolent-with presumption of prison, and violent. Pretrial is able to make an objective bond recommendation based on the level of risk and the type of charge in order present it to the court.

Interviews

Pretrial investigations are initiated after defendants charged with felony offenses are booked into the Summit County Jail. Once a defendant is booked, Pretrial staff conducts a criminal background investigation. As part of the investigation, the Pretrial officer will check multiple databases, including: Akron, Barberton, Stow and Summit County Clerk of Courts, Summit Court Online Record System, Ohio Department of Corrections website, and the Law Enforcement Automated Data System (LEADS) to get a comprehensive criminal history of the defendant. The history will include convictions of jailable offenses, failures to appear, and pending warrants and charges. After the investigation, the officer will conduct an interview using a standardized Pretrial Investigation Report. Prior to beginning the interview, the Pretrial officer will explain the pretrial process to the defendant and have them sign a

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Release of Information form. The purpose of the report is to elicit information from the defendant about his residence, family/community references, employment status, primary caregiver status, education, health issues, substance use/treatment, and criminal history. Immediately following the interview, the officer will attempt to contact references and confirm the information given by the defendant. Once the above information has been gathered, a report is created for the court. As part of the Pretrial report, if the defendant is eligible, a SCPRAI is generated to determine the defendant's level of risk. Eligibility criteria for the SCPRAI are: a pretrial interview must have been conducted, the defendant must have been "free" (not incarcerated) at the time of arrest or when the warrant was served, and the SCPRAI must be completed within 7 days of incarceration.

Pretrial staff will be present in Akron Municipal Court arraignments and Common Pleas arraignments to assist court officers in making bail decisions.

Bond reviews can be requested at the Common Pleas level, and are conducted in the same manner as a Pretrial investigation.

Supervision

Pretrial Supervision is provided by Oriana House, Inc. The Pretrial Office acts as a liaison between the Court and Oriana to enforce the court ordered Conditions of Release. A judge or magistrate can add different levels of pretrial supervision as a condition of bond (minimum, medium, maximum). If medium or maximum supervision is ordered, additional conditions of release can be added, such as electronic monitoring (Home Incarceration, SCRAM, and GPS), Half Way House, Employment Placement, and Work Release.

The Pretrial Office is ultimately responsible for monitoring compliance with the court ordered conditions of release. The office submits violation memorandums to the court and requests capiases when defendants are non-compliant. Information regarding non-compliance is provided by Oriana House monitors.

Emergency Release

Due to jail overcrowding conditions, the Common Pleas Court has a standing order to release inmates that meet certain criteria when the jail's population exceeds 467 county inmates. Currently, the jail has 671 beds available (Male - 564; Female - 89; Optional - 18). Of those 671 beds, Summit County only has 541 available, which actually includes felonies and misdemeanors.

The Pretrial Office is responsible for screening defendants who appear eligible for release pursuant to the Summit County Court of Common Pleas Miscellaneous Order Number 358 C. The order basically states that any person not charged with an offense of violence is eligible for emergency release. Pretrial officers screen persons who are appropriate for emergency release on a regular basis. If a defendant appears eligible, the pretrial officer will prepare a Judgment Order and submit it along with a Conditions of Release form to the presiding common pleas judge for review.

The Pretrial Office usually does not recommend emergency release until after the defendant has appeared with counsel in both Akron and Barberton Municipal Courts. It can, however, recommend release for eligible persons before preliminary hearings in the Stow Municipal Court.

Diversion

Another component of pretrial is diversion. The Summit County Court of Common Pleas currently has three diversion programs: Drug Court, Intervention in Lieu of Conviction, and the Prosecutor's Diversion Program. Pretrial plays a role in the first program, Felony Drug Court. If a defendant is arraigned in Akron Municipal Court and is charged with a drug related offense of the 4th or 5th degree, and the offenses do not include Trafficking, Distribution, Manufacturing, or Preparation for Sale charges, he qualifies to be screened for Drug Court. In addition to the above, the defendant must meet the following criteria:

- Must have police and prosecutor approval
- Case may have two Possession or Drug Abuse Charges
- Charges of Tampering with Evidence will be evaluated by police and prosecutor to determine eligibility
- Defendant must be mentally and physically able to participate
- Defendant is not eligible if he is:
 - Actively on parole/post release control
 - On community control
 - Currently participating in a diversion program or specialty court
 - Has previously participated in a Drug Court or IILC program
 - Has been convicted of a 1st or 2nd degree felony in the past 5 years
 - Has more than two felony convictions in the past 5 years
 - Has a substantial history of violent offenses (felony or misdemeanor)
 - Has a prior conviction for Trafficking, Distribution, Manufacturing, or Preparation for Sale
 - Has pending cases
 - Is a co-defendant
 - Has more than 3 Fail to Appear convictions
 - Is classified a Tier 3 Sex Offender or Sexual Predator
 - Holds a position of trust as deemed by the prosecutor
 - The underlying substance abuse issue involves a drug that cannot be tested

Companion Theft cases will be considered on a case by case basis by the prosecutor.

Conclusion

As the Summit County Justice System is forced to evolve to accommodate growing pressure from increased court caseloads, increased paper flow, budget cuts, and reduced staff, the Summit County Court of Common Pleas remains committed to implementing systematic planning that can affect the overall efficiency and effectiveness of our justice system. As part of that plan, Pretrial Services aims to preserve the integrity of the Court, maintain the constitutional rights of those accused of crimes, and ensure the safety of the community.

PRETRIAL INVESTIGATION REPORT

DEMOGRAPHICS

Name SSN Date
 DOB Age Marital Status Maiden Name
 Race Sex # Dependents # Living w/ Place of Birth
 US Citizen Documentation Interviewed By

ALIASES

RESIDENCE

Address Apt#
 City State Zip Residence Status
 Lives w/ Relation Able to Return
 Alternate Address upon Release
 Mailing Address
 Time at Current Address Time in Summit County Time in Ohio
 Phone Numbers Home Work Mobile Other
 Previous Address
 Time at Previous Address Residence Info Verified Verified By

FAMILY / REFERENCES

Name Relation Phone
 Address
 Name Relation Phone
 Address
 Name Relation Phone
 Address

EMPLOYMENT / PRIMARY CAREGIVER

Employed at Arrest Current Employer Phone
 Address
 Supervisor Phone Start Date Last Date Worked
 Position Permission to Contact Net Monthly Income
 Other Sources of Income Previous Employer Start Date End Date
 Primary Caregiver at Time of Arrest Employ / PC Verified Verified By
 Military Service Y or N Branch of Service Army, Navy, Air Force, Coast Guard, Marine, or Merchant Marines
 Years of Service- One day of active duty. Training and boot camp is not included. Discharged? Must be Honorable. Honorable or Dishonorable

EDUCATION

Current Student Institution Name
 Full/Part Time Time a Student Last Grade Completed

SUBSTANCE USE

Drug	Last Used	Frequency	Length of Use	Drug of Choice
Drug	Last Used	Frequency	Length of Use	Drug of Choice
Drug	Last Used	Frequency	Length of Use	Drug of Choice
Alcohol	Last Used	Frequency	Length of Use	Drug of Choice

Interested in Substance Abuse Treatment? If Yes, Drug and / or Alcohol

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 Public Access Under The Freedom Of Information Act.

SUBSTANCE ABUSE TREATMENT

Current Substance Abuse TX

Type Substance(s)
Location
Type Substance(s)
Location

Prior Substance Abuse TX

Date Entered Treatment
Date Entered Treatment

Status
Status

HEALTH ISSUES

Issue
Issue

TX Provider
TX Provider

Medications
Medications

CURRENT CHARGE(S)

Court
Charge(s)

Case Number

Arrest Date

CRIMINAL EVENTS

Pending Charge(s)

Arrest Date Charge(s)
Arrest Date Charge(s)

Locality
Locality

Outstanding Warrant(s)

Issue Date Charge(s)
Issue Date Charge(s)

Locality
Locality

Previous FTA Conviction(s)

Conviction Date Reason
Conviction Date Reason

Locality
Locality

Currently Under Community Supervision

Type

Department

Prior Criminal History (The following information is not an official record of criminal history)

Date Convicted Charge(s)

Locality

Additional Criminal History Attached
Prior Juvenile Convictions Reported

COMMENTS / RECOMMENDATIONS

Summit County Pretrial Risk Assessment Instrument Completed?

If No, Reason:

Summit County
Pretrial Risk Assessment Instrument

Instrument Completion Date: 06/07/2005

Court Date: 06/07/2005

Defendant Name: defendant, sample

SSN: 111- 11- 1111

Sex: Male

Race: Other

Date of Birth: 01/ 01/ 1970

Charges:

Grand larceny 3 cts

Risk Factors:

- The most serious charge is a felony
- Pending charges existed at the time of arrest
- Outstanding warrants existed in another locality at the time of arrest
- Adult criminal history includes at least one misdemeanor or felony conviction
- Two or more failure to appear convictions
- Two or more violent convictions
- Length at current residence is less than one year
- Not employed continuously for the past two years and was not a primary child caregiver at the time of arrest
- History of drug abuse



Additional Risk Considerations and/or Mitigating Factors:

The defendant has a juvenile criminal record.

The defendant admits to alcohol addiction and is willing to participate in treatment.

Recommendation:

The following recommendation is consistent with the risk assessment recommendation guidelines:

Low Signature Bond with Pretrial Supervision (medium level) with special conditions of random drug testing and a referral for treatment as needed.

Non-Violent Charges without Presumption of Incarceration or Mandatory Prison

Risk Levels	Option A			Option B				
	Bond Type	Amount*	Supervision	Special Conditions	Bond Type	Amount*	Supervision	Special Conditions
Low	Signature	Low	None	None	NA			
Below Average	Signature	Low	None	None	NA			
Average	Signature	Low	Minimum	None	Co-signature	Low	None	None
Above Average	Signature	Low	Medium	As Needed	Surety	Low	None	None
High	Signature	Low	Maximum	As Needed	Surety	Moderate	None	None

Non-Violent Charges with Presumption of Incarceration or Mandatory Prison

Risk Levels	Option A			Option B				
	Bond Type	Amount*	Supervision	Special Conditions	Bond Type	Amount*	Supervision	Special Conditions
Low	Signature	Low	None	None	NA			
Below Average	Signature	Low	None	None	NA			
Average	Signature	Low	Minimum	None	Co-signature	Low	None	
Above Average	Surety	Low	Medium	As Needed	NA			
High	Surety	Moderate	Maximum	As Needed	NA			

Violent Charges Not Detainable per Ohio Code

Risk Levels	Option A			Option B				
	Bond Type	Amount*	Supervision	Special Conditions	Bond Type	Amount*	Supervision	Special Conditions
Low	Signature	Low	None	No Contact**	NA			No Contact** & Others As Needed
Below Average	Signature	Low	None	No Contact**	Co-signature	Low	None	
Average	Surety	Low	Minimum	No Contact**	NA			
Above Average	Surety	Moderate	Medium	No Contact** & Others As Needed	NA			
High	Surety	High	Maximum	No Contact** & Others As Needed	NA			

Note: Recommendation Guidelines do not apply to violent charges that are detainable per Ohio Revised Code.

* Low = up to \$5000, Moderate = \$5001 to \$50,000, High = minimum of \$50,000

** No contact applies to all victims and potential witnesses

PRETRIAL JUSTICE REFORM STUDY

**Evaluation of Pretrial
Justice System
Reforms That Use
the Public Safety
Assessment**

Effects in Mecklenburg
County, North Carolina

1

**MECKLENBURG
COUNTY SERIES**

REPORT 1 OF 2

Cindy Redcross
Brit Henderson
with
Luke Miratrix
Erin Valentine

MARCH 2019

Arnold Ventures' Public Safety Assessment (PSA) is a pretrial risk assessment tool that uses nine factors from a defendant's history to produce two risk scores: one representing the likelihood of a new crime being committed and another representing the likelihood of a failure to appear for future court hearings. The PSA also notes if there is an elevated risk of a violent crime. The PSA is designed to provide additional information to judges and others making release decisions — decisions about whether a defendant will be released while waiting for a case to be resolved, and if so, under what conditions. The score is used in conjunction with a jurisdiction-specific decision-making framework that uses the defendant's PSA risk score in combination with local statutes and policies to produce a recommendation for release conditions. The goal of the PSA is to make the restrictions on a defendant's release conditions better align with that defendant's assessed risk of committing new crimes or failing to appear.

Over 40 jurisdictions across the country have implemented the PSA. Mecklenburg County, North Carolina was one of the first; it began using the PSA in 2014, switching from another risk assessment. This study presents the effects of the PSA and related policy changes in Mecklenburg County. The first report in the series describes the effects of the overall policy reforms on important outcomes. A supplemental second report describes the role of risk-based decision making in the outcomes and describes the effects of the PSA on racial disparities in outcomes and among different subgroups.

Overall, the findings are notable from a public-safety perspective: Mecklenburg County released more defendants and did not see an increase in missed court appointments or new criminal charges while defendants were waiting for their cases to be resolved.

- **The PSA policy changes were associated with less use of financial bail and a higher rate of defendants being released on a written promise or unsecured bond.** The proportion of defendants detained in jail was lower than it would have been in the absence of the policy changes. There was an improved alignment between defendant risk and the restrictiveness of release conditions.
- **Fewer cases resulted in guilty pleas and convictions than would have been the case in the absence of the reforms.** Because more defendants were released while their cases were pending, they may have had less incentive to plead guilty in order to get out of jail.
- Even though the PSA policy changes increased the percentage of defendants who were released pending trial — and even though a higher proportion of defendants were facing felony charges in the period after the PSA was implemented — **there was no evidence that the PSA policy changes affected the percentages of defendants who made all of their court appearances or who were charged with new crimes while waiting for their cases to be resolved.**
- Most of the changes in pretrial release conditions occurred at a step in the pretrial case process before the PSA report is completed. Thus, **having access to the information in the PSA could have had at most only a small effect on the way judges set release conditions.**
- **There was no evidence of racial disparity in the setting of release conditions and the PSA had no effect on racial disparities within the system.** Black defendants were more likely than other racial groups to be assessed by the PSA as being high-risk, though. ■

OVERVIEW

INTRODUCTION

In the United States, over 700,000 people are detained in local jails on any given day — the majority without having been convicted of a crime, often because they cannot afford to post even small amounts of monetary bail.¹ The negative financial, social, and human consequences associated with detaining nonviolent and low-risk defendants while they await court action on their cases has gained increasing attention in recent years. Many jurisdictions would like to reduce the number of people who are held in jail unnecessarily, while preserving public safety and making sure those people show up to court hearings for their cases. As a result, they are seeking alternatives to money-based bail. Often they move to incorporate risk assessments, which are actuarial tools that use data about individual defendants' past criminal histories to estimate their levels of risk if they are released — especially their risks of committing new crimes and of not showing up for their court dates. Although risk assessment tools have been used in the criminal justice system for decades, there has been a recent push to broaden their use in the pretrial phase, which is the period between an arrest and the resolution of the criminal case. These tools are designed to provide more information to the judges who must determine the pretrial release conditions to be imposed on defendants.²

Between 2011 and 2014, Arnold Ventures developed the Public Safety Assessment (PSA) with the help of a team of experts. The PSA uses nine factors from a defendant's criminal history to produce two risk scores: one representing the likelihood of a new crime being committed, and another representing the likelihood of a failure to appear for future court hearings. The PSA also notes whether there is an elevated risk of a violent crime. The score is then used in conjunction with a jurisdiction-specific decision-making framework that uses the defendant's PSA risk score in combination with local statutes and policies to produce a recommendation for release conditions. Jurisdiction officials determine the release conditions that correspond to risk levels. A unique feature of the PSA is that it uses only administrative data that can be gathered without the burden and cost of interviewing defendants (a requirement of many other risk assessment tools). The PSA is designed to provide additional information to judges and others making release decisions so that they can better align these decisions with each defendant's risk of failing to appear and committing new crimes.

1 Zeng (2018).

2 Bechtel, Lowenkamp, and Holsinger (2011).

Over 40 jurisdictions in the United States have implemented the PSA. Mecklenburg County, North Carolina was one of the first. It began using the PSA in 2014, switching from another risk assessment — the Virginia Pretrial Risk Assessment Instrument — that had been in use since 2011. This report is the first of a two-part series focused on the effects of the PSA and related policy changes in Mecklenburg County. It describes the effects of the overall policy reforms on pretrial release conditions, incarceration, case outcomes, court appearances, and new criminal charges. The second report in this series supplements these findings with more detail on the implementation of the PSA and the role risk-based decision making played in generating the observed effects. It will describe whether and how the PSA policies affected racial disparities in case and crime outcomes and whether the effects differ among important subgroups of defendants: defendants assessed to be at higher and lower levels of risk, those charged with more and less severe crimes, and those of different races and ages.

Financially based pretrial release conditions such as money bail can perpetuate racial and economic disparities in detention and case outcomes.

BACKGROUND

Judges must balance three goals when determining pretrial release conditions: (1) reasonable assurance that the public will be safe; (2) reasonable assurance that defendants will appear in court; and (3) due process for those accused of a crime. Their overall aim is generally to impose the least restrictive conditions necessary to insure public safety and defendants' appearance in court.³

In practice, most jurisdictions, including Mecklenburg County, use money bail or secured bonds to provide assurance that, if released, defendants will appear in court and will not commit new crimes (that is, endanger public safety): Defendants must put up a bond for an amount set by a judge, secured by a cash deposit, which they forfeit if they fail to appear in court.⁴ However, in recent years advocates and practitioners have become increasingly concerned that the use of monetary bail does little to ensure public safety, leads to the unnecessary detention of low-risk defendants who cannot afford to pay bail, and allows higher-risk defendants to pay for their release.⁵ Financially based pretrial release conditions such as money bail can also perpetuate racial and economic disparities in detention and case outcomes. In an effort to address

³ Clark, Schnake, and Ferrere (2016).

⁴ North Carolina Statute 15A-544.3.

⁵ In this document, “detention” is used to describe the circumstance where a defendant is held in jail before sentencing.

these concerns and to reduce costly and unnecessary jail detention, many jurisdictions are moving toward pretrial release systems that are based on defendants' risks of committing new crimes or not appearing in court for future hearings, as projected by validated risk assessment tools and decision-making frameworks. These tools come with other concerns (there is a possibility, for example, that they could perpetuate racial disparities),⁶ but they are generally thought to be an improvement over financial approaches.

Mecklenburg County is the most populous county in North Carolina; its largest major city is Charlotte. It is considered one of the more progressive jurisdictions in the state and is currently engaged in a number of reforms aimed at reducing unnecessary detention. Mecklenburg County introduced pretrial risk assessment in 2011, when it began using the Virginia Pretrial Risk Assessment Instrument (VPRAI). It switched to the PSA in June 2014. The major difference between the two tools is that the VPRAI uses historical criminal history data and other information that can only be obtained from a defendant interview; the PSA does not require information from a defendant interview. The analysis in this report is assessing the effect of the PSA as it was implemented compared with the policies that were in place before June 2014, including the VPRAI.

METHODS AND DATA SOURCES

This evaluation uses a mixed-methods research approach that combines qualitative information gathered through an implementation study with a statistical analysis of data drawn from administrative records (that is, data gathered in the normal course of administering the justice system). The effects presented in this report are estimated using an interrupted time series research design. Comparisons for the analysis are generated using cases initiated between January 2012 and May 2014 (the pre-policy period). The cases are grouped into monthly cohorts (for example, all cases where the arrest date was in January 2012 are included in the January 2012 cohort). For each outcome (for example, “new criminal charges”), the analysis creates a monthly average for each cohort, and those averages are plotted in a time series. Data from the cases initiated in the pre-policy months (January 2012 through May 2014) are then used to predict what the outcomes would have been for cases initiated in each of the post-policy months (July 2014 through December 2015) had no changes occurred. The difference in outcomes between the observed

⁶ Doleac and Stevenson (2016); Mayson (2018); Skeem and Lowenkamp (2015); Angwin, Larson, Mattu, and Kirchner (2016); Southerland (2018); Travis and Western (2014).

values in the post-policy period and the predicted values represents the “effect” of the policy changes.

Qualitative information was collected through interviews with stakeholders and staff members in Mecklenburg County, observations of first appearance hearings (explained below), and a review of statutes and policies. Quantitative data were obtained from the North Carolina Court System and the Mecklenburg County Sheriff’s office.⁷ The analysis uses data from January 2006 through June 2017. The study focuses on all cases with custodial arrests (that is, arrests where the defendant was taken into custody) in Mecklenburg County between January 1, 2012 and December 31, 2015. The PSA was implemented in the jurisdiction in June 2014, so the dates that were used allow for an analysis of outcomes for all cases initiated 30 months before the PSA was implemented and 18 months after it was implemented. The analysis covers 93,950 total cases for 59,906 individuals.

The analysis is conducted on the case level. All charges associated with a specific arrest date for an individual are considered a single “case.” (For ease of explanation, this report also uses the word “defendant” interchangeably with “case.”) Data through June 2017 are used to measure case and defendant outcomes for a year and a half after each case was initiated (the cases’ start dates in the time-series figures). Effects on pretrial release conditions are assessed for all cases initiated during the study’s time period (between January 2012 and December 2015). Effects on new criminal charges during the pretrial period are assessed for cases that were resolved within a year and a half after the initial arrest. Cases that were still open when the data were extracted cannot be used to measure certain outcomes that require the case to be resolved (for example, failure to appear and case disposition). About 95 percent of cases were resolved within the year-and-a-half time frame, so excluding those that were not resolved does not meaningfully affect the results of the analysis. More detailed information about the statistical methods used in this evaluation is available in a technical working paper.⁸ Box 1 explains how to read the time-series figures that illustrate the effects in this report.

This study is able to provide suggestive evidence about the effects of the PSA. It cannot isolate the effects of the PSA from other factors that may have af-

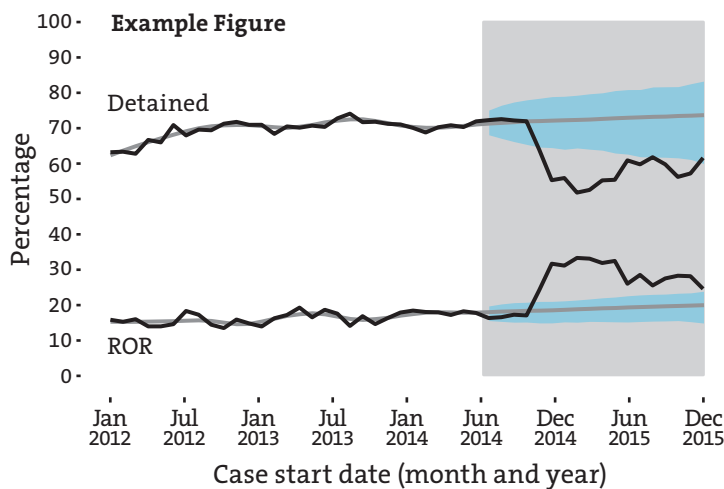
⁷ North Carolina Administrative Office of the Courts, Organizational Development Division (2014).

⁸ Miratrix (2019).

BOX 1 How to Read the Time-Series Figures

An example figure appears below. The x axis shows the month and year of the start of a case. The cases are grouped into monthly cohorts (for example, all cases with arrest dates in January 2012 are included in the January 2012 cohort). For each outcome, the analysis creates a monthly average for each cohort, and those averages are plotted in a time series. Cases initiated from January 2012 to May 2014 are considered to be in the pre-policy period; those initiated from June 2014 to January 2015 are considered to be in the post-policy period. The post-policy period is shown by the shaded area to the right. The follow-up period is 18 months unless the figure indicates otherwise. This time frame makes it possible to track case outcomes through June 2017.

In the figure, the observed monthly rates of detention and release are shown by black lines. The observed rates among cases in the pre-policy period are used to generate a time-trend model, resulting in predicted rates in the post-policy period that are indicated by the gray lines in the shaded area of the figure. The estimated effect of the PSA-related policies is the difference between the black observed line and the gray predicted line. The blue shaded area above and below the gray predicted line represents the confidence band around the predicted estimates. The thinner the confidence band, the less variable the predictions from the model are. As the predictions get further from the time of the policy changes, the prediction bands become wider, showing that there is less certainty in the predictions later in the follow-up period. The predicted and observed values for each outcome are presented in the table below each figure for cases initiated in December 2014, six months after the policies were implemented. December 2014 cases are the focal point for this analysis because an interrupted time series research design is based on observing abrupt shifts in outcomes shortly after a new policy or practice is put in place. Six months is reasonably soon after the PSA policies were adopted, but long enough afterward to ensure that they were fully in place.



December 2014 (Month 6) Cases (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Detained	51.1	40.4	-10.7	-20.9
ROR	36.9	46.6	9.7	26.3

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff's Office.

NOTES: *Difference* is the observed outcome minus the predicted outcome. *Percentage change* refers to the difference between the observed and predicted values as a percentage of the predicted value. *ROR* means the defendant was released on his or her own recognizance without any additional requirements.

affected the outcomes.⁹ Therefore, this document describes findings in suggestive rather than conclusive terms. Furthermore, the amount of variation in the outcome measures throughout the pre-policy period results in additional uncertainty regarding the accuracy of the predictions for the post-policy period. The statistical significance of the effects is therefore not reported. The upper and lower confidence intervals of the predictions are shown in the time-series figures with shading around the predicted trend lines in the post-policy period. When this document discusses the effects of “the PSA policy changes,” it is referring to the PSA, the decision-making framework, and other related policy changes implemented around the same time.

Jurisdictions implementing the PSA expect to see a reduction in the use of money bail, especially for lower-risk defendants.

THEORETICAL BACKGROUND

As discussed above, judges must determine the least restrictive conditions necessary to (1) ensure that a defendant who is arrested and charged with a crime will show up to future court dates and (2) ensure the safety of the public, typically by making it less likely that the defendant will commit a crime while waiting for the case to be resolved. Courts are especially concerned with the risk of a defendant committing a new felony or violent crime during the pretrial period.

Most pretrial reforms aim to shrink burgeoning jail populations and unnecessary detention: Detention has high financial costs for jurisdictions and high personal costs for defendants. However, stakeholders worry that if more defendants are released, more of them could miss court dates or could commit new crimes while waiting for their cases to be resolved.

Judges use money bail to try to ensure that defendants appear in court and to make it less likely that they will commit new crimes. But bail leads to unnecessary and costly detention because many defendants cannot afford to post even small amounts of money for the cash deposit. Furthermore, it does not effectively ensure public safety because high-risk defendants with enough money can simply pay the bail and be released immediately.

Jurisdictions implementing the PSA expect to see a reduction in the use of money bail, especially for lower-risk defendants. If money bail is used less and more defendants are released before trial, there may be corresponding effects on case outcomes. For example, there may be a reduction in convictions

⁹ Only a randomized controlled trial research design could make it clear whether the PSA caused the effects described here.

and guilty pleas because defendants who are not detained while they wait for their cases to be resolved may have less incentive to plead guilty as a way of getting out of jail more quickly.¹⁰ These may be desirable outcomes for the most part, but there is a trade-off: If fewer defendants are detained, more of them could miss court dates or incur new criminal charges.

BACKGROUND ON THE PRETRIAL CRIMINAL JUSTICE PROCESS AND THE PSA

As is the case in many jurisdictions that implement the PSA, when Mecklenburg County adopted the tool it was undergoing broad cultural and policy shifts that also included training for court staff members, magistrates, and judges in the best practices of pretrial release and detention and in how to use risk assessment to help determine release conditions.¹¹ Changes in leadership also occurred shortly after the PSA was adopted that led to additional shifts in policy and practice. This study is assessing the effect of all of these changes that occurred around the same time, referred to as the PSA policy changes. When possible, the analyses attempt to isolate the potential effects of the actual use of the PSA and the decision-making framework from the effects of the other shifts that occurred.

Of the initial group of jurisdictions that adopted the PSA, Mecklenburg County is the one of the few with Pretrial Services staff members whose only responsibilities are to generate PSA scores, produce recommendations based on the accompanying decision-making framework, and distribute the resulting reports in time for defendants' first appearance hearings.¹² In other jurisdictions, the staff members who generate PSA reports are typically also responsible for supervising defendants, and each has a caseload.

There are three points when pretrial release decisions are made in Mecklenburg. (Figure 1 presents a simplified illustration of the pretrial case process, with these decision points shown in darker blue.) The first decision point occurs just after an individual is arrested.¹³ At that point, a magistrate will de-

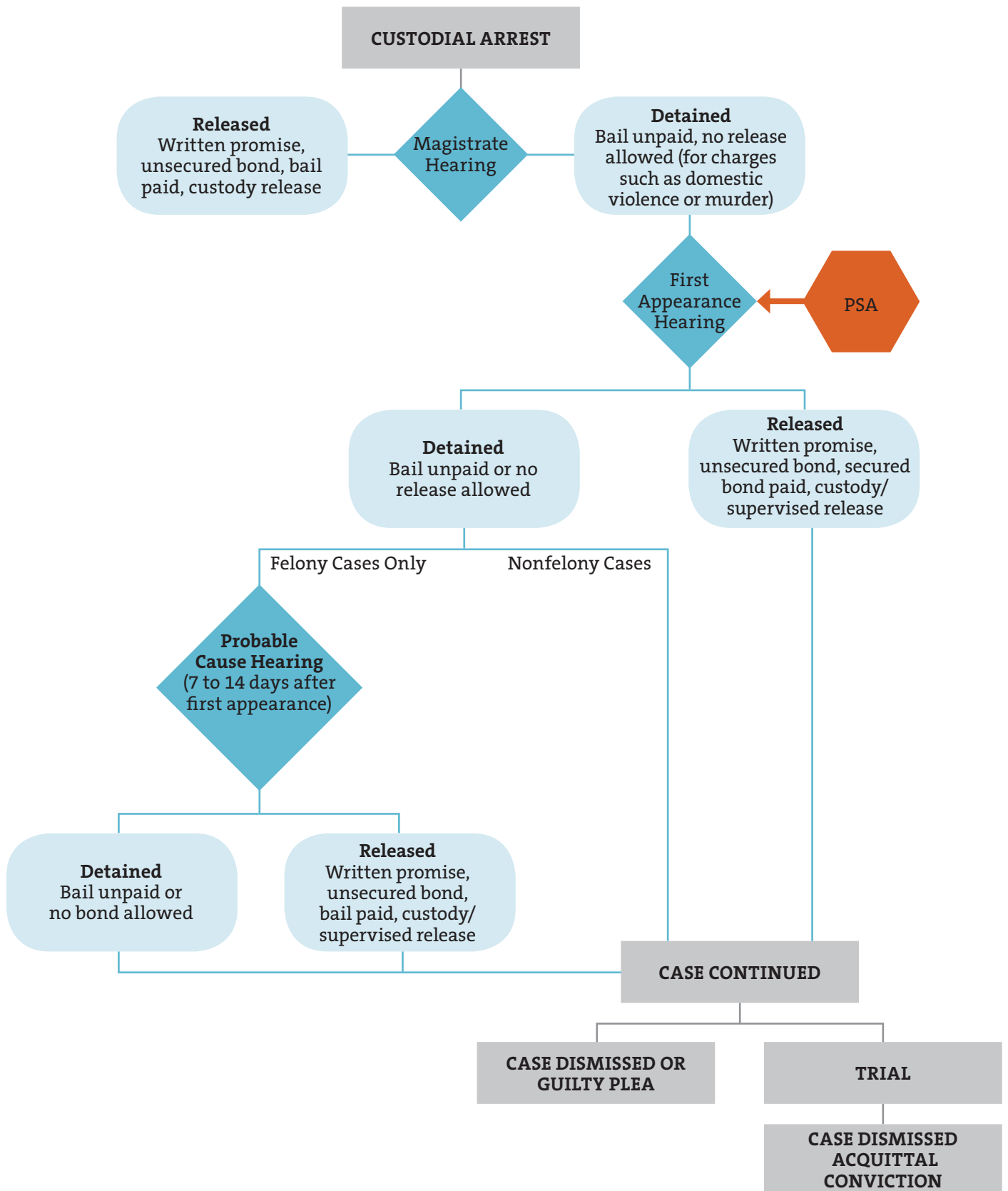
10 Dobbie, Goldin, and Yang (2016).

11 An example of best practices can be found in National Association of Pretrial Services Agencies (2004).

12 Pretrial Services is part of Mecklenburg County Criminal Justice Services.

13 The term "arrest" is defined as a defendant being taken into custody, typically referred to as a "custodial arrest" in Mecklenburg County. For the purposes of this analysis, the defendant is not considered detained at this stage in the pretrial case process because he or she has not been booked into jail.

FIGURE 1 Simplified Diagram of the Pretrial Case Process in Mecklenburg County, NC



cide whether to release the defendant on a written promise or an unsecured bond, set a secured bond (that is, money bail), or release the defendant into the custody of another party.¹⁴ For certain capital crimes and domestic violence offenses North Carolina statute stipulates that only a judge can set conditions of release, so a defendant charged with one of these kinds of crimes cannot have a bond determination made by a magistrate.¹⁵ The PSA report is not available to magistrates at this early decision point. Individuals who are not allowed bond due to the charges against them or who are not able to post the bail set by the magistrate are booked into jail and scheduled for a first appearance hearing, where they go before a judge.

The first appearance hearing is the second point in the process where decisions about release are made. When a defendant is not released by a magistrate, he or she is booked into jail and automatically scheduled for a first appearance hearing, which usually occurs on the next business day.¹⁶ The Pretrial Services staff is provided a list of those scheduled for first appearance hearings each morning, and this list triggers the staff members to create a PSA report for each defendant on the list. They check a series of local and national databases for the factors required to score the PSA. This information is entered into the PSA algorithm. Once the risk scores are generated, the staff members use the decision-making framework customized to the jurisdiction's release conditions and policies, and produce the PSA report. The PSA report is provided to the judge, the defense attorney, the prosecutor, and Pretrial Services representatives at all court hearings.

For felony cases, a third release decision point in the pretrial case process occurs at a probable cause hearing, where a judge determines whether there is enough evidence, or “probable cause,” for the prosecutor to pursue further action on the case against the defendant. Notably, separate bond review hear-

14 In North Carolina, magistrates are independent judicial officers of the district courts who are responsible for a variety of criminal and civil court proceedings. See North Carolina Judicial Branch (n.d.).

15 According to North Carolina Statute 15A-534.1(b): “A defendant may be retained in custody not more than 48 hours from the time of arrest without a determination being made under this section by a judge. If a judge has not acted pursuant to this section within 48 hours of arrest, the magistrate shall act under the provisions of this section.”

16 According to North Carolina Statute 15A-601: “Unless the defendant is released pursuant to Article 26 of this Chapter, Bail, first appearance before a district court judge must be held within 96 hours after the defendant is taken into custody or at the first regular session of the district court in the county, whichever occurs first. If the defendant is not taken into custody, or is released pursuant to Article 26 of this Chapter, Bail, within 96 hours after being taken into custody, first appearance must be held at the next session of district court held in the county.”

ings may be scheduled after the first appearance hearing for defendants who are detained or have not been able to pay the money bail set by the judge at the first appearance. PSA reports are available from Pretrial Services, but are not generated anew for bond review hearings.

EFFECTS ON PRETRIAL RELEASE CONDITIONS

As described above, the theory behind using the PSA and the associated decision-making framework recommendations is that judicial officers may impart different pretrial release conditions on defendants than they would without the additional information and recommendations. Specifically, low- and moderate-risk defendants may have money bail set less often and be more likely to be released until their cases are resolved. Conversely, higher-risk defendants may be more likely to have money bail set or have other more restrictive conditions placed on them while they await trial.

- **How did the PSA policy changes affect pretrial release conditions?**

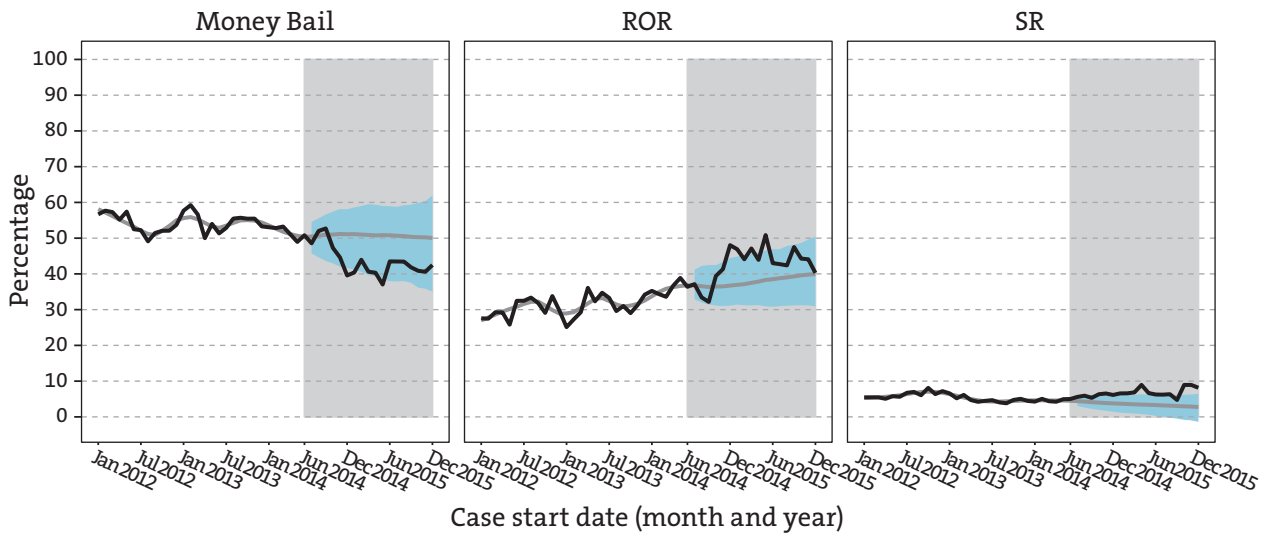
In Mecklenburg County, there are four commonly used release conditions: Written Promise to Appear, Unsecured Bond, Secured Bond, and Place in the Custody of a Designated Person or Organization.¹⁷ For the purposes of using language widely recognized in pretrial practice nationally, this study refers to the conditions of Written Promise to Appear and Unsecured Bond as “released on one’s own recognizance (ROR).” Secured Bond is referred to as “money bail,” and Custody of a Designated Person or Organization is referred to as “supervised release” (SR).¹⁸ Therefore, one of four things can happen to defendants when conditions of release are set: (1) They may be released on a written promise/unsecured bond (called ROR in this study). (2) They may be released on secured bond (money bail, requiring a payment for release). (3) They may be released into some other form of custody or given supervised release where they will have to report regularly to Pretrial Services. (4) They may be allowed no form of bond or release and be kept in jail.¹⁹ “No bond allowed” charges are not shown in the figures for the purposes

17 Technically, there is a fifth release condition: House Arrest with Electronic Monitoring. Only a few defendants in the sample were assigned this release condition. Furthermore, this condition is always accompanied by a secured bond. Therefore, these cases are included in the Secured Bond category. See North Carolina Statute 15A-534(a).

18 There are three types of release to Custody of a Designated Person or Organization in North Carolina. For clarity in describing this condition, this report combines all three under the general category referred to as supervised release.

19 North Carolina Statute 15A-534.1 requires that defendants charged with certain crimes (such as domestic violence or other serious, violent offenses) be detained until a first appearance hearing, where a judge decides on pretrial release conditions.

FIGURE 2 Effects of the PSA Policies on Final Pretrial Release Conditions



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Money bail	51.1	40.4	-10.7	-20.9
ROR	36.9	46.6	9.7	26.3
SR	3.7	6.3	2.6	69.4

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff’s Office.

NOTES: Here *bail* refers to monetary bail or a “secured bond.” ROR means the defendant was released on his or her own recognizance without any additional requirements, and SR means the defendant was released to the custody of Mecklenburg Pretrial Services for supervision or, in a small number of cases, to the custody of an adult. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

SHORTLY AFTER THE PSA POLICIES WERE IMPLEMENTED, THERE WAS A SHARP DECLINE FROM PREVIOUS TRENDS IN THE PROPORTION OF CASES WHERE MONEY BAIL WAS SET. THERE WAS A CORRESPONDING SHARP INCREASE IN THE PROPORTION WHERE DEFENDANTS WERE RELEASED WITH NO FINANCIAL CONDITIONS.

of presentation, but they are included in the analysis. (Very few charges fall into this category.)

Figure 2 shows the proportion of cases initiated in each month that received each of the first three pretrial release options. The release decision shown in this figure represents the last known decision, which could have been made at the magistrate hearing, first appearance hearing, or bond review hearing (whichever was the last decision before a person was released or the case was resolved). The table below the figure shows the effects among defendants arrested six months after the PSA policy changes (December 2014). December

2014 cases are the focal point for this analysis because an interrupted time series research design is based on observing abrupt shifts in trends for outcomes in the time shortly after a new policy or practice is put in place. Six months is reasonably soon after the PSA was adopted, but long enough afterward to ensure that the policy was fully in place. For the remainder of this report, the focus for assessing the effects of the PSA policy change is among those cases with custodial arrests in December 2014.²⁰ Nonetheless, to allow for a deeper understanding of the context, descriptions of trends over time are provided.

Figure 2 shows that the use of money bail was lower than the pre-policy-period trend predicted, as illustrated by the observed rate of 40 percent among cases initiated in December 2014 relative to the predicted rate of 51 percent for that cohort of cases. This observed rate represents a 21 percent decline from the trend. The reduction in the use of bail is accompanied by an increase in ROR of 26 percent above the predicted rate in December 2014. The increase above the predicted rate continued throughout the post-policy period, with some fluctuations from month to month. While supervised release was used relatively little, there was an increase above the predicted trend throughout the post-policy period, suggesting that judicial officers may have been setting nonfinancial supervision conditions instead of money bail for some defendants.

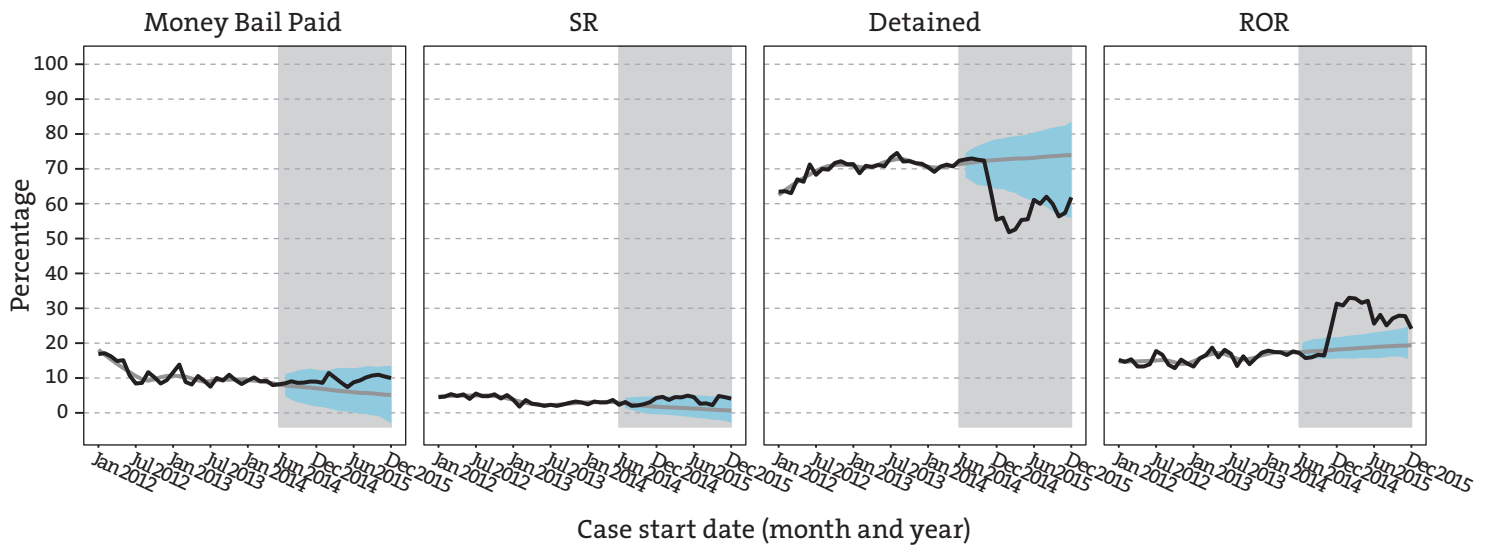
- **How much of the effect on release decisions can be attributed to the actual use of the PSA?**

As illustrated in Figure 1, each defendant arrested has a first hearing in front of a magistrate shortly after being taken into custody. The PSA is not available at this hearing; the magistrate makes a release decision based on the charge, the defendant's criminal history, and the arresting officer's report. Because the PSA is not available at this hearing, analyzing the release conditions set at this stage provides suggestive evidence about how much of the effects shown in Figure 2 can be attributed to mechanisms other than the PSA itself, for example, to training or other policy shifts that occurred alongside the adoption of the PSA.

Figure 3 shows that in the years before the PSA policy changes, more than three-fourths of defendants were detained after the magistrate hearing. Detention can occur either because the charges require the defendant to be detained until the first appearance hearing or because the defendant has

²⁰ Technically, the observed rate is smoothed by averaging it with nearby months to account for month-to-month random variation.

FIGURE 3 Effects of the PSA Policies on the Release Conditions Set at Initial Magistrate Hearings



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Money bail paid	6.9	8.7	1.7	24.5
SR	1.7	4.2	2.5	145.4
Detained (ineligible for release or did not pay bail)	72.8	57.3	-15.5	-21.3
ROR	18.0	29.8	11.8	65.5

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff’s Office.

NOTES: Here *bail* refers to monetary bail or a “secured bond.” *ROR* means the defendant was released on his or her own recognizance without any additional requirements, and *SR* means the defendant was released to the custody of Mecklenburg Pretrial Services for supervision or, in a small number of cases, to the custody of an adult. *Detained* includes cases where a defendant either failed to pay financial bail at the magistrate step or was not eligible for release due to the nature of the charges. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

AMONG CASES INITIATED IN THE MONTHS IMMEDIATELY FOLLOWING THE PSA POLICY CHANGES, THE PROPORTION OF DEFENDANTS DETAINED BY MAGISTRATES DECLINED SHARPLY FROM THE PRE-POLICY TREND. THERE WAS A CORRESPONDING INCREASE ABOVE THE PREDICTED TREND IN THE PROPORTION OF DEFENDANTS RELEASED WITHOUT CONDITIONS BY MAGISTRATES.

bail set and is unable to pay it. The data do not specify the exact reasons for detention after the magistrate hearing, but the current analysis determined that most of those defendants were detained by magistrates because they had money bail set and were unable to pay it immediately.²¹

The time trend analysis suggests a reduction in the setting of money bail by magistrates in the post-policy period, relative to the trend established in the pre-policy period. After about one year, the rate of detention remains consistently lower than the prediction. Among those arrested in December 2014, the proportion detained by magistrates was 57 percent, 16 percentage points less than the predicted rate of 73 percent. Among that same cohort of defendants the rate of ROR increased to 30 percent, 12 percentage points above the predicted rate of 18 percent (a 66 percent change).

These findings suggest that magistrates set money bail less frequently following the PSA changes, even though they did not have the PSA report itself. It seems likely that other aspects of the policy or cultural shifts that occurred along with the implementation of the PSA affected magistrates' decisions.

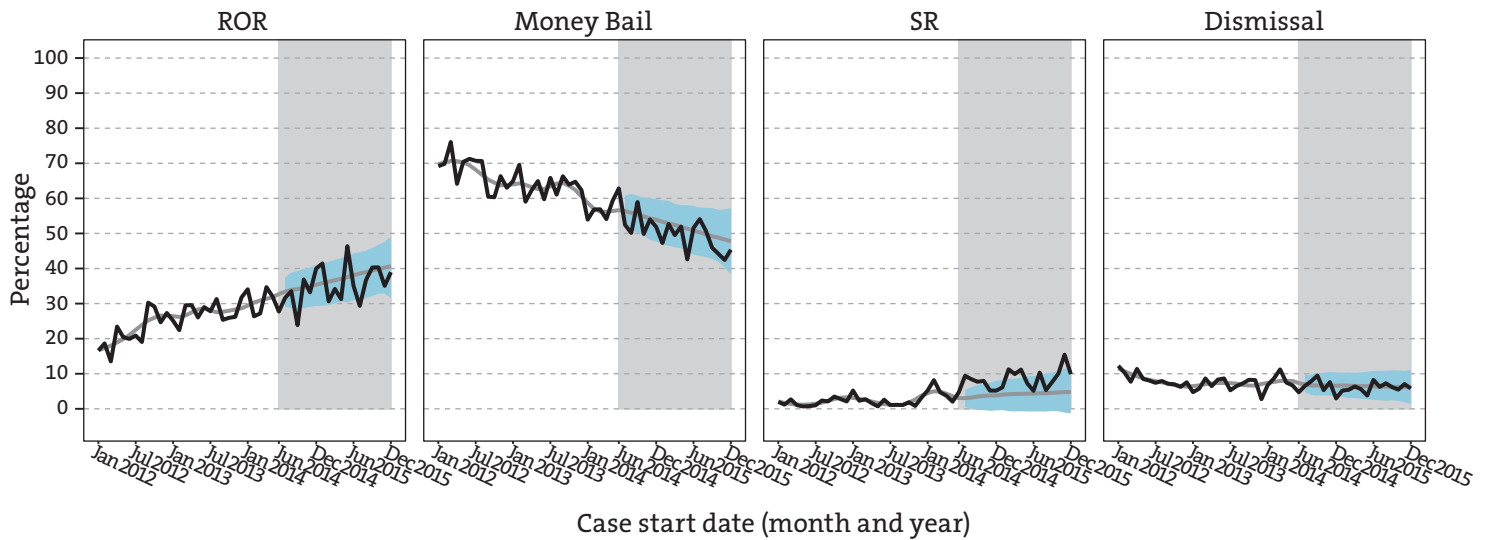
It is not possible to isolate the effects of judges' access to the information in the PSA at the first appearance hearing (where the report is made available), because the effects that occurred at the magistrate hearing changed the kinds of cases that made it to the first appearance hearing during the post-policy period. However, defendants facing domestic violence charges will be detained to await a first appearance hearing where a judge sets release conditions.²² So by analyzing effects at the first appearance hearing for domestic violence cases only, one can assess the effect the PSA report itself *might* have had on decision making, at least for those specific kinds of cases.

As Figure 4 shows, there was little change relative to the trend in money bail setting or ROR at the first appearance hearing among domestic violence cases, suggesting that judges' access to the PSA report itself did not affect their release decisions. Notably, there was already a downward trend in the use of bail and an upward trend in ROR in the months before the PSA was implemented. These trends were predicted to continue into the post-policy period. Thus, there was little significant deviation from the *predicted* value, even

²¹ Approximately 28 percent of defendants who were initially detained also had charges that made them ineligible for release by a magistrate.

²² North Carolina Statute 15A-534.

FIGURE 4 Effects of the PSA Policies on the Release Conditions Set at Initial Appearance Hearings, Among Domestic Violence Cases



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
ROR	35.6	39.3	3.7	10.4
Money bail	54	51.2	-2.8	-5.2
SR	4.1	4.8	0.7	17.3
Dismissal	6.7	4.7	-1.9	-28.5

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff’s Office.

NOTES: Here *bail* refers to monetary bail or a “secured bond.” *ROR* means the defendant was released on his or her own recognizance without any additional requirements, and *SR* denotes cases where a defendant was released to the custody of Mecklenburg Pretrial Services for supervision, or, in a small number of cases, to the custody of an adult. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

THERE WERE NO SIGNIFICANT EFFECTS OBSERVED ON BAIL SETTING OR ROR AMONG DOMESTIC VIOLENCE CASES AT THE INITIAL APPEARANCE HEARING. THIS FINDING SUGGESTS THAT JUDGES’ ACCESS TO THE PSA REPORT ITSELF HAD LITTLE EFFECT ON PRETRIAL RELEASE CONDITIONS FOR SUCH CASES.

though money bail was used less in general in the post-policy period than it was in the pre-policy period.

There are many reasons that domestic violence cases are not representative of most cases that make it to the first appearance hearing. While this analysis provides suggestive evidence about the influence of the PSA report on decision making for domestic violence cases, there is reason to be cautious about using that evidence to draw conclusions about the effects among other types of cases. Nonetheless, it is not surprising that first appearance judges did not appear to shift dramatically in setting release conditions because they had

already been provided with information from another risk assessment tool (the VPRAI) before switching to the PSA.

The second, supplemental report in this series examines the mechanisms causing the effects in more detail, specifically examining whether pretrial release conditions were more aligned with defendants' assessed risks after the PSA was adopted. If the release conditions *were* more aligned with defendants' assessed risks after the PSA was implemented, it would suggest that the jurisdiction was in some way taking those risks into account, possibly by making decisions informed by the PSA.

EFFECTS ON DETENTION IN JAIL

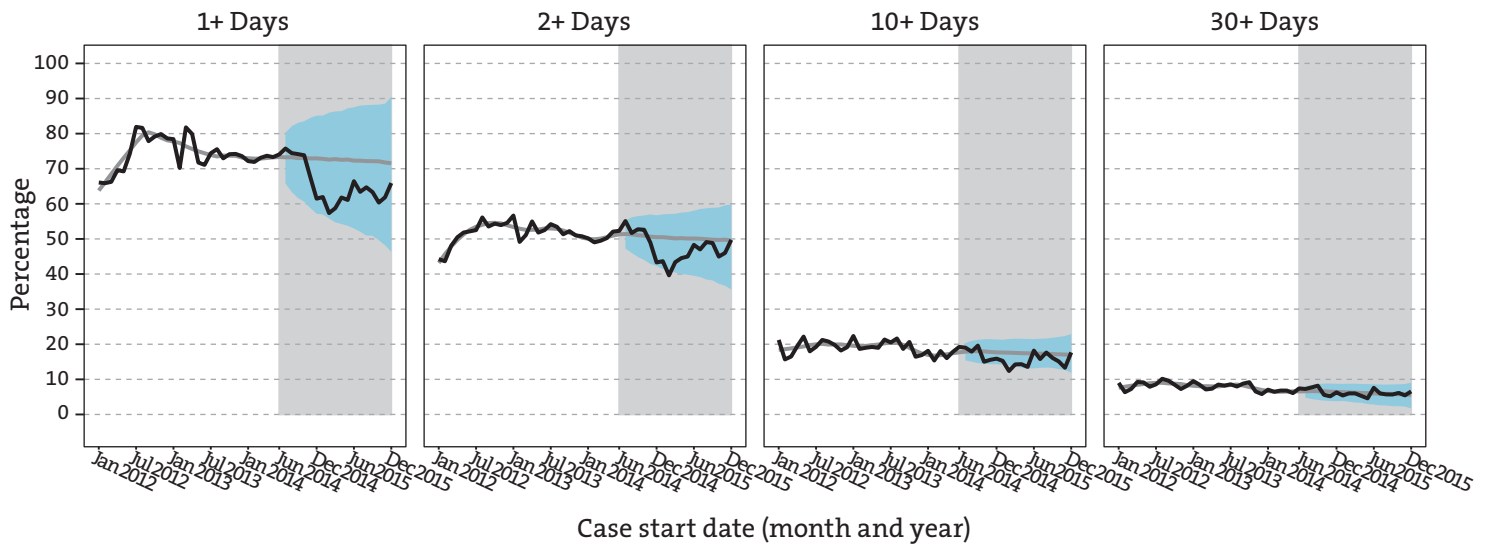
The PSA policy changes appear to have led to less use of money bail and reductions in initial detention (that is, defendants being booked into jail after arrest). This section examines whether those effects translated to reductions in jail detention overall.

- **How did the PSA policy changes affect pretrial detention?**

For each case, detention was measured in two ways: (1) an indicator of whether the defendant was initially detained due to that arrest and (2) the number of days of pretrial detention for the initial arrest. (If a defendant was not initially detained, the number of days of pretrial detention is considered to be 0 in the analysis.)²³ Figures 5 and 6 show both of these outcomes. As described above, detention in jail can occur either because the charges in the case required that the defendant be held until a first appearance hearing before a judge or because the defendant did not pay money bail set by magistrates. The “initially detained” (“1+ days”) line in Figure 5 shows that, on average during the pre-policy period, defendants in about 75 percent of cases were detained. About 25 percent of defendants were released immediately (either because they immediately paid money bail set by magistrates or were released on their own recognizance or under supervision). As the figure shows, the rate of initial detention fell sharply to 63 percent among defendants arrested six months after the PSA policies were implemented (in December 2014), about 10

23 Initial detention does not include jail time due to subsequent detention (after a release) either for that case or for arrests for new crimes or community-supervision violations. This analysis cannot detect whether total jail time reflects multiple cases if the jail time from those cases is overlapping, however, so some of the initial-detention lengths of stay could be inflated. This inflation should not be major concern for the analysis, though, because it should affect the measure the same way in the pre-policy and post-policy periods.

FIGURE 5 Effects of the PSA Policies on Days of Pretrial Detention



December 2014 (Month 6) Cases

Days Detained (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
1+	72.8	62.9	-9.9	-13.6
2+	50.8	44.7	-6	-11.8
10+	17.7	15.9	-1.8	-10.2
30+	6.4	5.8	-0.6	-9.4

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff’s Office.

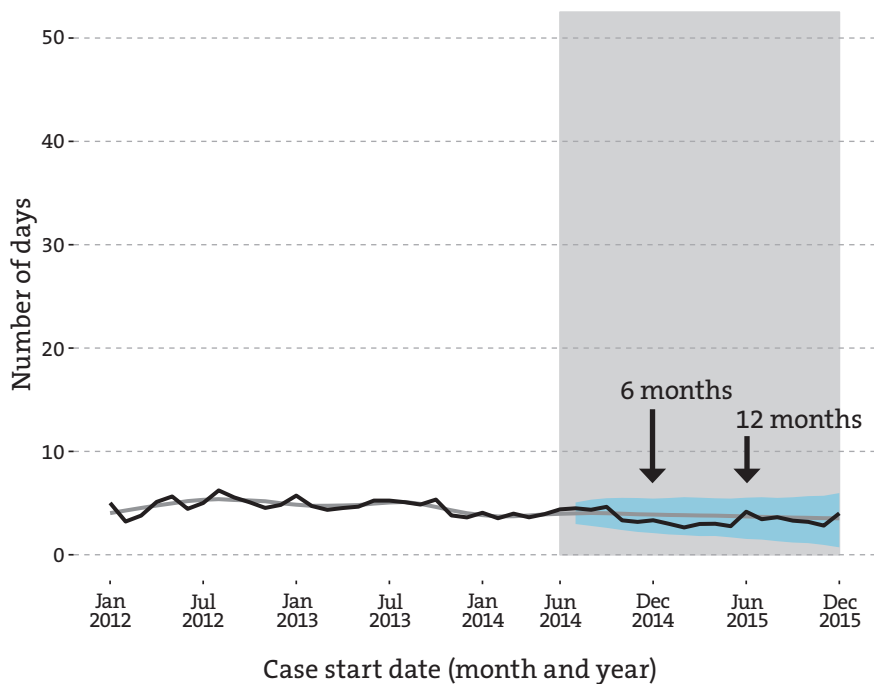
NOTES: *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

FEWER DEFENDANTS WERE DETAINED AFTER THE POLICY CHANGES WENT INTO EFFECT. MOST OF THE DECLINE FROM THE PRE-POLICY TREND IN PRETRIAL DETENTION OCCURRED AMONG DEFENDANTS WHO WOULD HAVE BEEN DETAINED ONE OR TWO DAYS.

percentage points below the predicted rate for that month. As illustrated by the wide shaded bands around the predicted trend, however, there is a good deal of uncertainty in the statistical model.

The three other graphs in Figure 5 show the proportion of cases that had initial detention spans longer than 2, 10, and 30 days. They show, for example, that about 51 percent of cases resulted in an initial detention for two or more days in the pre-policy period. Six months after the policy changes, defendants in 45 percent of cases were detained for two or more days, about 6 percentage points less than predicted. There is little to no difference from the predicted trends in the proportion of defendants detained more than 10 or 30 days.

FIGURE 6 Effects of the PSA Policies on Average Days Detained



December 2014 (Month 6) Cases

	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Number of days detained	3.9	3.2	-0.6	-15.5

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff's Office.

NOTES: This measure uses the 95 percent trimmed mean: the monthly average among cases with values no more extreme than the 95th percentile. This adjustment excludes extreme values that would otherwise exert a disproportionate influence on the mean. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

THERE WAS LITTLE DEVIATION FROM THE TREND IN DEFENDANTS' LENGTH OF DETENTION IN JAIL.

Figure 6 shows that, on average, defendants spent three to four days detained.²⁴ The PSA policies did not have an effect on this outcome. As shown, there were no detectable changes from the trend on the average number of days detained.

24 The average length of initial detention in the post-policy period was 3.2 days for the study sample, including zeros for those not detained. This average was calculated after trimming the longest 5 percent of cases. Doing so made sure that the cases that were still unresolved did not skew the average. Among those detained, the average length of detention was 6.5 days.

The pattern of findings suggests that there was a reduction in initial detention because magistrates set bail at lower rates and released defendants on their own recognizance (ROR) at higher rates after the PSA policies were implemented, but this reduction did not translate into an effect on days detained. The effect on days detained was muted for a couple of reasons. First, the reduction in pretrial detention seems to have occurred mainly among defendants who would have been detained for shorter periods, a day or two at most; there was no effect on defendants with longer stays in detention. Second, some of the increase in pretrial release (ROR) occurred among defendants who would have had bail set by magistrates and paid it immediately in the pre-policy period, and thus would have been released anyway.

- **How did the PSA policy changes affect the Mecklenburg County jail population?**

To the extent that the PSA policies reduced the number of people who were initially detained, they may have also affected the county jail population, that is, the total number of people detained in the county jail at a given time. However, it is important to note that jurisdictions often implement pretrial reforms such as the PSA as part of a larger effort to reduce the number of people in jail. In other words, while the PSA policies could have affected the jail population, a range of other factors also could have affected detention: the number of arrests in the jurisdiction, police practices, crime rates, sentencing, and other mechanisms. If the PSA policies are affecting the jail population, one would expect to see changes in the number of people detained while awaiting court action specifically. However, other things such as overall crime and police activity can also affect the number of people detained while they await court action because the number of people arrested to begin with can contribute substantially to the jail population. This section examines changes in the average jail population and in overall arrests in the county.

Figure 7 shows the number of people detained in Mecklenburg County jail on an average day in each month of the time period studied.²⁵ The analysis did find an effect on jail detention (less use of money bail and more ROR), and it is possible that the population in the county jail may have declined as a result. The three panels in Figure 7 show the total jail population as well as the number of people in jail awaiting court action on their cases and the number in

²⁵ This analysis of average daily population in the county jail is examining the time frame when pretrial detention among the study cohorts might have most affected the overall population in the county jail (January 2012 through December 2015, the period when the cases in the study sample were initiated).

FIGURE 7A Effects of the PSA Policies on the Average Daily Population in Mecklenburg County Jail

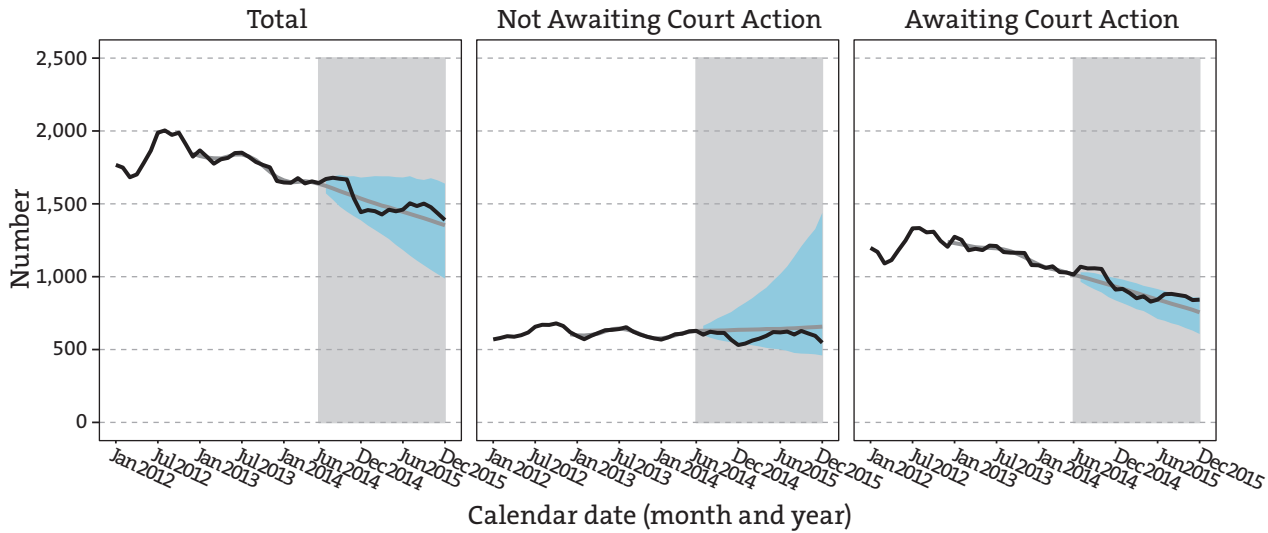
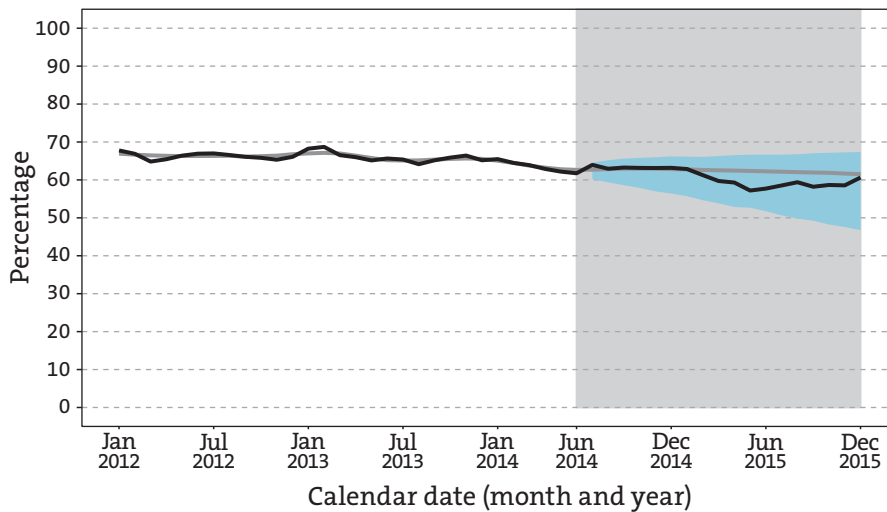


FIGURE 7B: Percentage of the Average Daily Population Detained While Awaiting Court Action



December 2014 (Month 6) Cases

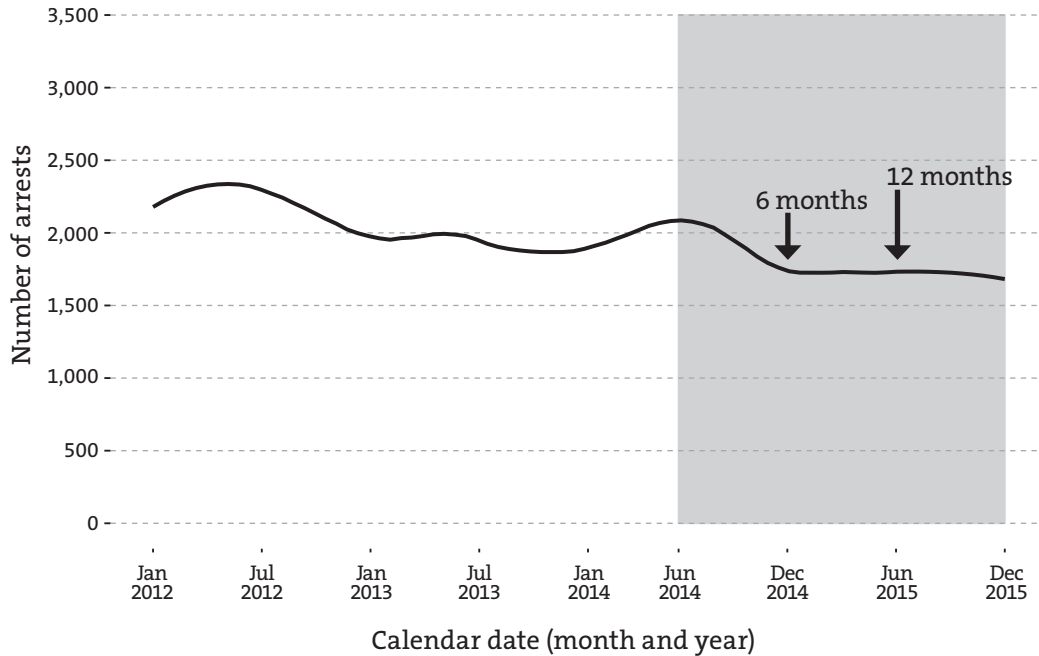
	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Daily Population				
Total	1,509	1,459	-50	-3.0
Not awaiting court action	585	537	-49	-8.4
Awaiting court action	942	922	-20	-2.1
Percentage awaiting court action	62.9	63.2	0.3	0.5

SOURCE: The analysis is based on data from the Mecklenburg County Sheriff’s Office.

NOTES: The monthly average daily population of the Mecklenburg County jail includes those who were waiting for their cases to be resolved (the pretrial population) and those detained for all other reasons, including serving sentences. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

MOST MECKLENBURG COUNTY JAIL INMATES WERE WAITING FOR THEIR CASES TO BE RESOLVED. THE AVERAGE NUMBER OF DEFENDANTS IN THE JAIL WHO WERE AWAITING COURT ACTION DECREASED STEADILY OVER TIME.

FIGURE 8 Total Number of Arrests in Mecklenburg County During the Period of the Study



SOURCE: The analysis is based on data from the Mecklenburg County Sheriff's Office.

NOTE: This measure includes all criminal custodial arrests in Mecklenburg County.

THE NUMBER OF ARRESTS DECLINED STEADILY OVER THE STUDY PERIOD, BEGINNING IN JANUARY 2013, MANY MONTHS BEFORE THE PSA WAS IMPLEMENTED. THERE DOES NOT APPEAR TO BE A SHARP BREAK FROM THIS TREND AFTER THE PSA POLICIES WENT INTO EFFECT.

jail for other reasons.²⁶ As the figure shows, the total jail population declined steadily over time, starting around January 2013, well before the PSA policies were implemented. That decline seems to have occurred mainly among pre-trial defendants.

Figure 8 presents the total number of arrests during the study period. Total arrests are an indicator of crime rates and of police activity, and can shed light on the mechanisms contributing to the changes in the jail population. As the figure shows, arrests declined slowly from about 2,200 per month in January

26 The county jail population includes individuals being held for a variety of reasons other than awaiting trial, including serving sentences and being held for substance abuse treatment, orders of extradition to other jurisdictions, and state confinement programs for misdemeanors.

2012 to around 1,600 per month during the post-policy period.²⁷ There is little evidence that the PSA policies affected the number of arrests.

An extended analysis of the number of people arrested and jailed through 2017 shows the jail population returning to its pre-policy level while arrests continued to decline.²⁸ This combination of findings provides evidence that fluctuations in the jail population are not fully explained by fluctuations in arrests, and that court practices may be contributing in some way to the changes in the jail population.

In summary: Reductions in arrests probably helped to reduce the jail population. Reforms in pretrial court practices also probably reduced the jail population.

EFFECTS ON CASE OUTCOMES

As described above, the PSA-related policy changes in Mecklenburg affected the pretrial release conditions set for defendants: Defendants were less likely to have bail set and were less likely to be detained before their cases were resolved. One possible result of those effects could be changes in case outcomes. If fewer defendants were detained while they waited for their cases to be resolved, they may have had less incentive to plead guilty, and therefore fewer cases may have resulted in convictions. It may have also taken more time to resolve cases.

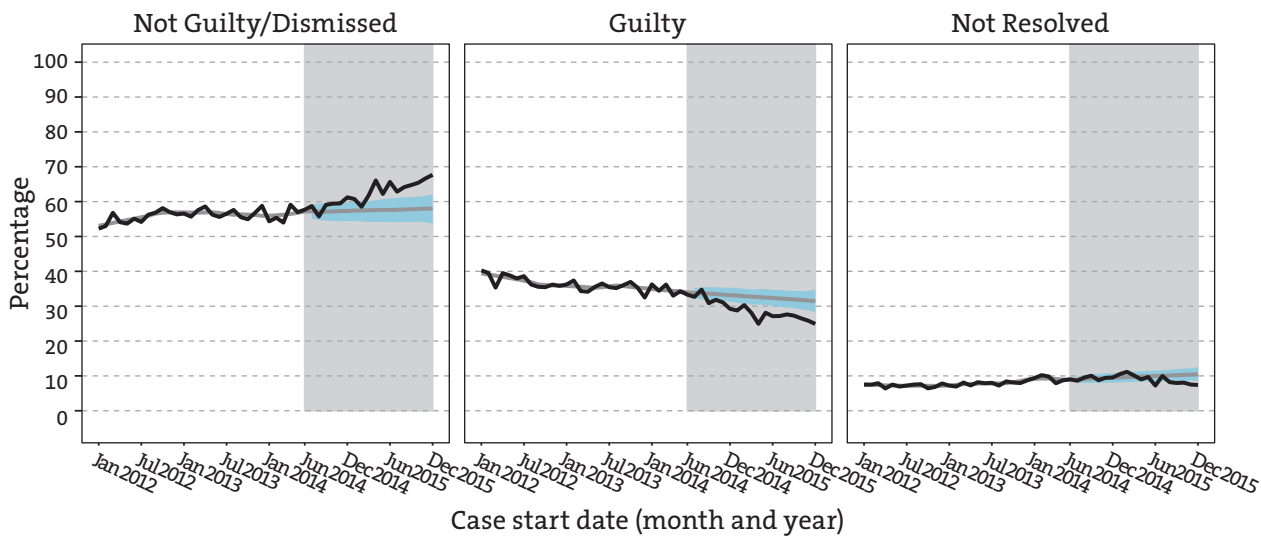
- **How did the PSA policy changes affect case outcomes?**

Figure 9 presents the effects of the policy changes on the proportions of cases resulting in guilty findings (usually through pleas) or complete dismissals of all charges. Not-guilty findings are combined with dismissals for the purposes of this analysis (fewer than 1 percent of all cases resulted in not-guilty findings).

27 Some of the fluctuation in the number of arrests observed over the study period is probably due to seasonal factors. It is widely recognized that crime patterns (and arrests) are affected by the temperature, with more crime occurring during warmer months and less crime during colder months. See Lauritsen and White (2014); McDowall, Loftin, and Pate (2012).

28 The pretrial jail population appeared to be growing in 2017, approaching the level it was at before the PSA policies were implemented. This pattern does not appear to be reflect increases in overall arrests or crime. Something about the court case process may have been shifting in recent years, leading to an increase in pretrial detention. This later shift is also unlikely to be an effect of the PSA policies.

FIGURE 9 Effects of the PSA Policies on Case Resolutions Within 18 Months After Cases Were Initiated



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Not guilty/dismissed	57.2	60.9	3.6	6.3
Guilty	33.2	29.4	-3.8	-11.5
Not resolved	9.5	9.7	0.2	2.1

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff's Office.

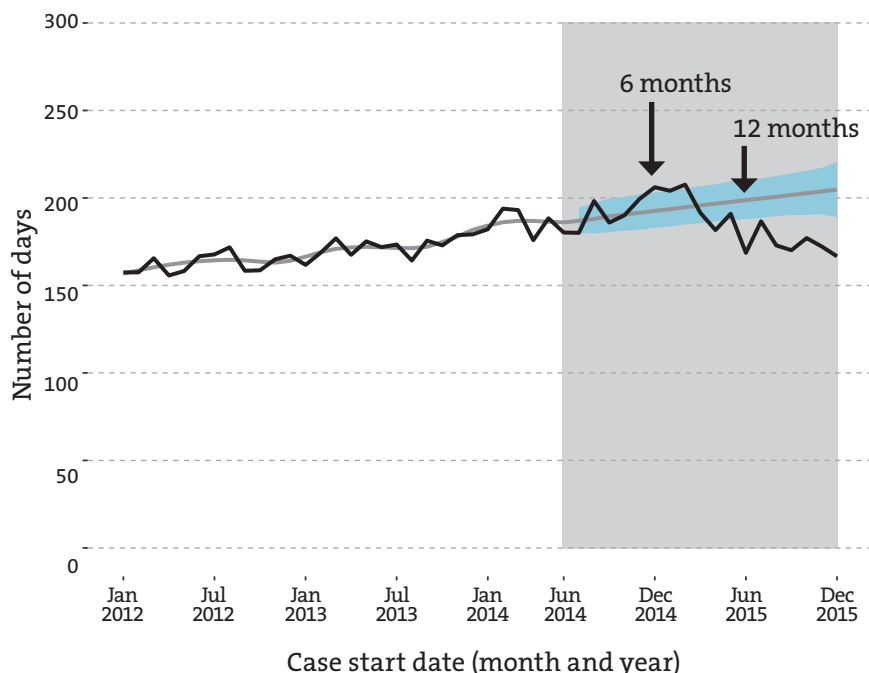
NOTES: *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

DISMISSALS IN THE POST-POLICY PERIOD WERE SOMEWHAT HIGHER THAN PREDICTED BASED ON PRE-POLICY TRENDS. SIMILARLY, CONVICTIONS WERE SOMEWHAT LOWER THAN PREDICTED.

Figure 9 shows that almost all cases initiated during the study period resulted in either dismissals or convictions, with the majority ending in dismissal. Among cases initiated in December 2014, the proportion of cases ending in convictions was somewhat lower than predicted based on the pre-policy trend. About 29 percent ended in guilty findings compared with the predicted rate of about 33 percent, a small reduction of 4 percentage points. This finding suggests that the PSA policy changes may have had a small effect on the outcomes of cases, and the pattern shown in the figure suggests that the effect may have grown somewhat over time.

Figure 10 shows that the PSA policy changes led to an increase of about 12 days in the time it took to resolve cases initiated in December 2014, compared

FIGURE 10 Days to Case Resolution



December 2014 (Month 6) Cases

Case Start Date	Predicted Outcome	Observed Outcome	Difference	Percentage Change
December 2014 (Month 6)	192.3	204.5	12.2	6.3
June 2014 (Month 12)	198.5	179.8	-18.7	-9.4
December 2015 (Month 18)	204.9	166.6	-38.3	-18.7

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff's Office.

NOTES: This measure uses the 95 percent trimmed mean, which is calculated by trimming the longest 5 percent of the observations and taking the mean of the remaining 95 percent. This adjustment reduces the influence of excessively long resolution times and avoids issues that could arise because some cases with long resolution times were still open when the data were extracted. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

CASES TOOK LONGER TO RESOLVE IN THE FIRST FEW MONTHS AFTER THE PSA POLICY CHANGES. HOWEVER, CASES BEGAN RESOLVING MORE QUICKLY AMONG CASES INITIATED LATER ON. THESE CHANGES REPRESENT A SMALL DEVIATION FROM THE PRE-POLICY TREND THAT MAY BE ASSOCIATED WITH THE PSA POLICY CHANGES.

with the amount of time predicted by the pre-policy trend (192 days predicted compared with 204 days observed). However, in later months a noteworthy shift in the other direction occurred, and about a year after the PSA policies were implemented, cases began to be resolved more quickly than predicted. Among cases initiated in December 2015, it took 38 fewer days to resolve the average case than predicted.

One hypothesis is that at least initially, both prosecutors and defendants behaved differently because defendants were less likely to be detained. For example, if defendants had less incentive to plead guilty quickly, cases that were previously resolved quickly through guilty pleas may have taken longer to reach disposition. Later on, prosecutors may have reacted and adjusted the way they processed cases to keep their caseloads from continuing to grow as a result of longer case-processing times.

But there is a good deal of uncertainty in these findings for reasons related to the data and the methods used. The case-resolution data are subject to updates by the court's staff (especially among cases initiated later in the follow-up period), and the statistical analysis predicting outcomes based on the pre-policy trend is less precise as one gets further from the time of the policy change.

EFFECTS ON APPEARANCES IN COURT AND NEW CRIMINAL CHARGES

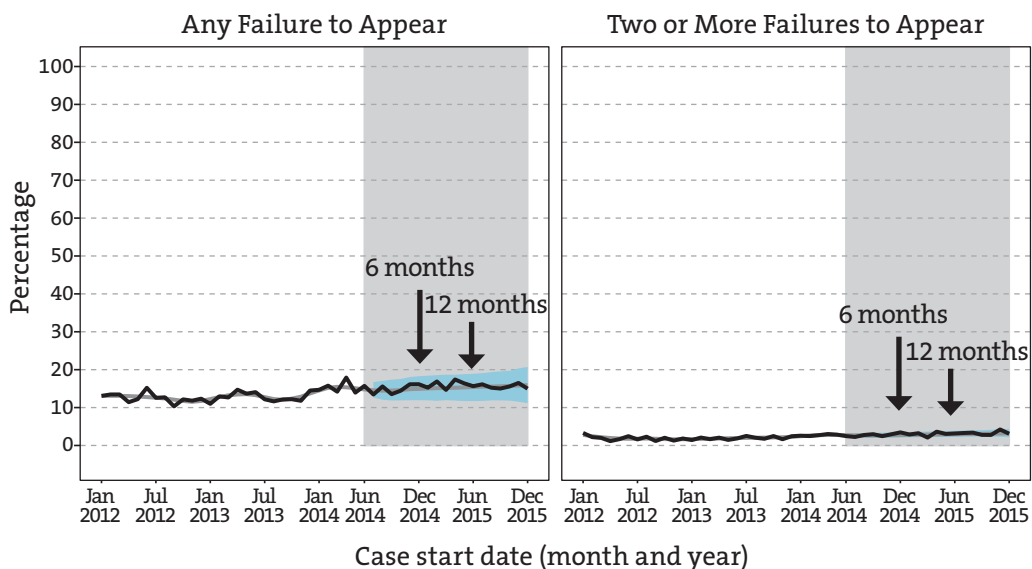
As a result of the PSA policy changes, fewer defendants were detained awaiting court action. One concern among judicial stakeholders is if more defendants are released without financial conditions, then more of them could miss court appearances or could jeopardize public safety by committing new crimes while awaiting trial. This section examines whether the PSA policy changes affected the rates of these pretrial "failures."

- **How did the PSA policy changes affect the percentage of defendants who appeared in court?**

Figure 11 presents the percentages of defendants who failed to appear for court dates on their cases over the study time period. More than 80 percent of defendants arrested before and after the policy changes made all of their court appearances (that is, they had zero failures to appear). The percentage of defendants who missed any court dates remained relatively stable throughout much of the post-policy period, averaging between 17 percent and 19 percent.

Missing one court date is viewed as a less serious offense because it can occur for any number of reasons (forgetting, a lack of transportation, etc.). It does not necessarily signal that a person is failing to show up on purpose or habitually. Therefore, the analysis also examines the effects on missing more than

FIGURE 11 Failure to Appear for a Court Hearing



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Any failure to appear	18.5	19.2	0.7	3.8
Two or more failures to appear	3.9	4.0	0.1	2.6

SOURCES: The analysis is based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff's Office.

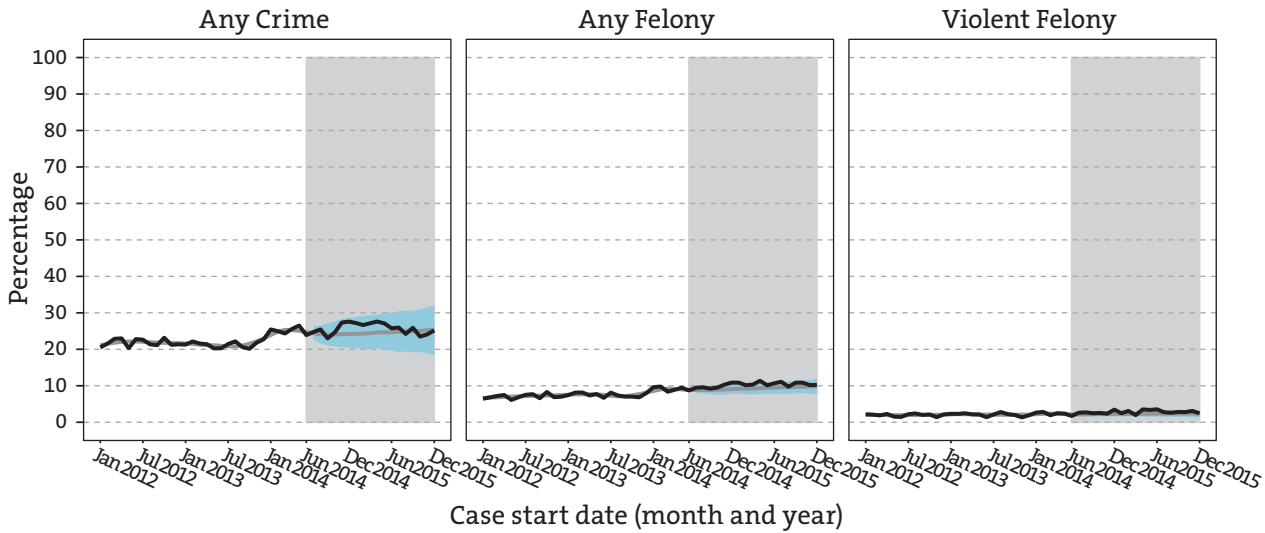
NOTES: *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

THE PSA POLICY CHANGES HAD LITTLE APPARENT EFFECT ON COURT APPEARANCE RATES, EVEN THOUGH MONEY BAIL WAS USED LESS AND FEWER DEFENDANTS WERE DETAINED.

one court date. Fewer than 4 percent of defendants missed two or more court appearances during much of the study time period.

For both of these measures (failing to appear at least once and failing to appear more than once), the observed percentages of defendants who failed to appear are similar to the percentages predicted using the pre-policy trends. This finding is important because it shows that while the PSA policy changes did increase the number of people who were released, they did not have an effect on the number who showed up for their court appearances.

FIGURE 12 New Criminal Activity Among Defendants Waiting for Their Cases to Be Resolved



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Any crime	25.3	27.7	2.4	9.5
Any felony	9.2	10.9	1.7	18.5
Violent felony	2.4	2.9	0.5	20.9

SOURCE: The analysis is based on data from the North Carolina Automated Criminal/Infractions System.

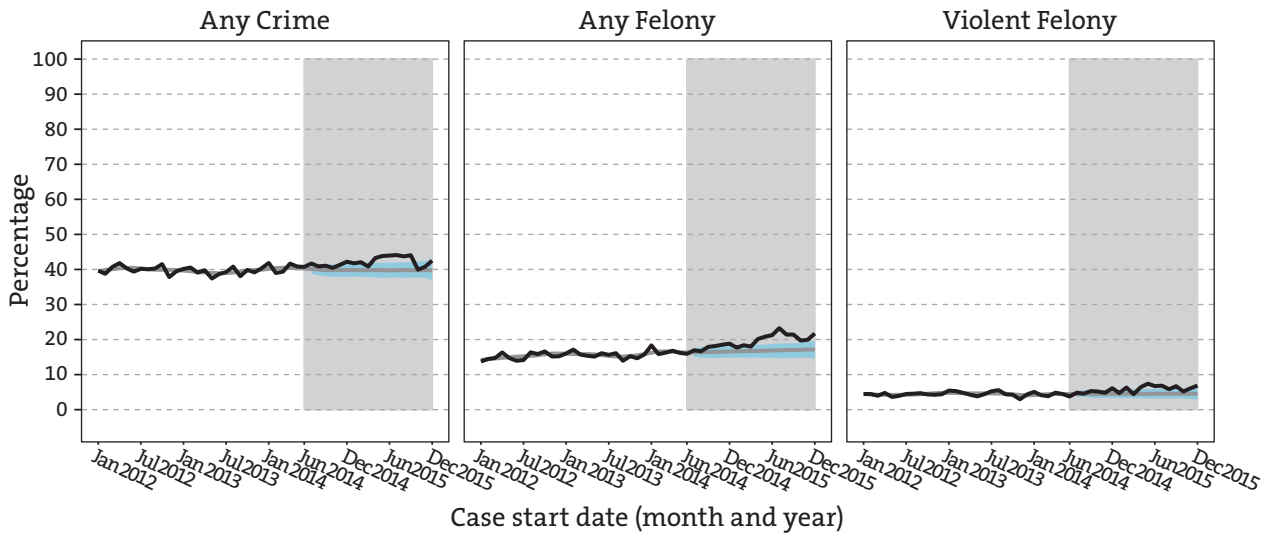
NOTES: These measures indicate whether a defendant waiting for a case to be resolved had a new criminal case opened for at least one offense punishable by jail time, whether the defendant was taken into custody or not. This measure is slightly different from the one used for the main analysis sample population, which is limited to cases initiated through custodial arrests. *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

THE PSA POLICY CHANGES HAD NO DETECTABLE EFFECT ON NEW CRIMINAL ACTIVITY WHILE DEFENDANTS WERE WAITING FOR THEIR CASES TO BE RESOLVED.

• **How did the PSA policy changes affect new criminal charges?**

Figures 12 and 13 show the percentages of defendants in the sample who incurred new criminal charges while waiting for their cases to be resolved. The analysis focuses only on those cases that were resolved within 18 months of the initial arrest (which captures 95 percent of all cases). “New criminal charges” means charges for any type of jailable offense. Felonies and violent offenses are of the most concern to stakeholders, so the analysis also examines effects on new charges for felonies and violent felonies separately.

FIGURE 13 New Offenses Within One Year After the Initial Arrest Date



December 2014 (Month 6) Cases

Outcome (%)	Predicted Outcome	Observed Outcome	Difference	Percentage Change
Any crime	39.8	41.9	2.1	5.3
Any felony	16.6	18.5	1.9	11.5
Violent felony	4.5	5.3	0.9	20

SOURCE: The analysis is based on data from the North Carolina Automated Criminal/Infractions System.

NOTES: *Difference* is the observed outcome minus the predicted outcome. *Percentage change* is the difference between the observed and predicted values as a percentage of the predicted value.

RATES OF NEW OFFENSES WITHIN ONE YEAR WERE HIGHER THAN PREDICTED AMONG DEFENDANTS WHOSE CASES WERE INITIATED AFTER THE PSA POLICY CHANGES. THIS INCREASE ABOVE THE PREDICTED TREND WAS PRIMARILY DUE TO CHARGES FOR NEW FELONIES.

Figure 12 shows the percentages of cases where new charges for offenses punishable by jail time were brought against defendants while they were waiting for their cases to be resolved. There was no effect on any type of new criminal charges. There is some fluctuation from month to month, but the percentages are relatively stable throughout the study period. Among defendants with cases initiated in December 2014, the prediction based on the pre-policy period is that 25 percent would be charged with new crimes, and the actual rate was 27 percent. The difference of 2 percentage points is somewhat higher than what was predicted.

Other factors could be influencing these results, however. For example, the PSA policy changes could have affected the opportunities defendants had to

commit new crimes not only because they appear to have made it more likely for them to be released but also because they appear to have changed the number of days it took for their cases to be resolved. As noted above, the PSA policy changes increased the number of days it took for cases to be resolved initially, and then later appear to have decreased that number.

Figure 13 therefore shows an alternative measure of new criminal activity: the proportion of cases where defendants incurred new criminal charges within one year of the initial arrest date. This measure, with its fixed one-year window, mitigates the concern that changes in the number of days it took to resolve cases could be influencing the number of new charges observed while defendants waited for their cases to be resolved. It is important to note that this fixed one-year window includes both times when defendants were awaiting resolution and times after their cases were resolved. This measure is referred to as “recidivism” for the purposes of this analysis.²⁹

Figure 13 shows that the predicted rate for recidivism within one year among defendants first arrested in December 2014 was 40 percent. The observed recidivism rate for that cohort was 42 percent, an increase of 2 percentage points above the predicted rate. The recidivism rate increased above the predicted trend somewhat more with later cohorts. The effect was mainly for new felony charges.

The estimated effect on recidivism is small, and though it may have been caused by the PSA policy changes, it also may have been caused by changes in the types of cases and defendants entering the courts. The next section examines case and defendant characteristics during the study time period.

CASE CHARACTERISTICS AND ARREST PATTERNS

If over time the types of cases entering the courts became more serious or involved higher-risk defendants, then the post-policy period could have seen a higher rate of recidivism than predicted because those kinds of defendants are more likely to be charged with new crimes in general. To explore which possible influence — the PSA policy changes or changes in the types of defendants entering the court system — was responsible for the effect, this section discusses patterns in the characteristics of defendants and cases during the study period.

²⁹ For defendants awaiting trial, the term “recidivism” to describe new arrests is not technically accurate. Nevertheless, it is used here for ease of presentation.

- **Did the kinds of cases or defendants change during the study period?**

Table 1 shows the demographic characteristics of the defendants in the sample during the pre-policy and post-policy periods. There were few notable changes in the ages and races of defendants. As shown in the table, in the post-policy period, defendants were slightly more likely to be assessed as being at high risk of failing to appear for court dates or of committing new crimes, and they were slightly more likely to have been arrested multiple times in the previous year. Although there were no large systematic changes in defendants' assessed levels of risk on average, those levels did fluctuate from month to month (not shown). In months when there were a greater proportion of high-risk defendants and felony cases in the courts, the rates of bail setting, new criminal charges, and failures to appear in court may also have been greater for that reason, and not for reasons having to do with the PSA policy changes.

The graphs in Figure 14 show the total numbers and percentages of custodial arrests over the study time period for felonies, misdemeanors, and traffic offenses. The left panel shows the number of arrests for each type of charge and the right panel shows the percentage for each. There appears to have been a decline in the total number of arrests during the pre-policy period that occurred entirely among arrests for misdemeanor charges. As shown in the left panel, the number of arrests for felonies was relatively stable, ranging between 500 and 600 per month during the pre- and post-policy periods. However, the number of misdemeanor arrests declined dramatically from 1,400 in January 2012 to about 800 in June of 2015.

As shown in the right panel of Figure 14, while the number of felony arrests was stable, because the number of misdemeanors declined, a larger proportion of cases in the court system had felony charges during the post-policy period than the pre-policy period. Thus, the proportion of defendants with felony charges changed after the PSA policy was implemented, meaning the defendants in the sample were charged with somewhat more serious crimes, on average, after the PSA policy changes.

These figures only include custodial arrests and do not reflect all cases. A separate analysis conducted of all cases (including summonses and citations) shows no significant changes during the same period. This analysis therefore shows that the decline in misdemeanors was not caused by police adjusting charges downward from misdemeanors to citations. The jurisdiction cannot

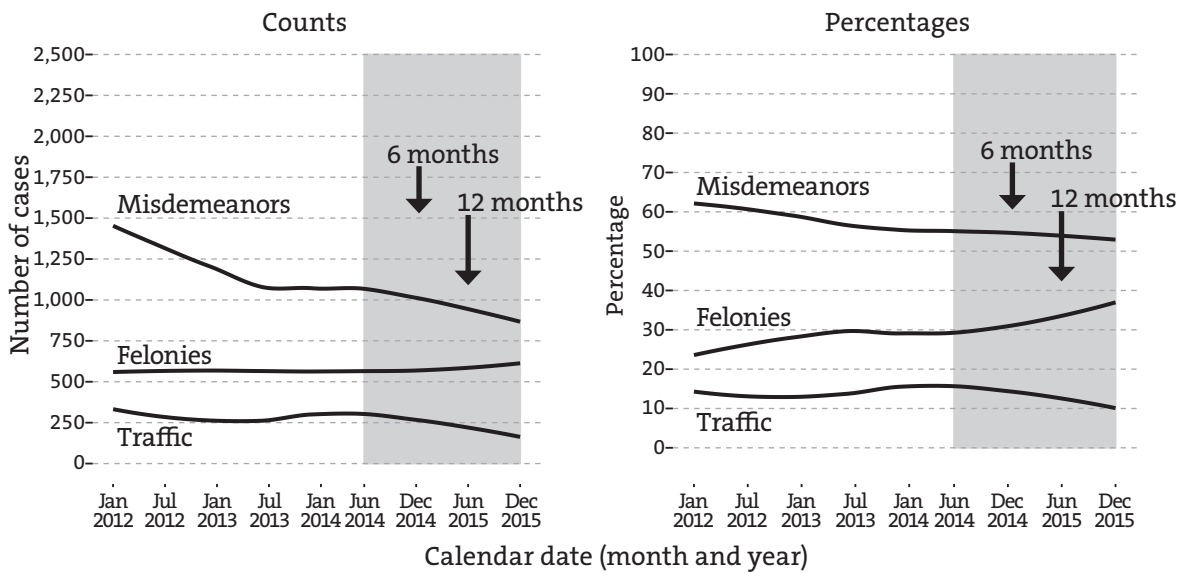
TABLE 1 Defendant and Case Characteristics

Characteristic (%)	Pre-Policy Average	Post-Policy Average
Highest charge class on the case		
Felony	29.5	31.7
Misdemeanor	55.1	54.6
Traffic	15.4	13.7
Defendant's assessed risk		
High	14.1	15.1
Moderate	43.6	44.1
Low	42.3	40.9
Defendant age		
Younger than 23	27.5	27.2
23 or older	72.5	72.8
Defendant race		
Black	68.4	68.3
White	25.8	26
Hispanic	4.6	4.3
Other	1.3	1.3
Defendant gender		
Male	78.2	78.4
Female	21.8	21.6
Number of arrests in the past two years		
None	42.3	40.9
1	21.1	20.4
2-3	20.5	20.8
4+	16.1	17.9

SOURCES: Values are based on data from the North Carolina Automated Criminal/Infractions System and the Mecklenburg County Sheriff's Office.

DEFENDANT AND CASE CHARACTERISTICS WERE RELATIVELY STABLE THROUGHOUT THE STUDY PERIOD. ON AVERAGE, IN THE POST-POLICY PERIOD DEFENDANTS WERE ASSESSED AS BEING AT SLIGHTLY HIGHER RISK OF FAILING TO APPEAR FOR COURT DATES OR COMMITTING NEW CRIMES, AND THE PROPORTION OF FELONY CASES IN THE COURTS WAS SLIGHTLY HIGHER.

FIGURE 14: Charge Class of Cases Entering Courts During the Study Period



SOURCE: The analysis is based on data from the North Carolina Automated Criminal/Infractions System.

NOTES: These measures are based on the class of the most serious charge for each case.

THERE WAS A MODEST AND STEADY DECLINE IN THE NUMBER OF MISDEMEANOR CHARGES FILED DURING THE POST-POLICY PERIOD. THIS SHIFT LED TO FELONY CHARGES MAKING UP A GREATER PROPORTION OF CASES IN THE COURTS DURING THE POST-POLICY PERIOD.

identify a statute or policy change regarding misdemeanors that occurred during this time. It is unclear what caused the change in arrest patterns.

Most felony charges were for property crimes (slightly over 200 arrests per month, not shown). Drug offenses and violent crimes averaged about 150 arrests per month each. Although the specific charge types were mostly stable, there was a small increase in the number of charges for property crimes and violent crimes starting around a year after the PSA policy changes (not shown).

These findings point to a system that was already changing before the PSA policies were implemented. Police arrested fewer people in the post-policy period, and the defendants who were arrested were a bit more likely to be assessed as being at higher risk of failing to appear for court dates or committing new crimes. These changes make it more difficult to be certain that

the predictions generated based on trends observed in the pre-policy period prediction are reliable. The evolution of the system also makes it difficult to know whether the PSA policies had an effect on recidivism, as that apparent effect could simply be the result of having more serious cases in the system.

SUMMARY OF FINDINGS

This report presents an assessment of the effects of the PSA-related policy changes in Mecklenburg County that occurred in June 2014. The accompanying second report in this series will examine the role of risk assessment in decision making and the PSA policy changes' effects on racial disparities in case and crime outcomes. It will also assess how the effects varied among important subgroups of the pretrial population.

Mecklenburg County's switch to the PSA was part of an overall cultural and procedural shift that changed the way that cases were processed. The jurisdiction expected that more low- and moderate-risk defendants would be released before trial without financial conditions, in part because decision makers were reminded of the existing policies and in part because they were provided with more information — in the form of the PSA — to assess defendants' risks of committing new crimes or failing to appear in court.

The analysis shows that the PSA policy changes produced a reduction in the use of money bail and an increase in defendants being released on their own recognizance. There was a corresponding reduction in the proportion of defendants admitted to jail awaiting court action. The PSA policy changes also reduced the number of guilty pleas and convictions and may have increased the number of cases dismissed.

In addition, during the first six months the PSA policies led to an increase in the time it took to resolve cases, as might be expected with fewer defendants detained. Being free to fight their cases may have given defendants less incentive to plead guilty quickly in order to be released from jail. However, there was a subsequent, opposing shift in case-processing time among cases initiated about a year after the PSA policies were adopted. Cases began resolving more quickly than predicted based on the pre-policy-period trend. There was also a sustained and even larger effect on the rate of case dismissals among cases initiated later in the post-policy period. One hypothesis is that prosecutors found it was taking more time to resolve cases and adjusted how they pro-

cessed cases in response to their growing caseloads. But there is much uncertainty about the data and the prediction model later in the follow-up period.

It is important to note that even though more defendants were released and fewer were convicted on their initial charges, the PSA policy changes had at most a small effect on the number who were charged with new crimes while waiting for their cases to be resolved. The rate of recidivism in a one-year fixed window after arrest was also somewhat higher than expected based on pre-policy-period trends. This analysis cannot isolate whether the small increase in recidivism can be attributed to the PSA policy changes because the defendants in the courts in the post-policy period were charged with more serious crimes, on average, than those in the courts in the pre-policy period. Defendants who were charged with more serious crimes were also assessed as being at higher risk of committing new crimes, which means they could be expected to have higher rates of recidivism.

POLICY IMPLICATIONS

When Mecklenburg County switched from the VPRAI to the PSA, the change was not made in isolation. A broad cultural shift was occurring in the jurisdiction that included training for court staff members and revisions to pre-trial case-processing policies and practices. These other changes could have worked in concert with or at cross-purposes to the goals of the PSA. This study attempts to disentangle the influences of various shifts in practices in Mecklenburg County by examining effects at different stages in the pretrial process. Specifically, the study seeks to isolate how much the PSA tool contributed to the overall effects and how other factors may have influenced the outcomes. The results from this study can inform other jurisdictions as they consider ways to make their pretrial justice systems fairer and more effective.

Policymakers recognize that pretrial reforms involve a trade-off: Releasing more people could lead to more new crime. But more careful decisions regarding which defendants can safely be released could also *reduce* rates of new crime. The results of this evaluation show that Mecklenburg County achieved its goals. The jurisdiction substantially reduced its use of money bail and detained fewer defendants, without sacrificing public safety or court appearance rates.

While these are promising achievements, there is still room for improvement and the jurisdiction will need to maintain its efforts to sustain the desired

The results of this evaluation show that Mecklenburg County achieved its goals.

outcomes. (For example, there appeared to be some reversal of the early improvements among cases initiated later in the study period.) Although the PSA policy changes significantly reduced pretrial detention, the rate of initial detention was still quite high — ranging from 60 percent to over 70 percent of defendants in each month.³⁰ Most of these defendants were detained initially because they could not post the money bail set by magistrates, and most of them ended up being released within days by other judicial decision makers (three days was the average length of initial detention).

Most defendants taken into custody ultimately had their cases dismissed by judges or prosecutors — as many as 60 percent of cases — and many of those defendants had spent time in jail before trial. Cases are typically dismissed when there is a lack of probable cause or insufficient evidence for prosecution. Mecklenburg County may want to consider whether the resources invested in cases that ultimately end in dismissal could be used more efficiently.

The analyses clearly show that the PSA policy changes led to a steep and abrupt drop in *initial* jail bookings. In other words, more defendants were released before having a first appearance hearing, the first point in the case process when the PSA report was available. Because a good deal of the observed effect on bail setting and initial detention occurred at a stage in the process before the PSA report was generated, it is nearly certain that factors other than the use of the PSA report contributed greatly to the observed effects. Further support for this conclusion can be found in other aspects of this study: First, an analysis of domestic violence cases (whose defendants' charges require a first appearance hearing before a judge where a PSA report is available) found that the PSA had little effect. In addition, another analysis found that the PSA policies reduced the time detained only among defendants who would have been detained for just one or two days in the absence of the policies, according to a comparison with the pre-policy-period trend. This amount of time is just how long it would have taken for the defendants to have first appearance hearings, had they not been released.

These findings do not necessarily mean that the PSA had no role in the effects. It is unlikely that judicial decision makers would be willing to risk releasing large numbers of defendants without additional tools available to help them. Most jurisdictions seeking to reduce their reliance on money bail will need to provide their judges with more information about which defendants can safe-

30 Of those defendants initially booked into jail, about 70 percent had been assigned money bail and were not able to pay it.

ly be released with few (or no) conditions and which defendants pose a greater risk requiring more restrictive conditions. Mecklenburg County is unusual in that the jurisdiction was already using a validated risk tool.³¹ So the fact that this new assessment of defendant risk appears to have had little effect on judicial decision making is not surprising. However, one should consider the findings from this study less applicable to other jurisdictions that are newly adding risk assessment tools to their pretrial processes.

A common alternative to bail often used in pretrial reforms — supervision — is also part of Mecklenburg County’s pretrial system. This study illustrates that pretrial supervision was used in only a small proportion of cases. Even this fact provides valuable insight. Broadly, it shows that it is possible to release more defendants with no conditions whatsoever and still achieve the desired effect of maintaining court appearance rates and public safety.

Since Mecklenburg County’s goal was to move toward a risk-based pretrial system using the PSA, the supplemental, second report in this series investigates what types of defendants the jurisdiction released. If the jurisdiction was applying the principles of risk-based decision making (the goal of the PSA), one would expect that implementing the PSA led decision makers to impose release conditions on defendants that were better aligned with their assessed levels of risk. Specifically, most of the increase observed in the pretrial release rate should be among low- and moderate-risk defendants. The supplemental report also further investigates the role of risk-based decision making in the observed effects. Finally, the supplemental report assesses the effects of the PSA policy changes on racial disparities in case and crime outcomes and examines the effects among subgroups of defendants defined by their races and ages and by the types of charges they faced.

31 Luminosity, Inc. (2017).

Angwin, Julia, Jeff Larson, Surya Mattu, and Lauren Kirchner. 2016. "Machine Bias." Website: www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

Bechtel, Kristin, Christopher T. Lowenkamp, and Alex Holsinger. 2011. "Identifying the Predictors of Pretrial Failure: a Meta-Analysis." *Federal Probation* 75: 78.

Clark, John, Timothy R. Schnacke, and Sue Ferrere. 2016. "Upgrading North Carolina's Bail System: A Balanced Approach to Pretrial Justice Using Legal and Evidence-Based Practices." American Bar Association Standards for Criminal Justice. Website: <https://nccalj.org/wp-content/uploads/2016/10/Upgrading-NCs-Bail-System-PJI-2016-003.pdf>.

Criminal Procedure Act § 15A-534. 2018. "Procedure for Determining Conditions of Pretrial Release." North Carolina General Statutes Chapter 15A.

Criminal Procedure Act § 15A-544.3. 2018. "Entry of Forfeiture." North Carolina General Statutes Chapter 15A.

Criminal Procedure Act § 15A-601. 2018. "First Appearance Before District Court Judge." 2018. North Carolina General Statutes Chapter 15A.

Dobbie, Will, Jacob Goldin, and Crystal Yang. 2016. "The Effects of Pre-Trial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges." *American Economic Review* 108, 2:201-240.

Doleac, Jennifer, and Megan Stevenson. 2016. "Are Criminal Risk Assessment Scores Racist?" Website: www.brookings.edu/blog/up-front/2016/08/22/are-criminal-risk-assessment-scores-racist.

Lauritsen, Janet L., and Nicole White. 2014. *Seasonal Patterns in Criminal Victimization Trends*. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics.

Luminosity, Inc. 2017. "Public Safety Assessment (PSA): Validation and Assessments of the Impact in Mecklenburg County, NC." Unpublished paper. Saint Petersburg, FL: Luminosity, Inc.

Mayson, Sandra. 2018. "Dangerous Defendants." *Yale Law Journal* 127: 490-568.

McDowall, David, Colin Loftin, and Matthew Pate. 2012. "Seasonal Cycles in Crime, and Their Variability." *Journal of Quantitative Criminology* 28, 3: 389-410.

REFERENCES

Miratrix, Luke. 2019. "Technical Paper for the Public Safety Assessment Impact Evaluation in Mecklenburg County, N.C." Unpublished paper. New York: MDRC.

National Association of Pretrial Services Agencies. 2004. *Standards on Pretrial Release, Third Edition*. Washington, DC: National Association of Pretrial Services Agencies.

North Carolina Administrative Office of the Courts, Organizational Development Division. 2014. "ACIS Public Inquiry Reference Guide." Raleigh, NC: North Carolina Administrative Office of the Courts, Organizational Development Division.

North Carolina Judicial Branch. n.d. "Court Officials: Magistrates." Website: www.nccourts.gov/learn/court-officials#magistrates-3629. Accessed on January 29, 2019.

Skeem, Jennifer, and Christopher Lowenkamp. 2015. "Risk, Race, & Recidivism: Predictive Bias and Disparate Impact." *Criminology* 54, 4: 680-712.

Southerland, Vincent. 2018. "With AI and Criminal Justice, the Devil Is in the Data." Website: www.aclu.org/issues/privacy-technology/surveillance-technologies/ai-and-criminal-justice-devil-data.

Travis, Jeremy, and Bruce Western, eds. 2014. *The Growth of Incarceration in the United States: Exploring Causes and Consequences*. Washington, DC: National Academies Press.

Zeng, Zhen. 2018. *Jail Inmates in 2016*. Washington, DC: Bureau of Justice Statistics, U.S. Department of Justice.

REFERENCES

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Updating the New York City Criminal Justice Agency Release Assessment

Maintaining High Court Appearance Rates, Reducing
Unnecessary Pretrial Detention, and Reducing Disparity

Luminosity & the University of Chicago's Crime Lab New York

June 2020

PREFACE

The data used in these analyses were provided by the New York State Division of Criminal Justice Services (DCJS), New York City Department of Correction (DOC), and the New York City Criminal Justice Agency. The opinions, findings, and conclusions expressed in this report are those of the authors and not those of DCJS or New York City. New York State, DCJS, nor New York City assumes liability for its contents or use thereof.

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INTRODUCTION

The New York City Criminal Justice Agency, Inc. (CJA) is a not-for-profit corporation serving New York City's criminal justice system under contract with the Mayor's Office of Criminal Justice (MOCJ). CJA was established in 1973 (as the Pretrial Services Agency) to provide pretrial services as pioneered and tested by the Vera Institute of Justice's Manhattan Bail Project in the early 1960s.

The mission of CJA is to assist the courts and the City in reducing unnecessary pretrial detention. In accordance with this mission, CJA provides the following primary services:

1. Conducts pre-arraignment interviews, performs assessments, and makes release recommendations to the court regarding the likelihood of continued appearance in court if the person is released in lieu of monetary bail;
2. Notifies released individuals of upcoming court dates to reduce the rate of non-appearance;
3. Operates Supervised Release programs to serve eligible individuals who would otherwise be held in jail;
4. Assists arrested individuals and their families in navigating bail payment with the intention of avoiding admissions to DOC facilities; and
5. Provides information and research services to criminal justice policy makers, City officials, and the public.

Consistent with the first primary service – conducting pre-arraignment interviews, performing assessments, and making release recommendations to the court – CJA interviews nearly all people who are held in NYC police detention prior to arraignment to determine their ties to the community. CJA attempts to verify the information provided during the interview, gathers prior court appearance and criminal history information, completes a research-based assessment of the likelihood of appearance, and makes a release recommendation. Personal and community ties related information, the assessment results, and the release recommendation are compiled in a report known as the CJA Release Assessment. The CJA Release Assessment is provided at arraignment to the court, defense, and prosecution, and is intended to assist the court in its determination of the likelihood that a person will return for court appearances and whether the individual should be released on their own recognizance (ROR), with nonmonetary conditions, or on bail. The assessment contains objective and research-based information designed to support, not replace, judicial discretion and decision-making.

The CJA Release Assessment that was in use until November 2019 was last updated in 2003 (henceforth referred to as the “2003 CJA Release Assessment”). As a result, CJA, with support from MOCJ, sought to update the assessment. The update was spurred in part by recognition of the changes in NYC's social conditions and justice system practices, and by the desire to benefit from the breadth and wealth of knowledge accumulated since the development of the 2003 CJA Release Assessment across many disciplines including social science, data science, and behavioral science.

The overarching goals of updating the assessment were to (1) maintain the current high court appearance rates in New York City for people released pretrial, (2) reduce the use of pretrial detention when possible, and (3) reduce racial and other disparities in pretrial settings. The following guiding principles steered the assessment update process: the assessment must be evidence-based and informed by data science; it should be developed in collaboration with judges, court actors, advocates, and affected communities and individuals; and it must be transparent and validated.

With these goals and guiding principles in mind, two independent research organizations – Luminosity, led by Dr. Marie VanNostrand, and the University of Chicago’s Crime Lab New York (CLNY), led by Dr. Jens Ludwig – were retained to lead the development of the updated assessment. Luminosity is a nationally recognized expert in the pretrial stage of the justice system and possesses decades of experience using traditional social science research methods to advance pretrial justice policies and practices. CLNY leverages data science to solve pressing social problems and is dedicated to the design, testing, and scaling of promising programs and policies to reduce crime and violence in NYC. Engaging two independent research organizations with different areas of expertise to analyze the data provided a unique opportunity to benefit from increased transparency and independently validated results. The pioneering behavioral science design firm ideas42 was also retained to ensure the development and design processes were informed by behavioral science. Together, Luminosity, CLNY, ideas42, and CJA, with support from MOCJ, formed a Research Partnership (see Appendix A for more detailed descriptions of each organization), which led the process of updating the CJA Release Assessment (henceforth referred to as the “updated CJA Release Assessment”).

The Research Partnership worked with judges, court actors, advocates, and affected communities and individuals throughout the entire development process. A public meeting was held at the beginning of the process to share information about the planned research and to solicit feedback. Judges, prosecutors, and defenders were consulted early on to learn more about how the 2003 CJA Release Assessment was used and to better understand the existing pretrial release decision-making process. Feedback was received from judges, prosecutors, defenders, and other criminal justice system actors as findings were shared throughout the research process. The Research Partnership also engaged in extensive outreach with community groups and affected individuals to solicit input, share findings, and provide updates on the development process.

The update process further benefitted from the creation of and consultation with an expert Research Advisory Council (RAC). The RAC members represent the areas of criminal justice, economics, addressing algorithmic bias, machine learning, and computer science, and hold varied perspectives on release assessments (see Appendix B for more information about the RAC members). The RAC reviewed analysis methods and results; requested additional analysis to be conducted; consulted on how the assessment might impact racial, ethnic, and other groups; and provided overall guidance and technical assistance. Partnering with the RAC – as well as extensive stakeholder engagement – had the added, intended benefit of increasing transparency when developing the updated CJA Release Assessment.

It is important to note that, as the revision of the CJA Release Assessment neared completion, the New York State legislature passed sweeping criminal justice bail reform legislation. This reform – effective January 1, 2020 – eliminates the use of money bail for most misdemeanor and non-violent felony offenses, specifies the presumptive use of appearance tickets by law enforcement officers for many charges, and includes specifications for the use of assessment tools in release decisions. Specifically, a tool used for considering a person’s pretrial release or bail must be (1) “designed and implemented in a way that ensures the results are free from discrimination on the basis of race, national origin, sex, or any other protected class” and (2) be “empirically validated and regularly revalidated.” As will be detailed in this report, decisions were made and analysis undertaken to ensure that the updated CJA Release Assessment is compliant with these standards, in addition to being consistent with the update’s overarching goals and guiding principles.

The 2003 CJA Release Assessment was phased out of use at the end of 2019, and the updated CJA Release Assessment was put into use in New York City courtrooms prior to January 1, 2020. This report provides an overview of the building, testing, and performance of the updated CJA Release Assessment in relation to the goals, guiding principles, and legislative mandates discussed above. When appropriate, comparisons are made between the 2003 and updated CJA Release Assessments. The performance of the updated CJA Release Assessment for groups (i.e., race/ethnicity and sex) is also examined. The report concludes with a discussion of the redesigned updated CJA Release Assessment report provided in hard copy to judges and court actors at arraignment.¹

¹ During the COVID-19 emergency, New York courts drastically scaled back operations and converted to virtual appearances for essential matters. During this period, the courts temporarily paused CJA pre-arraignment interviews and Release Assessment reports.

SAMPLE FOR ANALYSIS

Identifying the sample for analysis and generating a corresponding research dataset began with the compilation of data files. This multi-step process required cooperation from several local and state agencies and data sources. CJA generated an initial data file containing information for all summary arrests (people arrested and held in custody until arraignment) between January 1, 2009 and December 31, 2015. Each arrest record is known as an arrest cycle,² representing a single arrest for a person and including all charges that stemmed from the arrest. The CJA data file served as the primary file to which all other data files were matched.

The CJA data file includes information on individuals' community ties collected through pretrial interviews; arrest cycle related charge information sourced from New York City Police Department (NYPD) data; and court case related information (e.g., arraignment outcomes, charge resolutions, bench warrants) originating from the New York State Office of Court Administration (OCA). In addition, the New York City Department of Correction (DOC) compiled a data file containing records (admission and release related data) for all people admitted to the DOC during the same period.

The data files compiled by CJA and DOC were then sent to the New York State Division of Criminal Justice Services (DCJS). Using the person identifiers contained in the CJA data file, DCJS extracted the corresponding criminal histories from their Computerized Criminal History (CCH) system. DCJS then generated pseudo person and record identifiers needed for record linking, replaced the true identifiers with the pseudo identifiers, and removed all remaining personally identifiable information from all files. The CJA, DOC, and DCJS de-identified data files were then sent to the research teams for further processing.

DATASET

The research teams collaborated to create a dataset for analysis using the CJA, DOC, and DCJS data files. The preliminary dataset included 1,854,824 records, each representing an arrest cycle. The teams cleaned the data, resulting in the removal of 221,643 arrest cycles due to duplicate or incomplete information. Then, all arrest cycles that did not continue past arraignment were removed (616,425 records). In addition, all arrest cycles where the most serious charge at the time of arraignment was either a violation, infraction, or the charge severity was unknown were removed (16,587 records). The final dataset used for analysis (a.k.a. analysis file) includes 1,000,169 records that represent arrest cycles with arrest dates between January 1, 2009 and December 31, 2015 that were continued beyond arraignment, and the most serious charge at the time of arraignment was a felony or misdemeanor.

The analysis file was partitioned by the research teams into five subsets: train, test, imputation, validation, and 2015. The partitioning allows for the use of different subsets in specific steps of

² Arrest cycle serves as the unit of analysis, with each arrest cycle representing one row in the dataset.

developing, testing, and validating the updated CJA Release Assessment, as well as assessing the performance of the 2003 CJA Release Assessment. Arrest cycles were randomly assigned to their respective subsets. The train and imputation subsets each contain 50% of the arrest cycles from 2009 to 2013; the test and validation subsets each contain 50% of the arrest cycles from 2014; and the 2015 subset contains all of the arrest cycles from 2015.³ More detailed information about each subset is contained in Table 1 below.

Table 1. Description of Subsets

Subset	N	Percent	Timeframe	Purpose
Train	363,732	36.4	2009-2013	For building candidate models
Test	70,597	7.1	2014	For evaluating candidate model performance
Imputation	363,882	36.4	2009-2013	For building unrestricted imputation models (to impute unobserved outcomes for population not at risk [i.e., counterfactual outcomes for individuals not released pretrial])
Validation	70,250	7.0	2014	For computing final model metrics
2015	131,708	13.2	2015	Not included to prevent truncation bias due to limited tracking period (6 months following December 31 of the arrest year compared to 18 months for the years 2009 to 2014)

MEASURES

Before beginning any analysis, the research teams identified the dependent (outcome) variable and the data available for the creation of potential independent (risk factor) variables. In addition, the teams created measures of charge severity, race/ethnicity, and sex for use in determining how the 2003 and updated CJA Release Assessments perform for these different groups. Specifically, race/ethnicity and sex measures are used to establish the degree to which the updated CJA Release Assessment identifies risk of FTA equally well for the various groups. Charge severity – but not race/ethnicity or sex – is also used in combination with the assessment score to generate the release recommendation. All frequencies presented in this section (for charge severity, race/ethnicity, and sex) are provided for the entire analysis file.

³ The process of removing arrest cycles where the most serious charge at the time of arraignment was either a violation, infraction, or the charge severity was unknown took place after the analysis file was partitioned into subsets. As a result, despite being randomly assigned to their respective subsets, the number of arrest cycles is slightly different between the corresponding subsets.

Charge Severity

When considering all charges related to an arrest cycle, charge severity is determined by identifying the most serious charge at arraignment – violent felony offense (VFO),⁴ felony non-VFO, or misdemeanor. If one or more charge is a VFO, the charge severity is VFO. If no charge is a VFO but one or more charges is a felony, the charge severity is felony non-VFO. If no charge is a felony but one or more charges is a misdemeanor, the charge severity is misdemeanor. The charge severity distribution is VFO 12.7%, felony non-VFO 20.6%, and misdemeanor 66.7%.

Race/Ethnicity

During the CJA interview, people are asked to voluntarily self-report both their race and ethnicity for purposes of evaluating overall trends and impacts. The possible responses for race are White, Black, Asian, American Indian, or Other, and the possible responses for ethnicity are Hispanic or non-Hispanic. To determine how most appropriately to create a measure for research purposes that captures dimensions of both race and ethnicity, the Research Partnership examined several options in consultation with the Research Advisory Council. The RAC advised that the most appropriate measurement of race and ethnicity, in this context, is to use an encoding that represents the race/ethnicity as it would likely appear to a court actor (i.e., Black, Hispanic, White). This standard collapses the different race/ethnicity combinations into the groups as shown in Table 2 below. The race/ethnicity of Asian, American Indian, and Other non-Hispanic groups on their own constitute a small percentage of the sample. Therefore, these race/ethnicity groups are collapsed into Other race/ethnicity (108 arrests cycles with unknown race/ethnicity are excluded from the distribution).

Table 2. Distribution of Race/Ethnicity

Race/ethnicity combinations	N	Percent	Collapsed race/ethnicity	N	Percent
Black non-Hispanic	495,260	49.5	Black	561,105	56.1
Black Hispanic	65,845	6.6			
White Hispanic	222,885	22.3	Hispanic	268,920	26.9
Other Hispanic	46,035	4.6			
White non-Hispanic	115,607	11.6	White	115,607	11.6
Asian	32,750	3.3	Other	54,429	5.4
American Indian	1,068	0.1			
Other non-Hispanic	20,611	2.1			

⁴ VFO includes all offenses specified as VFOs per NYS Penal Law section 70.02, as well as certain VFO-like Class A offenses, as defined by DCJS. The rationale for these charges being treated like VFOs is explained on page 2 of the document General Law File Information (<https://www.criminaljustice.ny.gov/crimnet/clf/rel-db/general-law-file-info.pdf>) and the exact charges can be found in the Excel file Listing of NYS Laws (<https://www.criminaljustice.ny.gov/crimnet/clf/rel-db/Excel-Listing-of-NYS-Laws.xls>).

Sex

An indicator of sex is contained in the NYPD data and is provided as part of the arrest cycle information for each person. Based on this measure, 82.9% of the individuals in the sample are male and 17.1% are female.

Outcome Variable

In New York, the pretrial release decision is driven primarily by the need to assure that individuals appear for all required court hearings until all charges related to their court case(s) are resolved. As a result, the outcome variable of interest is failure to appear (FTA), which is provided in the CJA data file. Per the CJA definition, a person fails to appear when they do not appear for a required court hearing related to the arrest cycle, after arraignment and prior to the end of the tracking period, and the court issues a non-stayed bench warrant. Arrest cycles are tracked until the date when all related charges are resolved or 18 months following December 31st of the arrest year, whichever occurs first. Creating alternate methods for measuring FTA, such as considering stayed bench warrants or circumstances when a person returns voluntarily to court soon after the missed hearing, is not feasible with the data provided for analysis.

Potential Risk Factor Variables

Potential risk factor variables are created using information contained in the analysis file. These factors are grouped into four domains: prior convictions, prior bench warrants, pending cases, and community ties. The DCJS data file provides the prior convictions, prior bench warrants, and pending cases data. Community ties data describe the self-reported state of the individuals' circumstances at the time of the interview (e.g., length of residence, employment status, has a home or mobile phone) and are available in the CJA data file.

EXPUNGING MARIHUANA ARREST CYCLES

After the building and testing of the statistical model used to update the CJA Release Assessment were complete, but before its full implementation and operation, the New York State legislature passed a law that requires expungement of all arrest cycles where the resulting convictions were only for two specific marijuana charges, Penal Law § 221.10 and § 221.05. The development of the updated CJA Release Assessment model was completed prior to passage of this law, therefore the change in the law did not impact the statistical model.⁵ For this reason, the results pertaining to the

⁵ Within the context of the development of the updated CJA Release Assessment, the impact of the marijuana expungement law is relatively small. Applying marijuana expungement impacts the release recommendation of the updated CJA Release Assessment in less than 1% of arrest cycles. Given that marijuana expungement reduces potential criminal history factors, it can only result in a less restrictive recommendation.

statistical model itself, including comparisons to the 2003 CJA Release assessment model, are based on datasets that do not implement marihuana expungement.⁶

However, consistent with the updated New York State marihuana law, the updated CJA Release Assessment in practice excludes relevant past marihuana convictions and associated warrant history. For this reason, findings related to how the updated CJA Release Assessment likely will perform in practice, such as the computation of estimated appearance rates and release recommendations, are based on datasets that implement marihuana expungement.⁷ By employing the marihuana expungement, the findings better represent how the updated CJA Release Assessment will operate in practice.

⁶ This includes all results in the sections entitled “2003 CJA Release Assessment”, “Identifying Candidate Risk Factors”, “Building and Testing the Updated CJA Release Assessment”, “Updated CJA Release Assessment: Performance Comparison”, “Appendix D”, and “Appendix E”, as well as the comparison related results in the section entitled “Updated CJA Release Assessment: Performance by Race/Ethnicity and Sex”.

⁷ This includes all results in the sections entitled “Updated CJA Release Assessment: Estimated Appearance Rates” and “Updated CJA Release Assessment: Release Recommendations”, and the non-comparison results in the section entitled “Updated CJA Release Assessment: Performance by Race/Ethnicity and Sex”.

EXAMINATION OF THE 2003 CJA RELEASE ASSESSMENT

Creating an updated CJA Release Assessment begins with an examination of the 2003 CJA Release Assessment, which ceased to be used before January 2020. This includes an examination of the predictive validity and resulting release recommendations, as well as the identification of other critical measures (i.e., release status and failure to appear rates). These analyses are conducted to establish baseline measures to which the updated CJA Release Assessment will be compared. The 2014 test subset is used for these analyses.

The 2003 CJA Release Assessment was developed after extensive research conducted by CJA's research department.⁸ That assessment utilized the six factors listed below, which were weighted based on the strength of the relationship between the factor and failure to appear. The calculated score ranged from -13 to +12 and, in some instances, the weighting varied if the information was verified.⁹

1. Does the defendant have a working telephone in residence/cellphone?
2. Does the defendant report a NYC area address?
3. Is the defendant employed, or in school or training program, full time?
4. Does the defendant expect someone at arraignment?
5. Does prior warrant equal zero?
6. Does open case equal zero?

The score represented the likelihood of appearing for all court hearings (as measured by the absence of a non-stayed bench warrant) if the person was released on their own recognizance. The higher the score, the more likely the person was to appear. The scores on the 2003 CJA Release Assessment were grouped into three categories of recommendations to provide to the court: Recommended for ROR (low risk: +7 to +12 points); Moderate risk for ROR (+3 to +6 points), and Not recommended for ROR (high risk: -13 to +2 points). In addition to score results, some individuals received a Not recommended for ROR recommendation based on a policy rationale (e.g., active bench warrant, bail-jumping charge). Finally, a recommendation was not made when the assessment could not be completed or was prepared For Information Only due to murder or escape related charges or offenses that occurred while in-custody (No recommendation).

The assessment results (i.e., factors, responses, weights, and total score), personal and community ties related information, and the release recommendation were compiled in the CJA Release

⁸ See Qudsia Siddiqi, Ph.D. (2002) Prediction of Pretrial Failure to Appear and an Alternative Pretrial Release Risk-Classification Scheme in New York City: A Reassessment Study and Qudsia Siddiqi, Ph.D. (2003) An Examination of the Existing and New Pretrial Release Recommendation Schemes in New York City: A Pre-Implementation Analysis.

⁹ Qudsia Siddiqi, Ph.D. (2007) Research Brief No. 13: An Evaluation of CJA's New Release-Recommendation System.

Assessment report which was provided to the court, defense, and prosecution at arraignment. A sample of the report can be found in Appendix C.

PREDICTIVE VALIDITY

The 2014 test subset is used to establish the predictive validity of the 2003 CJA Release Assessment via bivariate analysis. The analysis indicates that all individual factors were statistically significantly related to FTA ($p < .001$) with the strongest predictive factor being “Does prior warrant equal zero” ($\Phi = -.161$), and the weakest predictive factor being “Does the defendant expect someone at arraignment” ($\Phi = -.038$). An examination of the assessment score and its relationship to FTA reveals rates ranging from 39.1 (score of -12) to 4.8 (score of 12).^{10, 11} The model Area Under the Curve for the Receiver Operator Characteristics (AUC-ROC), a common measure of assessment performance, is calculated ($AUC-ROC = .670$). The AUC-ROC gauges the performance of the total score in differentiating between individuals who do not experience an FTA from those who experience an FTA pending disposition. Appendix D contains the complete bivariate analysis results discussed here.

RELEASE RECOMMENDATIONS

The distribution of release recommendations provided to the court (Recommended for ROR, Moderate risk for ROR, and Not recommended for ROR) is presented in Table 3 below.¹² Approximately one-third of the sample (34.8%) were recommended for ROR, whereas 18.8% were identified as moderate risk for ROR, and 46.4% were not recommended for ROR at arraignment.

Table 3. Distribution of Recommendation Type Under the 2003 CJA Release Assessment

Recommendation type	Percent
Recommended for ROR	34.8
Moderate risk for ROR	18.8
Not recommended for ROR	46.4

¹⁰ Scores are not calculated for the 1,421 arrest cycles with incomplete interviews or the additional 65 arrest cycles missing the necessary address information and, therefore, are removed from this analysis. Analysis is also conducted by treating missing answers as negative responses, with similar results.

¹¹ FTA rates are not calculated for scores with less than 50 arrest cycles due to the instability of small samples. Specifically, FTA rates for scores of -13, -11, and 11 are not calculated due to there being none or a lower number of arrest cycles with each score (i.e., 0, 0, and 8, respectively).

¹² CJA did not make a release recommendation due to missing data (2.9%) and policy exceptions (0.4%). The arrest cycles without a release recommendation are excluded from the distribution.

Recommendations by Charge Severity, Race/Ethnicity, and Sex

The Recommended for ROR rates by charge severity, race/ethnicity, and sex are contained in Table 4 below. ROR was recommended at the highest rate for most serious charges of VFO (38.5%), followed by misdemeanor (36.3%) and felony non-VFO (28.1%). When considering race/ethnicity, White individuals received a recommendation for ROR at a rate of 41.1%, followed by Hispanic individuals at a rate of 35.6%, and Black individuals at a rate of 31.7%. Notably, the difference in Recommended for ROR rates between White and Black individuals was 9.4 percentage points. When examining release recommendations by sex, female individuals received a recommendation of ROR 40.7% of the time compared to 33.6% for male individuals.

Table 4. Distribution of Recommendation for ROR by Charge Severity, Race/Ethnicity, and Sex Under the 2003 CJA Release Assessment

Recommended for ROR	Percent
<i>Charge severity</i>	
Misdemeanor	36.3
Felony non-VFO	28.1
Violent felony offense	38.5
<i>Race/ethnicity</i>	
Black	31.7
Hispanic	35.6
White	41.1
<i>Sex</i>	
Female	40.7
Male	33.6

RELEASE STATUS

An individual can be released into the community or detained pending resolution of all charges. Based on the available data, an individual's release status is grouped into one of three categories: released on ROR at arraignment, released after arraignment and before disposition (either on ROR, with nonmonetary conditions, or on bail), or not released before disposition. The distribution of release status is provided in Table 5 below. Nearly 84% of all arraigned individuals were released while their charges were pending in court. Specifically, 65.4% of all arraigned individuals were released on ROR at arraignment, while an additional 18.4% were not released on ROR at arraignment but were released prior to disposition. The remaining 16.2% of individuals were not released pending disposition.

Table 5. Distribution of Release Status

Release status	Percent
Released on ROR at arraignment	65.4
Released after arraignment and before disposition	18.4
Not released before disposition	16.2

Status by Charge Severity, Race/Ethnicity, and Sex

To establish baseline data for comparison, release status is disaggregated by charge severity, race/ethnicity, and sex. As can be seen in Table 6 below, individuals with a most serious charge of misdemeanor were released on ROR at arraignment at a rate of 77.3%, followed by felony non-VFO (45.7%), and finally, VFO (33.9%). When considering individuals released on ROR at arraignment together with those released after arraignment and before disposition, the pattern remains; the release rate was highest when the most serious charge was a misdemeanor at 89.3%, followed by 73.1% for felony non-VFO, and 72.3% for VFO.

When comparing race/ethnicity groups, White individuals were released on ROR at arraignment 70.3% of the time compared to 66.2% for Hispanic individuals, and 62.7% for Black individuals. Notably, the difference in released on ROR at arraignment between White and Black individuals was 7.6 percentage points. Furthermore, female individuals were released on ROR at a higher rate (79.9%) compared to male individuals (62.3%).

Table 6. Distribution of Release Status by Charge Severity, Race/Ethnicity, and Sex

	Released on ROR at arraignment	Released after arraignment and before disposition	Not released before disposition
<i>Charge severity</i>			
Misdemeanor	77.3%	12.0%	10.7%
Felony non-VFO	45.7%	27.4%	27.0%
Violent felony offense	33.9%	38.4%	27.7%
<i>Race/ethnicity</i>			
Black	62.7%	19.2%	18.1%
Hispanic	66.2%	18.2%	15.6%
White	70.3%	17.0%	12.7%
<i>Sex</i>			
Female	79.9%	10.2%	10.0%
Male	62.3%	20.2%	17.5%

FAILURE TO APPEAR

The average FTA rate for individuals released prior to disposition in the 2014 test subset was 13.0%. For the purpose of establishing baseline measures, the FTA rate is calculated in relation to the release recommendation, charge severity, race/ethnicity, and sex.

As can be seen in Table 7 below, as the release recommendations became more restrictive (Recommended for ROR, Moderate risk for ROR, and Not recommended for ROR, respectively), the FTA rate increased.

Table 7. FTA Rates by Recommendation Type
Under the 2003 CJA Release Assessment

Recommendation type	FTA rate
Recommended for ROR	6.4
Moderate risk for ROR	11.1
Not recommended for ROR	20.0

As Table 8 below shows, when FTA rates are separated by charge severity, released individuals charged with a VFO had the lowest FTA rate (9.7%), followed by those charged with a felony non-VFO (12.0%), and those charged with a misdemeanor (13.7%).

Table 8. FTA Rates by Charge Severity

Charge severity	FTA rate
Misdemeanor	13.7
Felony non-VFO	12.0
Violent felony offense	9.7

Differences in FTA rates across charge severity should be considered in combination with other factors, such as the differences in rates and types of release. For example, as can be seen in Table 6 above, fewer individuals with a most serious charge of VFO were released relative to individuals with a misdemeanor most serious charge, and those with a most serious charge of VFO were less likely to be released on ROR.

FTA rates also vary by race/ethnicity and sex. As can be seen in Table 9, FTA rates vary amongst Black, Hispanic, and White individuals, as well as between female and male individuals.

Table 9. FTA Rates by Race/Ethnicity, and Sex

Failure to appear rates	Percent
<i>Race/ethnicity</i>	
Black	14.5
Hispanic	12.6
White	9.9
<i>Sex</i>	
Female	12.6
Male	13.0

UPDATED CJA RELEASE ASSESSMENT: IDENTIFYING CANDIDATE RISK FACTORS

As discussed in the Sample for Analysis section above, the research teams worked together to create an analysis file, partition it into five subsets (train, test, imputation, validation, and 2015), and create/identify key measures (e.g., release status, FTA outcome, charge severity). It was at this point in the process that the research teams separated to independently construct and test candidate risk factors using the train subset and to subsequently identify the strongest predictors of FTA. As expected, each team approached the task using methodologies from their respective disciplines (i.e., data science and more traditional social science). Although these approaches generated some differences in their output, there were many similarities in the processes, measures created and tested, and the identification of the strongest candidate risk factors. All candidate risk factors identified through the research are consistent with the factors that the bail law permits judges to consider when making release determinations.

CONSTRUCTING CANDIDATE RISK FACTORS: CRIMINAL HISTORY

Numerous candidate risk factors are constructed within each of three criminal history related domains: prior convictions, prior bench warrants, and pending case(s). Four primary approaches are used to construct criminal history measures including analyzing events (i.e., conviction, bench warrant, pending case) at varying levels of granularity, count of events, time-windows, and recency of occurrences. A brief explanation of each approach with additional examples is provided below.

Levels of Granularity

Domains are examined with varying levels of granularity. Prior convictions and pending cases, for example, are first disaggregated by charge severity (VFO, felony non-VFO, misdemeanor). Charges are also divided by class (e.g., A misdemeanor, D felony), by statute title (e.g., Title J - Offenses Involving Theft), and by code section (e.g., Section 155.30 - Grand Larceny). Prior bench warrants are categorized as pre-arraignment, pretrial, and post-disposition.¹³

Count of Events

Each candidate factor constructed at various levels of granularity is then examined as an indicator variable which measures the presence or absence of the event (e.g., has prior conviction) and as a count variable that measures the total number of events (e.g., 1, 2, 3, 4). The total count of events is also placed in various logical categories (e.g., none, 1 or 2, 3 or 4, 5 or more) for testing.

¹³ *Pre-arraignment* represents a bench warrant issued before the date of arraignment. *Pretrial* represents a bench warrant issued for failure to appear after arraignment but before disposition. *Post-disposition* represents a bench warrant issued for failure to appear or for failure to comply with a diversion or sentencing related court order (such as a fine or community service) that occurs after disposition.

Time-windows

Candidate factors constructed at varying levels of granularity and counts are additionally examined by use of a time-window strategy. A time-window is established by setting a number of years prior to the date of the arraignment for the arrest cycle under examination. For example, setting a time-window of 5 years for the misdemeanor conviction measure means that misdemeanor convictions that occurred within 5 years prior to the arraignment date are counted, and misdemeanor convictions that occurred longer than 5 years prior to the arraignment are not counted. Time-windows are set in yearly increments (1 year, 2 years, 3 years, 4 years) which are used in cumulative (e.g., number in the past 1 year, number in the past 2 years, number in the past 3 years) and non-cumulative (number in the past 1 year, number in the past 1 to 3 years, number in the past 3 to 5 years) approaches. The use of time-windows allows for testing the role of event type, frequency, and time simultaneously.

Recency

The recency of each event is explored. For example, when considering an individual with prior bench warrants, the recency of the bench warrant is measured as the time since the last bench warrant (e.g., within the past year, 1 to 2 years, 2 to 4 years). The recency of each event type serves as an additional measure of time and is often referred to as ‘time since’ (e.g., time since last bench warrant, time since last conviction).

CONSTRUCTING CANDIDATE RISK FACTORS: COMMUNITY TIES

The majority of the self-reported information contained in the CJA interview data relates to address, employment, school/training program, with whom the person lives, and the presence of a telephone in his or her residence or a cellphone. These measures are broken down at varying levels of granularity (e.g., location of address, relationship to the person they live with) and through the use of time measures (e.g., length at current address, length of current employment, length at last two addresses).

TESTING CANDIDATE RISK FACTORS

The process of constructing candidate risk factors described above results in approximately 2,000 factors, all representing ways of measuring prior convictions, prior bench warrants, pending case(s), and community ties. Testing of candidate risk factors involves conducting bivariate analysis to explore whether a relationship exists between a factor and the FTA outcome (Chi-square $p < .01$), and the strength of the association (e.g., Phi or Cramer’s V). The factors with the strongest relationship with FTA are then used to build multivariate models to assess the predictive value when grouped with other factors. A combination of bivariate analysis and statistical model building led each research team to narrow the candidate risk factors to 8 to 10 of the strongest predictors.

RECONCILING CANDIDATE RISK FACTORS

Following several months of independent candidate risk factor construction and testing, each research team shared their findings with the Research Partnership. Two overarching patterns emerged. Specifically, the number of criminal history events as well as the recency of those events are more strongly related to FTA. In addition, six themes related to the strongest predictors of FTA were identified including:

1. Prior bench warrants, including the count, time-window, and recency of the last bench warrant;
2. Prior misdemeanor convictions, including count, time-window, and recency of the last misdemeanor conviction;
3. Prior felony convictions, including count, time-window, and recency of the last felony conviction;
4. Pending misdemeanor or felony charge at the time of the arrest;
5. Length living at address; and
6. Telephone in his or her residence or a cellphone.

The findings from the two independent research teams were combined, and the teams worked together to refine candidate risk factors. Next, the results were shared with the RAC who provided insights into the findings and suggestions for additional analysis, as well as guidance for using the candidate risk factors to build and test statistical models.

UPDATED CJA RELEASE ASSESSMENT: MODEL BUILDING AND TESTING

The success and utility of the updated CJA Release Assessment hinges on two critical features: its accuracy and transparency. The importance of providing accurate predictions to judges and court actors about the likelihood of appearance in court cannot be overstated. Predictions are used to inform the discussion of pretrial release by court actors at arraignment, assist judges when making the pretrial release decision, and potentially affect pretrial outcomes. In addition to the importance of accuracy in predictions, transparency is similarly important – as evidenced by its inclusion in the three guiding principles of updating the assessment.

After consultation with the RAC and receiving input through stakeholder engagement, transparency was operationalized in at least five ways as it relates to model building:

1. Assessment factors, weighting, and scoring method must be known;
2. Judges, court actors, advocates, and affected communities and individuals must be able to understand how the assessment functions;
3. An individual's factor responses must be provided along with the supporting documentation that led to the response values;
4. Individual results must be open to inspection and be able to be challenged; and
5. Factors and scores must be able to be corrected during the arraignment.

BUILDING THE STATISTICAL MODEL

The commitment to achieving both accuracy and transparency led to the decision to build the statistical model using logistic regression¹⁴ in lieu of more opaque machine learning techniques (e.g., a random forest algorithm which is often referred to as a 'black box'). While the research teams worked independently to identify candidate risk factors, they built the statistical model together. Using the train subset, one research team (CLNY) led the model building process while the other research team (Luminosity) independently confirmed the results.

Model Factors

After an extensive testing and reconciliation process, eight factors were selected for inclusion in the model.

1. Years since last bench warrant (within the last five years)
2. Two or more bench warrants in the last five years
3. Number of misdemeanor or felony convictions in the last year
4. Number of misdemeanor convictions in the last three years

¹⁴ CLNY used a technique known as regularized logistic regression while Luminosity used a standard logistic regression. The two techniques yielded nearly identical results, but the ultimate model was created using an L2-regularized logistic regression.

5. Number of felony convictions in the last ten years
6. Number of pending cases
7. Number of years living at last two addresses
8. Reachable by phone

Converting Count Factors into Categories

Several of the factors are count variables (e.g., the number of bench warrants in the last five years). In predictive modeling, it is often best practice to convert count variables into categorical variables (e.g., 0, 1, and 2+) when the count factor exhibits diminishing marginal returns with the outcome. For example, as can be seen in Table 10, the increase in FTA rates is substantially higher between 0 to 1 bench warrants in the past five years than it is between 1 to 2 bench warrants in the past five years. The increase in the FTA rate from 0 prior bench warrants to 1 prior bench warrant is about 12 percentage points (from 11.3% to 23.2%), while the increase from 1 prior bench warrant to 2 prior bench warrants is about 4.5 percentage points. The smaller marginal difference suggests a non-linear relationship between the number of bench warrants in the past five years and FTA. Linear models, like logistic regression, are able to model this relationship better when using a categorical representation of the factor rather than a count variable.

Table 10. Failure to Appear Rate for Released Individuals by Number of Bench Warrants

Number of bench warrants in last 5 years	FTA rate
0	11.3
1	23.2
2	27.6

The exact categories are derived for each of the affected factors by testing which category definition yielded the most predictive model. The constraint of each factor category representing at least 5% of the sample was imposed in order to maintain a lower number of meaningful categories per factor. The categories or ‘bins’ that were adopted are shown in Table 11 below.

Table 11. Selected Factors and Categories for Updated CJA Release Assessment

Factor	Categories
Years since last bench warrant	<ul style="list-style-type: none"> ▪ Less than 1 year ▪ 1-2 years ▪ 2-5 years ▪ No bench warrant in last five years
Two or more bench warrants in the last five years	<ul style="list-style-type: none"> ▪ Yes ▪ No
Number of misdemeanor or felony convictions in the last year	<ul style="list-style-type: none"> ▪ 1 or more ▪ None
Number of misdemeanor convictions in the last three years	<ul style="list-style-type: none"> ▪ 3 or more ▪ 2 ▪ 1 ▪ None
Number of felony convictions in the last ten years	<ul style="list-style-type: none"> ▪ 1 or more ▪ None
Number of pending cases	<ul style="list-style-type: none"> ▪ 1 or more ▪ None
Years living at last two addresses	<ul style="list-style-type: none"> ▪ No reported address ▪ Less than three years ▪ Three or more years
Reachable by phone	<ul style="list-style-type: none"> ▪ No ▪ Yes

Assigning Weights (Point Values)

The final point values for the updated CJA Release Assessment factors derive from the logistic regression coefficient for each factor.¹⁵ Table 12 below shows the results of the logistic regression, the rounding procedure, and the final point values. The columns represent the following:

- First column shows each factor, broken down by each potential answer;
- Second column shows the coefficient from the logistic regression;
- Third column shows initial points, the value of the coefficient being scaled and rounded; and
- Fourth column shows the final points after converting all point values to have the same sign.

In the third “initial points” column, the values are mostly positive, which indicates that there is a positive relationship between an affirmative answer for most factors (e.g., prior bench warrants) and the likelihood of failure to appear. The exception is ‘Years living at last two addresses = 3 or more years’, where an affirmative answer decreases the likelihood of failure to appear, which results in a negative initial point value. Stakeholder engagement suggested that it would be easier to re-score

¹⁵ A variant of the select-regress-and-round procedure was used. This procedure involves fitting a linear model, and then rescaling and rounding the coefficients from the model to yield integer-valued weights. See Jung, J., Concannon, C., Shroff, R., Goel, S., & Goldstein, D. G. (2017). Simple rules for complex decisions. Available at [SSRN 2919024](https://ssrn.com/abstract=2919024).

the assessment if all factors had the same sign, so that computing the score would only involve subtraction instead of addition and subtraction. As a result, the initial integer points are converted to a final point value such that all points have the same sign (positive).

Table 12. Updated CJA Release Assessment Factor, Coefficient, Initial and Final Points

Factor	Coefficient	Initial points	Final points
Years since last bench warrant = 2-5 years	0.395	3	3
Years since last bench warrant = 1-2 years	0.544	4	4
Years since last bench warrant = Within past year	0.738	6	6
2 or more bench warrants in the last five years = Yes	0.179	2	2
Misdemeanor or felony conviction in last year = Yes	0.213	2	2
Misdemeanor conviction last 3 years = 1	0.097	1	1
Misdemeanor conviction last 3 years = 2	0.194	2	2
Misdemeanor conviction last 3 years = 3+	0.291	3	3
Felonies in last 10 years = 1+	0.128	1	1
Pending cases = 1+	0.308	3	3
Years living at last two addresses = 3 or more years	-0.146	-1	0
Years living at last two addresses = Less than 3 years	0.181	1	2
Years living at last two addresses = No address	0.477	4	5
Reachable by phone = No	0.455	3	3

Total Score

The updated CJA Release Assessment consists of a 26-point scale (scores ranging from 0 to 25). In lieu of providing the corresponding rates that reflect the likelihood of failing to appear, the decision was made to cast the assessment in more positive terms by providing the likelihood of appearing for all required court hearings (i.e., the inverse of FTA). To achieve this, each person begins with a score of 25 and points are subtracted when a factor is present. The result of this scoring strategy is that higher scores are associated with a greater likelihood of appearing for all required court hearings, while lower scores are associated with a lower likelihood of appearing for all required court hearings.

PREDICTIVE VALIDITY

While the train subset is used to build the statistical model, the 2014 test subset is used to establish the predictive validity of the updated CJA Release Assessment via bivariate analysis. The analysis reveals that all individual factors are statistically significantly related to FTA ($p < .001$) with the strongest predictive factor being “Years since last bench warrant” ($\Phi = .195$), and the weakest predictive factor being “Number of felony convictions in last 10 years” ($\Phi = .051$). An examination of the total score and its relationship to FTA reveals rates ranging from 47.3 (score of 3) to 6.6 (score of 25).^{16,17} Conversely, the appearance rates range from 52.7 to 93.4. The model Area Under the Curve for the Receiver Operator Characteristics (AUC-ROC), a common measure of assessment performance, is calculated ($AUC-ROC = .677$). The AUC-ROC gauges the performance of the total score in differentiating between individuals who do not experience an FTA from those who experience an FTA pending disposition. Appendix E contains the complete bivariate analysis results discussed here.

¹⁶ Scores are not calculated for the 1,421 arrest cycles with incomplete interviews or the additional 65 arrest cycles missing the necessary address information and, therefore, are removed from this analysis. Analysis is also conducted by treating missing answers as negative responses, with similar results.

¹⁷ FTA rates are not calculated for scores with less than 50 arrest cycles due to the instability of small samples. Specifically, FTA rates for scores of 0, 1, and 2 are not calculated due to the lower number of arrest cycles with each score (i.e., 11, 35, and 12, respectively).

UPDATED CJA RELEASE ASSESSMENT: ESTIMATING APPEARANCE RATES

In addition to generating a score between 0 and 25, the updated CJA Release Assessment introduces a new feature – the estimated appearance rate associated with a given score, which communicates the likelihood of individuals with that score appearing for all required court hearings. This feature is introduced with the goal of communicating more detailed and useful information to judges and court actors. The scores convey relative success rates (individuals with higher scores are estimated to appear at higher rates relative to individuals with lower scores), but they fail to communicate the magnitude of the differences. By including estimated appearance rates associated with the specific scores, the updated CJA Release Assessment moves beyond an abstract indication of more or less likely to appear at court hearings to a quantified understanding of likelihood of appearance.

Computing appearance rates involves calculating the percentage of arrest cycles without an FTA among the set of individuals with that score who continued beyond arraignment in 2014.¹⁸ Importantly, the average appearance rates are calculated for all continued arrest cycles, not just for the arrest cycles that were released pending disposition. Computing appearance rates using only individuals who are released pretrial would result in under-estimating FTA rates because individuals with higher risk for FTA are less likely to be released. This phenomenon is corrected by calculating the appearance rates among all continued arrest cycles. For individuals who were not released pretrial, a statistical technique known as imputation is used to estimate what the FTA outcome would have been.¹⁹ The estimated appearance rates are computed by averaging the FTA outcomes for all individuals, using the observed FTA outcomes for individuals who were released and using the imputed FTA outcomes for individuals who were not released.

The scores, number and percent of arrest cycles receiving each score, and the estimated appearance rates computed as described above are found in Table 13. An examination of the estimated appearance rates reveals that similar scores have similar appearance rates (e.g., scores of 19 and 20 with appearance rates of 81.6% and 82.9%, respectively). In addition, some scores consist of a relatively small number of arrest cycles, particularly as scores decline. In order to increase precision and reduce the visual complexity of showing appearance rates, the scores are grouped into 10 score ranges, which are also contained in the table below.

¹⁸ The test and validation subsets are merged (together reflecting 100% of the 2014 data) in order to obtain more precise estimates of appearance rates, particularly for scores with a small number of arrest cycles. In addition, the merged dataset implements marijuana expungement, as discussed on page 7, in order to best reflect the data source that the updated CJA Release Assessment will be operationalized on. Last, scores and appearance rates were calculated for any row for which a score could be calculated under the updated Release Assessment (rows with phone and address information).

¹⁹ Imputation involves estimating a statistical model to predict FTA based on all observable information in the dataset. The imputation model was built on the imputation subset, which includes half of continued arrest cycles from 2009-2013.

Table 13. Updated CJA Release Assessment Score, Range, and Appearance Rate

Score	Total N	Total percent	Appearance rate	Score range	Appearance rate
25	50,640	36.7	93.0	25	93.0
24	5,527	4.0	88.3	23-24	89.1
23	8,741	6.3	89.7		
22	22,370	16.2	87.4	21-22	86.8
21	4,878	3.5	84.3		
20	6,682	4.8	82.9	19-20	82.3
19	6,215	4.5	81.6		
18	3,079	2.2	79.7	16-18	76.3
17	4,310	3.1	76.0		
16	5,095	3.7	74.6		
15	2,117	1.5	74.5	12-15	71.0
14	4,176	3.0	71.4		
13	2,619	1.9	70.5		
12	2,102	1.5	67.1		
11	2,426	1.8	65.0	9-11	63.0
10	1,205	0.9	65.3		
9	1,818	1.3	58.8	7-8	56.8
8	1,344	1.0	57.9		
7	549	0.4	54.1		
6	874	0.6	51.9	4-6	49.9
5	390	0.3	50.1		
4	358	0.3	44.6	0-3	41.7
3	276	0.2	44.3		
2	49	0.0	35.8		
1	165	0.1	39.4		
0	90	0.1	41.1		

UPDATED CJA RELEASE ASSESSMENT: GENERATING RELEASE RECOMMENDATIONS

CJA's Release Assessments have included a recommendation regarding release on recognizance, dating back to the 1960s. The decision to continue this practice in the updated CJA Release Assessment was made after extensive consultation with judges and court actors.²⁰ Given that the updated CJA Release Assessment has a new scoring model, it was also necessary to revise the recommendation framework. The goals of updating the assessment guided the process of designing a recommendation framework. To reiterate, the goals were to: (1) maintain the current high court appearance rates for people released pretrial, (2) reduce the use of pretrial detention when possible, and (3) reduce racial and other disparities in pretrial settings. Input received through consultation with the RAC, judges, court actors, advocates, and affected communities and individuals, also played a substantial role during the recommendation framework revision process. Although recommendation frameworks by their very nature require policy evaluations – which is true for all release or risk assessments not just those in the pretrial setting – it is critical that they be research-informed. To balance the goals of maintaining the current high court appearance rates for people released pretrial and reducing pretrial detention when possible, a strategy called failure to appear matching (a.k.a. FTA matching) was employed as described below.

FTA MATCHING STRATEGY

The goals of maintaining the current high court appearance rates while simultaneously reducing pretrial detention when possible and reducing disparities in pretrial settings are operationalized by adopting the following strategy: recommend ROR for as many individuals as possible, subject to the constraint that the projected number of FTAs does not increase. Specifically, the projected number of FTAs among those recommended for release under the updated CJA Release Assessment should approximately match the observed number of FTAs based on recent pretrial practices during the tenure of the 2003 CJA Release Assessment. The FTA matching strategy essentially sets the threshold for recommending ROR (reducing pretrial detention) at the point where the projected number of FTAs is approximately equal to the number of observed FTAs (maintaining New York City's high court appearance rates).

This process begins by counting the observed number of FTAs in the 2014 test subset, (which is a random sample of 50% of continued arrest cycles from 2014, N = 70,597).²¹ The number of observed FTAs disaggregated by the most serious charge at arraignment is shown in Table 14.

²⁰ The Research Partnership considered only showing the scores and corresponding appearance rates without including a release recommendation on the updated CJA Release Assessment report. However, stakeholders largely concurred that the inclusion of an explicit recommendation is helpful.

²¹ Marijuana expungement is applied to the test subset in this section (Updated CJA Release Assessment: Release Recommendations) in order to best estimate the distribution of updated CJA Release Assessment recommendations that will be seen in practice.

Table 14. Observed FTA by Charge Severity

Charge severity	FTA count
Misdemeanor	5,648
Felony non-VFO	1,274
Violent felony offense	588
Total	7,510

Initially, setting a single threshold for ROR was considered (no differentiation by the most serious charge at arraignment). That strategy would simply require that the projected number of FTAs approximately matches the 7,510 FTAs observed in the test subset. It was identified early on that this thresholding strategy would significantly change the composition of FTAs. Specifically, the projected number of FTAs would be lower for those charged with a misdemeanor (a decrease of 6%); substantially higher for those charged with a felony non-VFO (an increase of 22%); and greater still for those charged with a VFO (an increase of 41%). As a result, the decision was made to develop the recommendation framework using the FTA matching strategy for each charge severity. This decision is supported by the bail law, which permits judicial consideration of the charges presently filed against a defendant.²²

ROR RECOMMENDATION THRESHOLDS

The process of selecting the threshold or ‘cutoff’ for Recommended for ROR for each charge severity (i.e., misdemeanor, felony non-VFO, VFO) is performed by identifying the projected number of FTAs related to each score, then selecting the score that most closely approximates the observed number of FTAs for that charge severity.²³ For example, if the Recommended for ROR threshold is set at a score of 24 for misdemeanor arrest cycles, meaning that any misdemeanor arrest cycle with a score of 24 or above would be recommended for ROR, it is projected there would be 1,437 arrest cycles resulting in an FTA in the Recommended for ROR group. This is significantly less than the 5,648 observed in the test subset. On the other hand, if the Recommended for ROR threshold is set at a score of 5, it is projected there would be 7,001 arrest cycles with an FTA, which is more than observed. Setting the misdemeanor threshold at a score of 12 yields 5,836 FTAs, which closely matches the observed number. This selection process is performed for each charge severity, resulting in

²² Until January 1, 2020, Criminal Procedure Law § 510.30 permitted judges to consider various aspects of the present charges against an individual when making release determinations. Effective January 1, 2020, § 510.30, as amended by changes to the statute enacted in 2019, the bail law expressly permits judges to consider “the charges facing the principle” when making such determinations. The amended law also takes charge severity into account in other ways, including by preserving bail as an option for most violent felony offenses and under other specified circumstances. Further amendments enacted in 2020 taking effect July 2020 make additional offenses bail eligible.

²³ One constraint imposed is that the number of projected FTAs could not exceed the observed number of FTAs for VFOs.

recommendations for ROR score thresholds of 12 for misdemeanor, 16 for felony non-VFO, and 19 for VFO. This approach sets ROR recommendation thresholds that are projected to yield approximately the same number of failures to appear for each of the three charge severities as those observed under recent pretrial practice and the tenure of the 2003 CJA Release Assessment.

THREE-CATEGORY RECOMMENDATION SYSTEM

One final consideration related to the ROR recommendation score thresholds is whether the remaining scores, those below the threshold, would be considered as simply not recommended for ROR or would receive a different recommendation. As discussed on page 9 above, the 2003 CJA Release Assessment contained three recommendation types: Recommended for ROR, Moderate risk for ROR, and Not recommended for ROR. Whether to maintain the existing three-category system of release recommendations or change to a two-category system is primarily driven by the guiding goals and principles of the update process. Input from judges and court actors, as well as the RAC and other stakeholders, was solicited. This resulted in maintaining, but updating, a three-category system of release recommendations: Recommended for ROR, Consider all options, and Not recommended for ROR.

RECOMMENDATION FRAMEWORK

The result of the FTA matching strategy based on charge severity, combined with the decision to utilize a three-category release recommendation system, is shown in Table 15. As can be seen below, the threshold for Not recommended for ROR is the same for all charge severities, while the Recommended for ROR and Consider all options thresholds vary.

Table 15. Recommendations Based on Score and Charge Severity

Charge severity	Scores 0-11	Scores 12-15	Scores 16-18	Scores 19-25
Misdemeanor	Not rec. for ROR	Rec. for ROR	Rec. for ROR	Rec. for ROR
Felony non-VFO	Not rec. for ROR	Consider all options	Rec. for ROR	Rec. for ROR
Violent felony offense	Not rec. for ROR	Consider all options	Consider all options	Rec. for ROR

RELEASE RECOMMENDATIONS

The distribution of projected release recommendations (Recommended for ROR, Consider all options, Not recommended for ROR), based on continued arrest cycles from the 2014 test subset, is presented in Table 16. For the purposes of best estimating the performance of the operationalized updated CJA Release Assessment, these projections show how the assessment would perform with marijuana expungement in effect (marijuana expungement affects the recommendation in less than 1% of arrest cycles).

For individuals with the most serious charge of misdemeanor, 93.6% would be recommended for ROR, 0% would be recommended for consider all options, and 6.4% would not be recommended for ROR. For individuals with the most serious charge of felony non-VFO, 81.4% would be recommended for ROR, 9.7% would be recommended for consider all options, and 8.9% would not be recommended for ROR. For individuals with the most serious charge of VFO, 76.4% would be recommended for ROR, 17.8% would be recommended for consider all options, and 5.8% would not be recommended for ROR.

Table 16. Recommendation by Charge Severity

Charge severity	Recommended for ROR	Consider all options	Not recommended for ROR
All	89.0%	4.1%	6.8%
Misdemeanor	93.6%	0.0%	6.4%
Felony non-VFO	81.4%	9.7%	8.9%
Violent felony offense	76.4%	17.8%	5.8%

Across all severities, it is projected that 89.0% of all individuals would be recommended for ROR. Because the recommendation thresholds were chosen using the FTA matching strategy, these recommendation rates would not result in an increase in the projected number of failures to appear, under the updated CJA Release Assessment.

UPDATED CJA RELEASE ASSESSMENT: COMPARING PERFORMANCE TO THE 2003 ASSESSMENT

The process of updating the CJA Release Assessment was undertaken to achieve the overarching goals of (1) maintaining the current high court appearance rates in New York City for people released pretrial, (2) reducing the use of pretrial detention when possible, and (3) reducing racial and other disparities in pretrial settings. This section compares and contrasts the performance of the 2003 and updated CJA Release Assessments, with an emphasis on how the updated assessment achieves the three overarching goals.

The 2003 and updated CJA Release Assessments have several similarities. Both consist of less than 10 research-based factors, which are weighted based on the strength of the relationship between each factor and FTA. The weights (point scores) are totaled to calculate a single score on a 26-point scale (i.e., -13 to 12, 0 to 25). The score, combined with other decisions, is used to provide a release recommendation. There are also some meaningful differences between the two assessments, including the factors that are considered, the weightings that are applied, the inclusion of appearance rates in the updated CJA Release Assessment, and the components of the recommendation framework. The details of each assessment's development, how it was operationalized, the recommendation framework, and overall performance are contained in earlier sections of this report. In this section, the 2014 test subset²⁴ is used to compare the performance of the updated CJA Release Assessment in relation to the 2003 CJA Release Assessment in terms of predictive validity, release recommendations, and false positive rates.

As the analysis below demonstrates, the updated CJA Release Assessment has greater predictive validity at the risk factor, score, and statistical model levels. It also recommends a far greater number of people for ROR while maintaining the current high court appearance rates, substantially reduces the disparity in recommendation rates when considering race/ethnicity and sex, and dramatically reduces the magnitude of false positive rates and the differences in false positive rates based on race/ethnicity and sex. The updated CJA Release Assessment outperforms the 2003 assessment when considering predictive validity, release recommendations, and false positive rates, and is forecast to advance all of the overarching goals of the updated CJA Release Assessment.

PREDICTIVE VALIDITY

The factors, as well as the strength of their relationship with FTA, differ between assessments. The analysis presented in earlier sections reveals that constructing factors using varying levels of granularity, count of events, time-windows, and measures of recency, identified factors with stronger relationships to FTA. In the 2003 CJA Release Assessment, for example, the factor with the strongest relationship to FTA ($\Phi = -.161$) is a single factor "Does prior warrant equal zero" used to measure

²⁴ In this section, the marijuana expungement logic is not applied for the purposes of comparing the performance of the 2003 and updated CJA Release Assessments. In addition, when showing projections for release recommendation rates, the analysis excludes arrest cycles where a recommendation was not made.

prior bench warrants. This factor represents whether the person’s criminal history contains a prior bench warrant, with no consideration to the number of bench warrants or the recency of the bench warrants. Alternatively, the updated CJA Release Assessment uses two separate factors – “Years since last bench warrant” (Less than 1 year, 1-2 years, 2-5 years, No bench warrant in last five years) and “Two or more bench warrants in last five years” (Yes, No). These two updated prior bench warrant factors add to the strength of the assessment with *Phi* values of .195 and .154, respectively. Seven of the eight updated factors have *Phi* values equal to or greater than .100, compared to three of the six factors in the 2003 CJA Release Assessment.

When considering the 26-point scale, the 2003 CJA Release Assessment FTA rates for released individuals vary from 4.8 to 39.1, while the updated CJA Release Assessment FTA rates vary from 6.6 to 47.3. The updated assessment has a larger amount of dispersion (difference between the lowest and highest scores), 40.7 vs. 34.3, respectively. The greater dispersion means that a one-point decrease on the updated CJA Release Assessment’s scale communicates more information about the likelihood of FTA than it did on the 2003 CJA Release Assessment. In addition, the model AUC-ROC²⁵ is higher for the updated assessment, .677 vs. .670, respectively.

Furthermore, there is a greater difference in FTA rates based on the release recommendations. For the 2003 CJA Release Assessment, the FTA rates by recommendation categories are 6.4% (Recommended for ROR), 11.1% (Moderate Risk), and 20.0% (Not Recommended for ROR). Using the updated CJA Release Assessment, the FTA rates by recommendation categories are 11.7% (Recommended for ROR), 18.5% (Consider all options), and 34.8% (Not Recommended for ROR). The greater differences in FTA rates between recommendation categories means that the recommendations on the updated CJA Release Assessment communicate more information about the likelihood of FTA.

RELEASE RECOMMENDATIONS

Recall that two of the overarching goals of updating the assessment are to maintain the current high court appearance rates in New York City for people released pretrial while simultaneously reducing the use of pretrial detention when possible. Determining the extent to which the updated assessment achieves these goals involves an examination of the distribution of release recommendations for both the 2003 and updated CJA Release Assessments (see Table 17 below). When using the updated CJA Release Assessment, 88.4% of all individuals are recommended for ROR, compared to 34.8% for the 2003 CJA Release Assessment. The 2003 CJA Release Assessment recommended against ROR for 46.4% of arrest cycles, compared to 7.2% for the updated CJA Release Assessment. Understanding that the recommendation thresholds were chosen specifically such that the projected number of

²⁵ The model Area Under the Curve for the Receiver Operator Characteristics (AUC-ROC) is a common measure of assessment performance. The AUC-ROC gauges the performance of the total score in differentiating between individuals who do not experience an FTA from those who experience an FTA pending disposition. The difference in AUC-ROC is statistically significant.

failures to appear for each charge type would remain consistent with those observed under recent pretrial practice, the increase in the rate of recommendations for ROR is accomplished without an increase in FTAs. As such, the increase in rates of recommended for release on ROR is consistent with both the goal of maintaining the current high court appearance rates in New York City for people released pretrial and the goal of reducing the use of pretrial detention when possible.

Table 17. Distribution of Recommendation Type

Recommendation type	2003 assessment	Updated assessment
Recommended for ROR	34.8%	88.4%
Moderate risk for ROR (2003)	18.8%	-----
Consider all options (updated)	-----	4.3%
Not recommended for ROR	46.4%	7.2%

Recommendations by Race/Ethnicity and Sex

The third overarching goal of updating the assessment is to reduce racial and other disparities in pretrial settings. Pursuant to this goal, the absolute rates and relative differences in ROR recommendations across race/ethnicity and sex are adopted as metrics of fairness. An additional metric of fairness – false positive rates – is discussed in the subsection below.²⁶

As can be seen in Table 18, the updated CJA Release Assessment is estimated to increase the rate of ROR recommendations by approximately 50 percentage points for all race/ethnicity groups and for both sexes. In addition to recommending release on recognizance for significantly greater proportions of all race/ethnicity and sex groups, the updated Release Assessment also reduces the disparities in the rates of recommendation for ROR. The difference in the rates of recommendation for ROR across all race/ethnicities is cut in half (from 9.4 percentage points under the 2003 CJA Release Assessment to 4.3 percentage points in the updated version), as is the difference between sexes (from 7.1 percentage points to 3.4 percentage points).

²⁶ As recent research has demonstrated, it is difficult and sometimes impossible to simultaneously satisfy all notions of algorithmic fairness, particularly when the base rates (average failure rates) vary across groups, as is the case here (see Kleinberg, J., Mullainathan, S., & Raghavan, M. (2016). Inherent trade-offs in the fair determination of risk scores <https://arxiv.org/pdf/1609.05807.pdf>). To that end and consistent with the goal of reducing racial and other disparities in pretrial settings, the Research Partnership strove to minimize disparities whenever possible throughout development of the updated CJA Release Assessment.

Table 18. Distribution of Recommendation for ROR by Race/Ethnicity and Sex

Recommended for ROR	2003 assessment	Updated assessment
<i>Race/ethnicity</i>		
Black	31.7%	86.6%
Hispanic	35.6%	89.6%
White	41.1%	90.9%
<i>Sex</i>		
Female	40.7%	91.2%
Male	33.6%	87.8%

In addition, examining the number of individuals represented by the above percentages may be helpful in conveying the magnitude of this shift. For example, projections show that using the updated CJA Release Assessment would result in an increase in ROR recommendations – relative to the prior assessment – for an additional 41,700 Black individuals, 19,800 Hispanic individuals, and 8,000 White individuals over the course of the year.²⁷

Given both the increase in overall rates of recommendation for all individuals, as well as the reduction in disparities across race/ethnicity and sex, the performance of the updated CJA Release Assessment is consistent with the overarching goal of reducing racial and other disparities in pretrial settings.

FALSE POSITIVE RATES

False positive rates are another metric used to assess the degree to which the updated CJA Release Assessment achieves the overarching goal of reducing racial and other disparities in pretrial settings. False positive rates measure the fraction of people who – despite the fact that they appeared for all of their court hearings – had low scores (representing higher risk of FTA) and were not recommended for ROR. Table 19 contains the false positive rates by race/ethnicity and by sex. As can be seen below, false positive rates are estimated to decrease substantially under the updated CJA Release Assessment. The overall false positive rate for the 2003 Release Assessment is 36.9%, compared to 3.1% for the updated Release Assessment. The expected result when using the updated CJA Release Assessment in the future is that far fewer people who would actually attend all required court appearances would receive low scores on the assessment (representing higher risk of FTA) and thus not be recommended for ROR.

²⁷ While all other results presented in this section are calculated using the 2014 test subset, the numbers related to the additional individuals recommended for ROR in the course of a year are calculated using the test and validation subsets, which represents *all* arrest cycles that occurred in 2014.

In addition to the updated CJA Release Assessment reducing the overall false positive rate, it also considerably reduces the differences in false positive rates between groups. While the disparity in false positive rates with the 2003 CJA Release Assessment for race/ethnicity was 15.4 percentage points (42.0 vs. 26.6), it is projected to be 0.9 percentage points (3.6 vs. 2.7) for the updated assessment. Similarly, when considering sex, the difference in false positive rates shrink from 13.3 percentage points (39.5 vs. 26.2) to 1.1 percentage points (3.3 vs. 2.2) in the updated assessment. The considerable reduction in disparity in false positive rates is consistent with the overarching goal of reducing racial and other disparities in pretrial settings.

Table 19: Updated CJA Release Assessment False Positive Rate by Race/Ethnicity and Sex

False positive rate	2003 assessment	Updated assessment
All individuals	36.9	3.1
<i>Race/ethnicity</i>		
Black	42.0	3.6
Hispanic	36.6	3.0
White	26.6	2.7
<i>Sex</i>		
Female	26.2	2.2
Male	39.5	3.3

COMPARISON SUMMARY

The process of updating the CJA Release Assessment was undertaken to achieve the overarching goals of (1) maintaining the current high court appearance rates in New York City for people released pretrial, (2) reducing the use of pretrial detention when possible, and (3) reducing racial and other disparities in pretrial settings. The above analysis examined the performance of the updated CJA Release Assessment in relation to the 2003 assessment, with an emphasis on how the updated assessment achieves the three overarching goals. The updated CJA Release Assessment demonstrates greater predictive validity at the risk factor, score, and statistical model levels. The 26-point scale has a larger amount of dispersion (difference between the lowest and highest scores) as does the recommendation framework (greater difference in FTA rates based on the release recommendations). These attributes mean that the updated CJA Release Assessment is able to communicate more information about the likelihood of FTA.

When considering the absolute rates and relative differences in ROR recommendations across race/ethnicity and sex, as well as the false positive rates (an adopted metric of fairness), the updated CJA Release Assessment outperforms the 2003 assessment on every metric. The updated CJA Release

Assessment recommends substantially more individuals (an increase of 50 percentage points and tens of thousands of people) for ROR while maintaining the current high court appearance rates. It is projected to cut in half the disparity in recommendation rates when considering race/ethnicity and sex, and to reduce by more than 10-fold the false positive rates and the differences in false positive rates based on race/ethnicity and sex. In short, the updated CJA Release Assessment outperforms the 2003 assessment when considering predictive validity and all metrics of fairness, and it is forecast to significantly advance all of the overarching goals of the updated CJA Release Assessment.

UPDATED CJA RELEASE ASSESSMENT: CALIBRATION OF APPEARANCE RATES

One of three overarching goals of updating the assessment is to reduce racial and other disparities in pretrial settings. In the previous section, three metrics of fairness are examined, including the absolute rates and relative differences in ROR recommendations, as well as false positive rates. As discussed above, when considering these three metrics of fairness, the updated CJA Release Assessment substantially outperforms the 2003 assessment on every metric. In this section the fourth and final metric of fairness is examined – calibration by race/ethnicity and sex.

Recall that the updated CJA Release Assessment introduces the new feature of displaying projected appearance rates for each score range. This new feature lends itself to the fairness metric of calibration by race/ethnicity and sex, which tests whether the displayed appearance rates are equally informative for all groups.²⁸ Specifically, calibration across race/ethnicity or sex requires that, within each score range, the appearance rates of different groups are similar. The Research Partnership chose to operationalize calibration in more concrete terms by testing the following criterion: is the average appearance rate for individuals of a particular race/ethnicity or sex closer to the average appearance rate for all individuals in that score range or the average appearance rate for a different score range?

Recent scholarship has shown that ensuring exact calibration across groups is difficult in algorithms and assessments that either use a small number of factors or communicate risk using a limited number of categories.²⁹ Given that the updated CJA Release Assessment was guided by the principle of transparency and the many ways that it was operationalized (see Updated CJA Release Assessment: Model Building and Testing section above), it was not expected to achieve exact parity in calibration.

In the instances when the calibration criterion was not met (i.e., the appearance rate for a given group is not closest to the average appearance rate for all individuals in that score range, but rather the average appearance rate for a different score range) then the impact of the miscalibration is examined using the standard proposed in Corbett-Davies et al. This standard states that groups with similar appearance rates should receive similar recommendations. Specifically, how any miscalibration affects the recommendation is examined by comparing the updated CJA Release Assessment's actual performance to a hypothetical benchmark that is adjusted to improve calibration. This hypothetical benchmark is constructed by adjusting scores (for score ranges where

²⁸ An analysis of the calibration of the 2003 CJA Release Assessment was not performed because a direct comparison cannot be conducted. The 2003 CJA Release Assessment did not group individual scores into score ranges, as the updated Release Assessment does, and it did not display the appearance rates on the associated form.

²⁹ See Kleinberg, J. & Mullainathan, S. (2018). Simplicity Creates Inequity: Implications for Fairness, Stereotypes, and Interpretability. Available at [arXiv: 1809.04578](https://arxiv.org/abs/1809.04578) and Corbett-Davies, S., & Goel, S. (2018). The Measure and Mismeasure of Fairness: A Critical Review of Fair Machine Learning. Available at [arXiv: 1808.00023](https://arxiv.org/abs/1808.00023). In particular, Corbett-Davies et al. note that ensuring exact calibration is difficult, and sometimes impossible, when a risk assessment uses a limited number of categories to communicate risk, as is the case here.

calibration is weaker) so that all groups with approximately the same appearance rate have the same adjusted score. The adjusted scores are then used to compare recommendations of the actual assessment to what the recommendations would be under this hypothetical benchmark with improved calibration.³⁰

As the analysis below demonstrates, the assessment overall shows strong calibration; appearance rates across race/ethnicity are very similar in all score ranges and appearance rates between sexes are also very similar in score ranges for the vast majority of individuals. Recommendations of the updated CJA Release Assessment and the hypothetical benchmark agree for over 98% of individuals, and when they disagree, the updated CJA Release Assessment makes a less restrictive recommendation compared to the benchmark.

CALIBRATION BY RACE/ETHNICITY

Table 20 below shows the appearance rates for each race/ethnicity group.³¹ The group-specific appearance rates are very similar (within 0-3 percentage points) within each score range, indicating good calibration. There is one instance where the calibration criterion is not met for White individuals (score of 21-22). Considering the hypothetical benchmark, there is no effect on the recommendation for these individuals because people in the 23-24 range and the 21-22 score range receive the same recommendation (Recommended for ROR for all charge severities).

Table 20: Appearance Rates by Score Range for All Individuals, and by Race/Ethnicity

Score range	All individuals	Black individuals	Hispanic individuals	White individuals
25	93.0	92.1	93.2	94.6
23-24	89.1	88.3	89.2	90.1
21-22	86.8	86.2	86.7	89.0
19-20	82.3	81.4	82.7	84.1
16-18	76.3	75.5	77.0	79.0
12-15	71.0	70.0	72.3	72.8
9-11	63.0	62.3	63.3	66.5
7-8	56.8	56.7	56.5	59.7
4-6	49.9	48.9	52.9	47.2
0-3	41.7	42.7	41.0	38.8

³⁰ The score adjustment procedure is an application of the thresholding equity criteria discussed in Corbett-Davies et al., who argue that individuals with similar appearance rates should be treated similarly.

³¹ The appearance rates are calculated in the same manner as those in the Updated CJA Release Assessment: Estimating Appearance Rates section above.

CALIBRATION BY SEX

Table 21 shows the appearance rates for each sex. Appearance rates in the top four score ranges are very similar (within 0 to 2 percentage points) for both male and female individuals. These score ranges account for the vast majority of individuals (81% of women and 75% of men fall into these top four score ranges). However, appearance rates in the lower score ranges start to diverge, with female individuals having lower average appearance rates relative to male individuals with the same scores.³²

Table 21: Appearance Rates by Score Range for All Individuals, and by Sex

Score range	All	Male	Female
25	93.0	92.9	93.6
23-24	89.1	88.9	90.4
21-22	86.8	86.8	87.3
19-20	82.3	82.2	82.8
16-18	76.3	77.0	71.6
12-15	71.0	71.9	65.1
9-11	63.0	64.8	54.1
7-8	56.8	58.5	46.8
4-6	49.8	51.7	42.0
0-3	41.7	42.6	37.2

The appearance rates displayed on the updated CJA Release Assessment are forecast to overstate the appearance rates of female individuals in lower score ranges – from 16-18 through 0-3. In each of these score ranges, the appearance rate of female individuals is closer to the average appearance rate of the score range directly below (with the exception of 0-3, which has no score range below it).

Using the hypothetical benchmark strategy discussed above to determine the effect on recommendation, the score adjustment would affect the recommendation in two circumstances. The first is female individuals with a score between 16-18, who would have an adjusted score of 12-15. This adjustment only affects the recommendation for female individuals facing non-violent felony charges³³ and causes the recommendation to move from “Recommended for ROR” to “Consider all Options”. The second circumstance is female individuals who score between 12-15, who would have

³² The appearance rate for male individuals is always closer to the average appearance rate within each score range because male individuals represent 82% of all arraigned cases. Within each score range, the portion of arraignments that involve male individuals ranges between 78% to 88%.

³³ The recommendations for misdemeanor and violent felony charges do not change between 12-15 and 16-18.

an adjusted score of 9-11. This would result in a change in recommendation from “Recommended for ROR” or “Consider All Options” to “Not Recommended for ROR”.

CALIBRATION SUMMARY

The updated CJA Release Assessment introduces the new feature of displaying projected appearance rates for each score range. This new feature led the Research Partnership to adopt calibration as a metric of fairness related to appearance rates. This approach includes determining if the average appearance rate for individuals of a particular race/ethnicity is closer to the average appearance rate for all individuals in that score range. When this is not the case, the effect on the recommendation is examined using the hypothetical benchmark approach.

The assessment overall shows strong calibration; appearance rates across race/ethnicity are very similar in all score ranges and appearance rates across sex are also very similar in score ranges for the vast majority of individuals. Recommendations of the updated CJA Release Assessment and the hypothetical benchmark agree for over 98% of individuals, and when they disagree, the updated CJA Release Assessment makes a less restrictive recommendation than the benchmark. As with all metrics of fairness, including those used in this research, calibration should be monitored during implementation and modifications to the assessment or recommendation framework should be made if needed.

UPDATED CJA RELEASE ASSESSMENT: REPORT

The redesign of the CJA Release Assessment report (provided in hard copy to judges and court actors at arraignment) was informed by both behavioral science and the guiding principle of transparency. Ideas42, a member of the Research Partnership, led the effort to redesign the report, working in partnership with the RAC, judges, and court actors. At the outset of the redesign process, ideas42 conducted a diagnostic assessment – including extensive interviews with judges and court actors – to learn how people use the CJA Release Assessment. Following those interviews, ideas42 used its expertise in behavioral design to draft several options for the visual representation of the report. Refinements were incorporated into the interface as a direct result of feedback from the RAC, outreach sessions, focus groups, and user testing. In particular, the Research Partnership user-tested a beta version of the report interface in focus groups with judges; the feedback informed the final design of the updated CJA Release Assessment report (see Appendix F for a sample report).

SCORING TRANSPARENCY

As discussed in the Building and Testing the Updated CJA Release Assessment section above, transparency was operationalized in five ways, with three having a direct impact on the report.

1. An individual's factor responses must be provided along with the supporting documentation that led to the response values;
2. Individual results must be open to inspection and be able to be challenged; and
3. Factors and scores must be able to be corrected during the arraignment.

The report was designed to ensure it met all of these criteria. As can be seen in Appendix F, the report displays each assessment factor, the individual's response to the factor, and the supporting documentation that led to the response (i.e., the arrest cycles or interview answers). It also displays the weight applied to each factor response, followed by the total score. Not only does the display of information ensure that the assessment results are completely transparent, it allows for the judge and court actors to inspect and challenge the results. If it is determined that an error is present, the factors and scores can be corrected during the arraignment and made available to all parties.

APPEARANCE RATES

The updated CJA Release Assessment report also communicates more information about what a score means, in particular by introducing appearance rates. The estimated appearance rate reflects the person's likelihood of appearing for all required court hearings based on the performance of other individuals with the same score. These estimated appearance rates were introduced, in part, due to feedback provided during the initial diagnostic interviews. During the diagnostic interviews, some court actors reported a lack of understanding regarding what the assessment represented when it deemed someone as Moderate risk for ROR or when it displayed a certain numerical score. These

estimated appearance rates provide more context for understanding the updated CJA Release Assessment score.³⁴

In addition, the updated CJA Release Assessment focuses on the affirmative rates of court appearance rather than on rates of failure to appear. The new report highlights individuals' likelihood of court appearance because a significant majority of people *do* appear for their future court hearings.

RECOMMENDATION

A recommendation regarding pretrial release is provided in the report based on the recommendation framework discussed above. In addition to the release recommendation, the report includes a recommendation key, which is designed to convey the recommendations for any score and charge severity. This key allows judges and court actors to understand why a particular recommendation is made for any given individual. Moreover, should any adjustment of the score be necessary, this layout allows stakeholders to determine if the recommendation should also be adjusted.

³⁴ When appearance rates are presented, this rate is presented as individuals who appear out of 100 people. This decision was based on behavioral science research that suggests human decision makers can more readily reason about numbers presented as frequency rates, rather than percentages. See Gigerenzer, G. (1996). The Psychology of Good Judgment: Frequency Formats and Simple Algorithms. *Medical Decision Making*, 16(3), 273–280. <https://doi.org/10.1177/0272989X9601600312>

APPENDIX A – RESEARCH PARTNERSHIP

LUMINOSITY

Luminosity, Inc. is a women-owned, small business whose mission is to advance pretrial justice in America. For nearly two decades, Luminosity has leveraged data analytics and implementation science to improve public safety, fairness, and cost effectiveness in communities across the country. The Luminosity team is led by Dr. Marie VanNostrand, an experienced practitioner, skilled researcher, and nationally recognized expert in the pretrial stage of the justice system. She has presented her work at more than 100 national and state conferences, including a White House Convening on Criminal Justice Reform, the US Attorney General’s Symposium on Pretrial Justice, and the Congressional Briefing on Pretrial Justice. Under her leadership, Luminosity’s Data Analytics Team conducted the largest study on the effectiveness of alternatives to pretrial incarceration and developed the nation’s first statewide, data-driven, pretrial assessment. They also conducted the research credited as the catalyst for criminal justice reform in New Jersey and worked in partnership with the New Jersey Courts to implement those reforms. As part of New York City’s Research Partnership, Luminosity researchers leveraged their pretrial expertise, extensive experience in conducting pretrial research, and expertise in implementation science to support the development of the updated CJA Release Assessment.

THE UNIVERSITY OF CHICAGO’S CRIME LAB NEW YORK

Crime Lab is a nonprofit, faculty-led research center of the University of Chicago, with offices in both Chicago and New York City. Crime Lab is dedicated to working closely with public sector partners, leveraging data science to solve pressing social problems. Crime Lab projects have been supported by federal government agencies such as the U.S. Department of Justice, the U.S. Department of Education, and the National Institutes of Health, as well as private foundations. Previous projects of the Crime Lab and its sister organization the Education Lab have been featured in national news outlets such as the *New York Times*, *Washington Post*, *Wall Street Journal*, NPR and PBS News Hour. Crime Lab used a team of data scientists with machine learning expertise who worked on developing the updated CJA Release Assessment and supported its implementation.

IDEAS42

Ideas42 is a nonprofit design firm that uses insights from behavioral science to create innovative solutions to complex social problems. Ideas42 aims to achieve impact at scale by applying the latest research on human behavior to policy, program, and product design. This work involves educating decision makers and leaders about the power of behavioral science and how to apply it; improving existing products, policies, and programs; and inventing new products that draw on behavioral insights. Ideas42 applies their expertise to a range of domains including consumer finance, education, economic opportunity, energy consumption and environmental conservation, healthcare, and criminal justice.

NYC CRIMINAL JUSTICE AGENCY

The New York City Criminal Justice Agency, Inc. (CJA), is a not-for-profit organization incorporated in 1977. CJA has over 200 employees in offices in all five boroughs of the City. CJA works under contract with the Mayor's Office of Criminal Justice and assists the courts and the City in reducing unnecessary pretrial detention. In accordance with this mission, CJA conducts a pre-arraignment interview and makes a release recommendation assessing individuals' likelihood of appearing for all required court hearings; notifies released individuals of upcoming court dates to promote appearance at all required court hearings; operates Supervised Release programs to serve those eligible who would otherwise be held in jail; assists alternatives-to-incarceration programs in screening individuals for a range of noncustodial sentencing sanctions; and provides information and research services to criminal justice policy makers, city officials, and the public.

THE MAYOR'S OFFICE OF CRIMINAL JUSTICE

The Mayor's Office of Criminal Justice (MOCJ) advises the Mayor and First Deputy Mayor on criminal justice policy and is the Mayor's representative to the courts, district attorneys, defenders, and state criminal justice agencies, among others. The office designs, deploys, and evaluates citywide strategies to drive down crime, reduce unnecessary arrests and incarceration, and improve the system's fairness. MOCJ works with law enforcement, city agencies, nonprofits, foundations, and others to implement data-driven strategies that address current crime conditions, prevent offending, and build the strong neighborhoods that ensure enduring safety.

APPENDIX B – RESEARCH ADVISORY COUNCIL

Seven leading academic and policy experts generously contributed their expertise to this process by serving on the Research Advisory Council (RAC). The RAC reviewed analysis methods and results; requested additional analysis to be conducted; consulted on how the assessment might impact racial, ethnic, and other groups; and provided overall guidance and technical assistance. Participation in the RAC is not an endorsement of the updated CJA Release Assessment or the contents of this report.

GEOFFREY BARNES, PH.D., DIRECTOR OF CRIMINOLOGY FOR WESTERN AUSTRALIAN POLICE

Dr. Geoffrey Barnes is the Director of Criminology for the Western Australian Police, where he works on developing research-based policing strategies. He is also an Affiliated Lecturer in Evidence-Based Policing at the University of Cambridge's Institute of Criminology, and a Fellow of the Academy of Experimental Criminology. Previously, he held appointments at the University of Pennsylvania, University of Maryland, and Australian National University. His work involves utilizing machine learning to predict crime and forecast future criminal behavior.

MICHAEL KEARNS, PH.D., NATIONAL CENTER CHAIR AND PROFESSOR OF MANAGEMENT & TECHNOLOGY COMPUTER AND INFORMATION SCIENCE AT THE UNIVERSITY OF PENNSYLVANIA

Dr. Michael Kearns is a Professor and National Center Chair of Computer and Information Science at the University of Pennsylvania. He is also a Senior Advisor in Machine Learning and AI for Morgan Stanley, and a Fellow of the American Academy of Arts and Sciences, the Association for Computing Machinery, the Association for the Advancement of Artificial Intelligence, and the Society for the Advancement of Economic Theory. Previously, he worked for AT&T Bell Laboratories. His research interests involve machine learning, computational social science, and data science.

JON KLEINBERG, PH.D., TISCH UNIVERSITY PROFESSOR OF COMPUTER SCIENCE AT CORNELL UNIVERSITY

Dr. Jon Kleinberg is a Professor of Computing and Information Science at Cornell University. He is a member of the National Academy of Sciences, the National Academy of Engineering, and the American Academy of Arts and Sciences. His work has been supported by an NSF Career Award, an ONR Young Investigator Award, a MacArthur Foundation Fellowship, a Packard Foundation Fellowship, and a Sloan Foundation Fellowship. Much of his research focuses on machine learning, and how to minimize bias in the use of algorithms.

KRISTIAN LUM, M.S., PH.D., LEAD STATISTICIAN AT THE HUMAN RIGHTS DATA ANALYSIS GROUP

Dr. Kristian Lum is the Lead Statistician at the Human Rights Data Analysis Group, a nonprofit that applies rigorous data science to analysis of human rights violations around the world. Previously, Kristian worked as a Research Assistant Professor in the Virginia Bioinformatics Institute at Virginia Tech and as a Data Scientist at DataPad. Her research focuses on machine learning applied to predictions in the criminal justice system.

OJMARRH MITCHELL, PH.D., ASSOCIATE PROFESSOR OF CRIMINOLOGY & CRIMINAL JUSTICE AT ARIZONA STATE UNIVERSITY

Dr. Ojmarrh Mitchell is an Associate Professor of Criminology at Arizona State University. Previously, he held appointments at the University of South Florida, University of Cincinnati, University of Nevada Las Vegas, and the Urban Institute. He is also appointed to the U.S. Attorney General's Science Advisory Board. His research has been involved in the impact of race on sentencing, effectiveness of drug courts, and evaluations of juvenile justice facilities.

VINCENT SOUTHERLAND, L.L.M., J.D., EXECUTIVE DIRECTOR AT THE CENTER ON RACE, INEQUALITY, AND THE LAW AT NEW YORK UNIVERSITY SCHOOL OF LAW

Vincent Southerland is the Executive Director of the Center on Race, Inequality, and the Law, at New York University School of Law. He was previously an Assistant Federal Public Defender with the Federal Defenders for the Southern District of New York, a Senior Counsel at the NAACP Legal Defense and Educational Fund, a Staff Attorney at the Bronx Defenders, and an E. Barrett Prettyman Fellow and Georgetown University Law Center. He began his legal career as a law clerk to the Honorable Theodore McKee, of the United States Court of Appeals for the Third Circuit, and the Honorable Louis H. Pollak, of the United States District Court for the Eastern District of Pennsylvania. His work involves litigation, advocacy, and public education at the intersection of race and the criminal legal system.

SURESH VENKATASUBRAMANIAN, PH.D., PROFESSOR IN THE SCHOOL OF COMPUTING AT THE UNIVERSITY OF UTAH

Dr. Suresh Venkatasubramanian is a professor in the School of Computing at the University of Utah. He previously worked at AT&T Labs. He is also a member of the Computing Community Consortium Council of the Computing Research Association and a member of the board of the ACLU in Utah. His research interests are in the social ramifications of automated decision making, and algorithmic fairness.

APPENDIX C – 2003 CJA RELEASE ASSESSMENT REPORT

NEW YORK CITY CRIMINAL JUSTICE AGENCY Interview

Arrest #

INTERVIEW REPORT	CJA LOG Page	Line #	Precinct	K19600999
	06	07	068	

Name: DOE, JOHN		Name (on this arrest) from NYSID/Arrest	
Age: 28	Interview Date: 2019-05-17	Report: DOE, JOHN	
DoB: 1991-03-26	Interview Time: 11:47:00	NYSID: 12345678J	
Sex: MALE	CJA Interviewer: K999	Arrest Date: 2019-05-16	Arrest Time: 01:09:00
Hispanic? NO	Interview Location: CB	Arrest Charges: 1. 120.20 2. VTL 1212	
Race: WHITE	Interview Language: ENGLISH	3. LOC 000V 4. VTL 000.00	

RESIDENCE/FAMILY

Current Address: 1851 GODFREY ROAD,	Prior Address: DOES NOT KNOW ADDRESS
City, State, Zip: BROOKLYN, NY, 10036	City, State, Zip: BROOKLYN, NY
Lives With: Mother;Father;Brother;Sister	
Contact: MOM DOE	Contact: MOM DOE
Relationship: MOTHER	Relationship: MOTHER
Phone #: 929-999-9999	Phone #: NA
Length at Current Address: Years Months Weeks	Length at Prior Address: Years DK Months
05	Contact still Resides at Prior Address? NO
Alternate Address:	Expects Someone at Arraignment? NO
City, State, Zip:	Name:
Contact:	Relationship:
Relationship:	
Phone #:	

EMPLOYMENT

Employed? FULL TIME	Does Defendant Provide Support for Others? NO
Job/Position: SALES MANAGER	If "Yes" How Many?
Employer: COFFEE RIDGE	Other Sources of Financial Support: None
Address: 4201 GERALDINE LANE	
City, State, Zip: BROOKLYN, NY	Highest Grade: 16
Length of Employment: Months: 06	In School? NO
Hours Worked/Week: 40	Name:
Avg. Net Pay: 35000	In Training Program? NO
Pay Period: ANNUAL	Name:
Length of Unemployment:	In Treatment Program? NONE
Other Employment Status:	

CRIMINAL RECORD

First Arrest (Excluding Violations)?	Warrant Attached to NYSID?	Prior Warrant?	# of Prior Felony Convictions	# of Prior Misdemeanor Convictions	Open Cases
NO	NONE	NO	1	2	0

Gray Shading = Information from Official Sources

Miscellaneous Comments

LEGEND: **NP** = No Phone **RA** = Refuses to Answer
DK = Doesn't Know **NC** = Not Calculated
NA = Not Applicable **No Shading** = Information from Defendant

This report assesses the defendant's risk of flight by considering the following: community ties and warrant history as defined in sections 2(a)(ii) and 2(a)(iii)&(vi) of CPL 510.30 and open cases. However, a positive assessment is withheld for defendants with outstanding bench warrants attached to their NYSID sheet at the arrest. This report does not consider other criteria listed in CPL 510.30 such as the defendant's mental condition, the weight of the evidence, or the possible sentence.

DEFENDANT'S RESPONSE VERIFICATION **CJA RECOMMENDATION**

	DEFENDANT'S RESPONSE VERIFICATION	CJA RECOMMENDATION
1	Has the defendant lived at his/her current address for 1.5 years or more?	RECOMMENDED FOR ROR
2	Does the defendant live with parent, spouse, C/L spouse of 6 months, grandparent, or legal guardian?	
3	Does the defendant have a working telephone in residence/cell phone?	
4	Does the defendant report a NYC area address?	
5	Is the defendant employed, or in school or training program, full time?	
6	Does the defendant expect someone at arraignment?	
7	Does Prior Warrant equal Zero?	
8	Does Open Case equal Zero?	
	TOTAL POINTS	7

Verification Reference Source: NO CONTACTS PROVIDED

APPENDIX D – 2003 CJA RELEASE ASSESSMENT BIVARIATE ANALYSIS

Bivariate Analysis of Factors and FTA (Test Subset, Released Arrest Cycles, N = 59,181)³⁵

Factor	Values	Total N	Total percent	FTA N	FTA rate	X ²	p	Phi
Does the defendant report a NYC area address?	Yes verified	14,248	24.7	1,249	8.8	396.635	.000	.083
	Yes unverified/unresolved conflict	40,357	69.9	5,517	13.7			
	No unverified or verified	3,090	5.4	632	20.5			
Does the defendant have a working telephone in residence/cellphone?	Yes unverified or verified	47,289	82.0	5,203	11.0	787.595	.000	.117
	Unresolved conflict	1,111	1.9	200	18.0			
	No unverified or verified	9,295	16.1	1,995	21.5			
Is the defendant employed, or in school or training program, full time?	Yes unverified or verified	28,383	49.2	2,813	9.9	429.026	.000	.086
	No unverified or verified	28,068	48.6	4,417	15.7			
	Unresolved conflict	1,244	2.2	168	13.5			
Does the defendant expect someone at arraignment?	Yes	21,324	37.0	2,378	11.2	84.478	.000	-.038
	No/doesn't know	36,371	63.0	5,020	13.8			
Does prior warrant equal zero?	Yes	37,831	65.6	3,375	8.9	1,496.126	.000	-.161
	No	19,864	34.4	4,023	20.3			
Does open case equal zero?	Yes	43,368	75.2	4,728	10.9	576.269	.000	-.100
	No	14,327	24.8	2,670	18.6			

³⁵ The test subset contains 59,181 arrest cycles where a person was released prior to trial. However, a subset of these arrest cycles (N = 1,486) have missing or unscorable interview information, and therefore cannot be scored under either the 2003 or updated CJA Release Assessment. To that end, the bivariate analysis is conducted on released cycles in the test subset for which a score can be calculated (N = 57,695). When conducting bivariate analysis for the 2003 CJA Release Assessment (in Appendix D) and updated CJA Release Assessment (in Appendix E), expungement logic is not applied for purposes of comparison.

APPENDIX D (CONTINUED) – 2003 CJA RELEASE ASSESSMENT BIVARIATE ANALYSIS

Bivariate Analysis of Score and FTA³⁶

Score	N	Percent	FTA N	FTA rate
-13	0	0.0	----	----
-12	243	0.4	95	39.1
-11	0	0.0	----	----
-10	1,120	1.9	358	32.0
-9	75	0.1	19	25.3
-8	1,722	3.0	480	27.9
-7	1,832	3.2	436	23.8
-6	1,009	1.7	251	24.9
-5	4,532	7.9	937	20.7
-4	691	1.2	119	17.2
-3	3,821	6.6	659	17.2
-2	1,505	2.6	234	15.5
-1	1,226	2.1	191	15.6
0	2,213	3.8	382	17.3
1	54	0.1	15	27.8
2	2,672	4.6	411	15.4
3	1,488	2.6	219	14.7
4	1,817	3.1	236	13.0
5	7,945	13.8	808	10.2
6	845	1.5	77	9.1
7	10,818	18.8	793	7.3
8	2,071	3.6	142	6.9
9	3,482	6.0	197	5.7
10	4,115	7.1	225	5.5
11	8	0.0	----	----
12	2,391	4.1	114	4.8
Base Rate	12.8			
AUC-ROC	0.670			

³⁶ FTA and appearance rates are not presented for scores with less than 50 arrest cycles due to the instability of small samples. There is small percentage of cycles for which scores cannot be calculated (N = 1,486) which are excluded from the analysis, resulting in a difference between the full population base FTA rate (13.0) and completed interview base FTA rate (12.8).

APPENDIX E – UPDATED CJA RELEASE ASSESSMENT BIVARIATE ANALYSIS

Bivariate Analysis of Factors and FTA (Test Subset, Released Arrest Cycles, N = 59,181)³⁷

Factor	Values	Total N	Total percent	FTA N	FTA rate	χ^2	<i>p</i>	Phi
Years since last bench warrant	Within last year	5,375	9.3	1,637	30.5	2,197.159	.000	.195
	1 to 2 years	2,193	3.8	524	23.9			
	2 to 5 years	3,534	6.1	646	18.3			
	No prior BW in last 5 years	46,593	80.8	4,591	9.9			
Two or more bench warrants in last 5 years	Yes	4,804	8.3	1,438	29.9	1,372.522	.000	.154
	No	52,891	91.7	5,960	11.3			
Misdemeanor/felony conviction in last year	1 or more	6,090	10.6	1,481	24.3	804.959	.000	.118
	None	51,605	89.4	5,917	11.5			
Misdemeanor convictions in last 3 years	3 or more	3,041	5.3	880	28.9	1,011.673	.000	.132
	2	1,970	3.4	388	19.7			
	1	4,970	8.6	858	17.3			
	None	47,714	82.7	5,272	11.0			
Felony convictions in last 10 years	1 or more	7,387	12.8	1,279	17.3	152.894	.000	.051
	None	50,308	87.2	6,119	12.2			
Pending cases	1 or more	15,353	26.6	2,917	19.0	714.048	.000	.111
	None	42,342	73.4	4,481	10.6			
Years living at last two addresses	No address	1,431	2.5	421	29.4	546.702	.000	.097
	Less than 3 years	8,490	14.7	1,439	16.9			
	3 or more years	47,774	82.8	5,538	11.6			
Reachable by phone	No	9,295	16.1	1,995	21.5	740.023	.000	.113
	Yes	48,400	83.9	5,403	11.2			

³⁷ The test subset contains 59,181 arrest cycles where a person was released prior to trial. However, a subset of these cycles (N = 1,486) have missing or unscorable interview information, and therefore cannot be scored under either the 2003 or updated CJA Release Assessment. To that end, the bivariate analysis is conducted on released arrest cycles in the test subset for which a score can be calculated (N = 57,695). When conducting bivariate analysis for the 2003 CJA Release Assessment (in Appendix D) and updated CJA Release Assessment (in Appendix E), expungement logic is not applied for purposes of comparison.

APPENDIX E (CONTINUED) – UPDATED CJA RELEASE ASSESSMENT BIVARIATE ANALYSIS

Bivariate Analysis of Score and FTA & Appearance Rates³⁸

Score	N	Percent	FTA N	FTA rate	Appearance rate
0	11	0.0	3	-----	-----
1	34	0.1	20	-----	-----
2	12	0.0	8	-----	-----
3	55	0.1	26	47.3	52.7
4	66	0.1	29	43.9	56.1
5	86	0.1	35	40.7	59.3
6	190	0.3	75	39.5	60.5
7	114	0.2	42	36.8	63.2
8	329	0.6	123	37.4	62.6
9	444	0.8	162	36.5	63.5
10	346	0.6	94	27.2	72.8
11	714	1.2	217	30.4	69.6
12	653	1.1	207	31.7	68.3
13	945	1.6	264	27.9	72.1
14	1,508	2.6	408	27.1	72.9
15	738	1.3	152	20.6	79.4
16	2,045	3.5	492	24.1	75.9
17	1,566	2.7	380	24.3	75.7
18	1,225	2.1	230	18.8	81.2
19	2,462	4.3	438	17.8	82.2
20	2,694	4.7	421	15.6	84.4
21	1,895	3.3	258	13.6	86.4
22	9,508	16.5	1,116	11.7	88.3
23	3,891	6.7	365	9.4	90.6
24	2,250	3.9	246	10.9	89.1
25	23,914	41.4	1,587	6.6	93.4
Base Rate	12.8				
AUC-ROC	0.677				

³⁸ FTA and appearance rates are not presented for scores with less than 50 arrest cycles due to the instability of small samples. There is small percentage of arrest cycles for which scores cannot be calculated (N = 1,486) which are excluded from the analysis, resulting in a difference between the full population base FTA rate (13.0) and completed interview base FTA rate (12.8).

CJA Pretrial Release Assessment

Name on NYSID/Arrest Report Doe, John		First Arrest No	
NYSID 09991100J		Arrest Charges (up to 4)	
Age 30	Precinct 014	1. 155.25	2.
Sex Male	Arrest # 000000	3.	4.

CJA Interview		Interview Date & Time 12-01-19 12:00 AM	
		Language & Service Type	
Address Yes, Verified 3146 Alfred Drive Brooklyn, N.Y. 11206	Employed Full-time Length of Employment 3 yr.	In School No	
Phone Yes, Verified (212) 555-1234	Job/Position Ramp Agent	In Training Program No	
Lives with Mother	Employer JFK	In Treatment Program No	
Caretaker for Others No	Est. Monthly Net Income \$1,234	Served in the U.S. Armed Forces, National Guard, or Reserves	
	Financial Support for Others No		
CJA Notes			

Release Assessment Scoring

	Assessment Factors	Cycles Considered/Details	Points
		<i>All start with 25 points</i>	25
A	Years since last bench warrant <u>N/A</u>	No counted warrants from last 5 years	0
B	Two or more bench warrants in last five years <u>No</u>		0
C	Misdemeanor or felony convictions in last year <u>0</u>		0
D	Misdemeanor convictions in last three years <u>0</u>		0
E	Felony convictions in last ten years <u>0</u>		0
F	Pending cases <u>1+</u>	Cycle/Date: 2 (10-29-2019)	-3
G	Years living at last two addresses <u>3+</u>	Current Address: 3 years Prior Address: 2 years	0
H	Reachable by phone <u>Yes</u>		0
* Indicates Potential Discrepancy		Total Score	22/25
		Of those released with this score	87 out of 100 return for all required court appearances

Reappearance Score and Recommendation Key

Score	0-3	4-6	7-8	9-11	12-15	16-18	19-20	21-22	23-24	25
Reappearance Rate (#out of 100)	42	50	56	63	71	76	82	87	89	93
Recommendation	ROR Not Recommended				Misd ROR	Misd/NVF ROR	ROR			
					NVF/VFO Consider all options	VFO Consider all options				

CJA Recommendation

ROR

RISK ASSESSMENT FACTSHEET

Ohio Risk Assessment System - Pretrial Assessment Tool (ORAS-PAT)

LAST UPDATED: May 6, 2019

REVIEWED BY: Ed Latessa, Tammy Dean and Jennifer Lux, University of Cincinnati Corrections Institute

Who created the risk assessment? Are they a public or private organization?

The ORAS was created through a partnership between The Ohio Department of Rehabilitation and Correction and the University of Cincinnati, Center for Criminal Justice Research. The ORAS-PAT is one of the “instruments” included in ORAS.¹

How large was the training data set?

The ORAS-PAT tool was created using data from 452 adults charged with a criminal offense.

How was the training data set collected and assembled (i.e., what jurisdiction(s) is it from)?

The data came from seven Ohio counties and was collected through individual interviews with adult defendants charged with a criminal offense. These defendants had been recently referred to pretrial services during the time of data collection.

Over what time frame was the data collected?

Initial interviews were conducted between September 2006 and June 2007. In April 2008 and May 2009 outcome measures were gathered (regarding whether defendants in the initial interviews had been arrested for a new crime or failed to appear).²

The initial interview period “did not provide enough Ohio cases to construct and validate an assessment instrument,” so more data was collected between October 2008 and March 2009.³ Outcome measures for these cases were recorded within a yearlong period.

What factors (i.e., defendant characteristics) were included in the data set? This question pertains to all the factors that were available about defendants, not necessarily all the factors that were used to train or develop the model.

Interviews consisted of the completion of a form that gathered information on 35 items. Data was also collected through a self-report questionnaire that included “criminal thinking, drug use, medical and mental health, pro-criminal peers and family, residential stability, and employment.”⁴ In total, “the original pretrial data collection instruments provided over 100 potential predictors of recidivism.”⁵

Does the dataset include instances of defendants who were detained? If so, does the data include outcomes for those people (i.e., was counterfactual estimation involved; if so, how)?

The dataset does not include instances of defendants who were detained.

¹ See Source 1

² See Source 1, page 10

³ See Source 1, page 14

⁴ See Source 1, page 12

⁵ See Source 1, page 19

Are there any known issues or errors with the data?

“Certain types of cases may be underrepresented in the population (e.g. sex offenders, Hispanic offenders, female offenders). The underrepresentation in the population leads to small numbers of these types of offenders in the sample.”⁶

Another limitation is “measurement error. The major source of data collection for this study was the structured interview, which was undertaken by trained research staff from the University of Cincinnati. Further, the informed consent process identified a sample of offenders who were willing to undergo the interview process. In short, the structured interview process utilized to gather the data will likely be somewhat different than the process used by criminal justice officials to interview cases and assign risk once ORAS is implemented.”⁷

In addition, the average follow-up time for measuring outcomes (recidivism and failure to appear) was 12 months. “Although an average of 12 months is adequate, research suggests that 18 to 24 month follow-up times are optimal.”⁸

In what year was the risk assessment created?

The risk assessment was created between 2006 and 2009.

What factors, among all the factors in the training data, were considered in the development of the risk assessment? If not all factors were considered, how were those that were considered chosen?

All 100 factors were considered for inclusion.

How were factors that were considered ultimately chosen for exclusion or inclusion in the final model (the risk assessment itself)?

“Items gathered from the structured interviews and self-report surveys that were associated with recidivism were used to create each tool.”⁹

Does the final model include as a factor(s) arrests that did not lead to convictions?

The final model does include “Three or more Prior Jail Incarcerations” as a factor, which may include incarcerations from arrests that did not lead to convictions.

Does the final model include socioeconomic factors such as housing and employment status?

Yes - the final model includes “Residential Stability” as a factor.

Does the final model include personal health factors such as mental health or substance abuse?

Yes - the final model considers “Illegal Drug Use during Past Six Months” and “Severe Drug Use Problem.”

How were weights assigned to each factor included in the final model? (rounding correlation coefficients, Burgess Method, etc.)

A “modified Burgess” method was used to assign point values; the method “assigns a point (a score of 1) to the presence of the risk factor, and assigns a score of zero when it is false or not present. Some items have

⁶ See Source 1, page 45

⁷ See Source 1, page 45

⁸ See Source 1, page 46

⁹ See Source 1, page 17

multiple increasing risk scores, and as a result were scored with increasing values (i.e., 0, 1, 2).¹⁰ These factors were combined to create a risk scale. To be clear, the value(s) assigned to a particular factor was not based on the strength of the relationship between that factor and the outcomes.

How does the final model define outcomes (i.e., during the model development process, was there a distinct outcome defined for each type of failure (failure to appear, new crime, new violent crime, etc.) or were outcomes compounded?

There were two outcomes considered: failure to appear and rearrest. The two outcomes were compounded together in the model development process and are compounded in the final model.

What does the output of the model look like (i.e. a score on a scale of 1-10, etc.)?

The output of the model is a score on a scale of 0-9.

Does the model output risk level designations or convert raw scores into risk level designations such as “low risk,” “moderate risk,” and “high risk”?

The model classifies defendants into risk “categories” based on their score (for example, a score between 0 and 2 classifies a defendant as “Low Risk.” These categories were created by looking for natural “cut points” where the failure rates changed.

What proportion of samples in the training data set failed at each risk score and/or level (for example, what percentage of people with a score of 5 or a label of “moderate risk” actually failed to appear)?

From Source 1:

Scores	Rating	% of Failures	% of FTA	% of New Arrest
0-2	Low	5%	5%	0%
3-5	Moderate	18%	12%	7%
6+	High	29%	15%	17%

Did the model developers assess the predictive validity of the model? If so, how (reported AUC, FPR, TPR, etc.)?

The researchers created a chart with the percentage of defendants who had a new arrest or FTA in the training set as a function of their risk category (low, moderate, or high; see chart replicated above). “The chart illustrates that each risk level is associated [with] progressively higher rates of recidivism.”¹¹ The researchers also calculated an “r-value,” which is a measure of the correlation between risk level and likelihood of recidivism.

Where is the risk assessment used?

Officials at the University of Cincinnati stated that a number of jurisdictions in many states throughout the U.S. use some of the risk assessment tools included in ORAS, but were unable to provide a precise list of

¹⁰ See Source 1, page 17

¹¹ See Source 1, page 21

the jurisdictions using the ORAS-PAT tool. It is known that the ORAS-PAT is used in Ohio as well as a number of counties in California; it may be used in other jurisdictions as well.

Are the factors and weights of the risk assessment publicly available?

Yes; the factors and weights are available publicly.¹²

Does the risk assessment cost money for a jurisdiction to adopt?

According to the University of Cincinnati Corrections Institute, “There is not a cost involved for agencies who are only looking to adopt the ORAS Pre-Trial tool. However, should agencies be interested in any additional tools, we require a fee for training. While a copyrighted program of the University of Cincinnati, there are no ongoing costs to use the instrument as permission is granted to print/photocopy forms as needed to conduct assessments.”

Does the adoption of the risk assessment require training? If so, by who?

As stated above, if an agency adopts both the ORAS-PAT and at least one other ORAS tool, training is required. According to the University of Cincinnati Corrections Institute, “We require that training be conducted by a UCCI certified Master Trainer (either staff member or contract employee).”

Does the risk assessment come with any sort of software or software package?

According to the University of Cincinnati Corrections Institute, “No. UCCI offers a risk assessment automated system in partnership with University of Cincinnati’s IT Solutions Center, should agencies be interested, but it is not a software package that is given with the assessment training.”

Does the risk assessment involve or require an in-person interview?

The risk assessment does require an in-person interview.

How does the risk assessment account for missing information?

According to the University of Cincinnati Corrections Institute, “We have staff consult the client’s official record (NCIC, III) and take any collateral information into account. We also have staff utilize the information gained during the interview process.”

Has the risk assessment been analyzed on non-training data for predictive validity? Has the risk assessment been analyzed with training data or non-training data for predictive power/calibration by race? Has the risk assessment been analyzed for predictive power/calibration by gender? If so, by who, when, and using what data?

Ventura County (California) is currently assessing the use of ORAS in a validation study. Results have not yet been published.

Information retrieved from:

[1]: Creation and Validation of the Ohio Risk Assessment System Final Report dated July 2009

[2]: Information from Ed Latessa, University of Cincinnati Corrections Institute

[3]: Information from Jennifer Lux and Tammy Dean, University of Cincinnati Corrections Institute

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¹² See Source 1, page 49

Practitioner's Guide to COMPAS Core



APRIL 4, 2019

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Chapter 1

Introduction

The Practitioner's Guide provides an overview of the COMPAS Core Module in the Northpointe Suite. The Northpointe Suite is an integrated web-based assessment and case management system for criminal justice practitioners. The Northpointe Suite has modules designed for pretrial, jail, probation, prison, parole and community corrections applications. COMPAS Core is designed for both male and female offenders recently removed from the community or currently in the community. The Practitioner's Guide to COMPAS Core covers case interpretation, validity and reliability, and treatment implications. Most of the information provided is specific to COMPAS Core. Throughout this text we use the term COMPAS Core to distinguish an element (scale, typology, decile type) specific to COMPAS Core from general elements in the Northpointe Suite, such as scales found in both COMPAS Core and COMPAS Reentry.

COMPAS is a fourth generation risk and need assessment instrument. Criminal justice agencies across the nation use COMPAS to inform decisions regarding the placement, supervision and case management of offenders. COMPAS was developed empirically with a focus on predictors known to affect recidivism. It includes dynamic risk factors, and it provides information on a variety of well validated risk and need factors designed to aid in correctional intervention to decrease the likelihood that offenders will reoffend.

COMPAS was first developed in 1998 and has been revised over the years as the knowledge base of criminology has grown and correctional practice has evolved. In many ways changes in the field have followed new developments in risk assessment. We continue to make improvements to COMPAS based on results from norm studies and recidivism studies conducted in jails, probation agencies, and prisons. COMPAS is periodically updated to keep pace with with emerging best practices and technological advances.

COMPAS has two primary risk models: General Recidivism Risk and Violent Recidivism Risk. COMPAS has scales that measure both dynamic risk (criminogenic factors) and static risk (historical factors). Additional risk models include the Recidivism Risk Screen and the Pretrial Release Risk Scale II.

Statistically based risk/need assessments have become accepted as established and valid methods for organizing much of the critical information relevant for managing offenders in correctional settings (Quinsey, Harris, Rice, & Cormier, 1998). Many research studies

have concluded that objective statistical assessments are, in fact, superior to human judgment (Grove, Zald, Lebow, Snitz, & Nelson, 2000; Swets, Dawes, & Monahan, 2000). COMPAS is a statistically based risk assessment developed to assess many of the key risk and need factors in adult correctional populations and to provide information to guide placement decisions. It aims to achieve these goals by providing valid measurement and concise organization of important risk/need dimensions. Northpointe recognizes the importance of case management and supports the use of professional judgment along with actuarial risk/need assessment. Following assessment, a further goal is to help practitioners with case plan development/implementation and overall case management support.

In overloaded and crowded criminal justice systems, brevity, efficiency, ease of administration and clear organization of key risk/need data are critical. COMPAS was designed to optimize these practical factors. We acknowledge the trade-off between comprehensive coverage of key risk and criminogenic factors on the one hand, and brevity and practicality on the other. COMPAS deals with this trade-off in several ways; it provides a comprehensive set of key risk factors that have emerged from the recent criminological literature, and it allows for customization inside the software. Therefore, ease of use, efficient and effective time management, and case management considerations that are critical to best practice in the criminal justice field can be achieved through COMPAS.

1.1 Overview for Practitioners

COMPAS Core is comprised of a total of forty-three scales, including four higher order scales that use items from several domains and seventeen scales from the women's risk/needs assessment (WRNA) developed by Van Voorhis, Wright, Salisbury, and Bauman (2010). This document provides an overview of COMPAS Core. Supplemental materials are available that provide details about the scales not covered in the Practitioner's Guide (see, e.g., "Measurement and Treatment Implications of the COMPAS Core Scales").

The COMPAS Core assessment is designed to be configurable by the user at decision points within the local criminal justice system and with different populations. For example, Pre-trial Services may choose to use only the Pretrial Release Risk Scale II to make recommendations to the court regarding pretrial release. Probation may then use the Violent Recidivism Risk and General Recidivism Risk Scales to "triage" their caseloads by recidivism risk, and choose to complete the full assessment only on the higher risk individuals. The full assessment provides a holistic view of the person to address supervision and treatment needs for rehabilitation.

Chapter 2

Case Interpretation

2.1 Introduction

This chapter gives an introduction to the interpretation of a COMPAS assessment. After completing an assessment in the COMPAS software, the practitioner will generally interpret the bar chart that displays scale scores. The bar chart indicates in what areas the person scores higher or lower – that is, which risks or criminogenic needs may exist. The practitioner will also interpret the type assigned by the typology if enabled by the site. The implications for treatment and intervention are discussed in Chapter 4.

Collecting assessment information is important, yet the information is only helpful when we can make sense of it and understand how it can inform our case planning and interaction with the offender. Interpretation skills and activities include accessing and using:

1. The assessment results
2. The criminological theories used in COMPAS
3. The Typologies

A model that everyone can relate to is the medical model for interpretation of information gathered on a person. Think about the different steps taken in the medical field to find a solution to an illness or a problem. When you don't feel well and you go to the doctor, what is the first thing that the doctor does – Asks about symptoms: When did they start? How severe are they? She asks about your medical history: Are you taking any medications? Have you had this or a similar problem before? And, she runs tests, takes your temperature, takes your blood pressure, takes blood samples, orders MRIs, etc. What does she do with all of this information? She makes a diagnosis and prescribes an effective treatment.

Case interpretation involves connecting the dots to understand the relationship between a person's criminal behavior and her history, beliefs, and skills.

2.2 COMPAS Scores

The COMPAS assessment system consists of predictive risk scales for risk prediction and separate need scales for identifying program needs in the domains of employment, housing, substance abuse, and others. Agencies commonly adhere to the risk principle to target individuals for treatment programs who have high recidivism risk scores and high need for treatment (e.g., high substance abuse scores).

2.3 Levels of Interpretation

Skills and issues to consider when interpreting assessment information:

1. Interpretation is a skill that needs to be honed over time.
2. People are complex and multi-faceted. Interpretation is hard, yet is necessary for understanding behavior and for determining strategies for intervention.
3. From research in the field we have several criminological theories to help us understand the paths to criminal behavior.

There are different levels of interpretation.

1. **Level 1:** “Big bars, bad – little bars, good.” Crime-producing issues are viewed largely in isolation, thus disregarding the influence high-scoring needs have on one another. This is a simplistic interpretation that fails to consider a chain of possible precursors and antecedents. It is, however, a good place to start, by identifying the areas of need for further consideration.
2. **Level 2:** Helps strengthen the interpretation process beyond Level 1 by identifying criminogenic factors that are interrelated. In particular, Level 2 begins the process of looking at areas of need that influence one another. [Palmer \(1994\)](#) identified three areas of commonality: environmental issues, skill deficiencies, and cognitive/mental health/psychological areas. This level of interpretation allows practitioners to begin developing interventions that might address clusters of needs, rather than individual needs in isolation of others.
3. **Level 3:** This is a fully integrated interpretation, using criminological theories to explain patterns of criminal behavior and help practitioners begin understanding possible underlying causes or contributors to the person’s behavior. This approach enables the practitioner to consider a mix of explanatory theories that help “connect the dots” of need and other influencing factors to paint a picture of the individual’s pathway to crime.

The needs measured by the scales are often interwoven and co-occurring. Accurately interpreting a COMPAS bar chart requires the practitioner to take into account all the high scoring needs. Criminological theories provide a framework to help understand the interrelationship between the different needs.

2.4 Criminological Theories

People are complex creatures. To obtain a holistic picture of an individual, salient life events and influences must be considered. Criminological theories explain how people become involved in criminal behavior and may provide guidance for effective interventions. Several important criminological theories are outlined below.

Social Learning Theory

1. This theory matches the traditional way we think about learning through modeling of behavior.
2. The basic principle of the theory is that behavior is modeled, imitated, and if reinforced, then likely to occur again.

Sub-Culture Theory

1. The theory was developed from the Chicago School on Gangs.
2. The theory was developed to explain delinquency and gang behavior.
3. The theory suggests that norms are transmitted through social interactions.
4. Norms in subcultures are different than those in the main culture.
5. Certain behaviors (crime, substance abuse) become the cultural norm within the sub-culture.
6. All individuals in society are driven toward economic success. Some subcultures aim to achieve that success through illegitimate means.
7. Fischer (1995) defines subculture as “a large set of people who share a defining trait, associate with one another, are members of institutions associated with their defining trait, adhere to a distinct set of values, share a set of cultural tools and take part in a common way of life” (p. 544).

Control/Restraint Theory

1. This theory suggests there are different types of control. These include internal control (bonding to values, beliefs, etc.), external control (bonds to family, friends, social networks, co-workers), and psychological control (emotional attachments, cognitions, etc.).
2. The lower an individual’s level of social bonding (or less pro-social) and self control, the more crime-prone they will become (less to lose).
3. Or, they may be bonded to antisocial social norms values and associations, and their level of status depends on adherence to the restraints of that norm group.

Sociopathic/Socialization Breakdown Theory

1. Within this theory lies the concept of the sociopathic offender, which has more layers than the commonly stated “criminal personality.”
2. Sociopathic is a specific personality disorder. Personality disorders can be described as a person’s world view. A person with a personality disorder does not usually see themselves as needing help to remedy their behavior and typically blames consequences on other people and events.
3. A sociopath is characterized by selfishness, ruthlessness, and the inability to feel guilt or empathy.
4. This cluster of deviant personality traits and behaviors may not include criminal behavior.

Criminal Opportunity Theory (including Routine Activity)

1. This theory draws on the economic theory of markets to describe and predict criminal behavior.
2. The theory suggests that if you alter the quality of opportunity for crime you will reduce criminal behavior.
3. Both individual and environmental factors across time affect criminal acts.
4. The convergence in time and place of a motivated offender, suitable target, and absence of guardianship are strong predictors of criminal behavior.
5. Crime is most likely to occur in the presence of a suitable target (victim) and a motivated offender, and in the absence of inhibiting factors (law enforcement, neighbor, witnesses).

Social Strain Theory

1. This sometimes is referred to as the “means–end” theory of deviance.
2. Crime breeds in the gap between culturally induced aspirations and structurally distributed possibilities for success.
3. It is the combination of cultural emphasis and social structure which produces intense pressure for deviation-criminal behavior.
4. This is an economic explanation for crime. Crime occurs largely in poverty-stricken areas where opportunities to attain the “American Dream” by legitimate means is blocked, producing frustration and a desire to pursue monetary success by any means necessary.

2.5 AIPIE

Interpretation and the related events around case management can be a complex set of activities for professionals. One model that helps to explain the procedures of evidence-based practice is known as AIPIE. The AIPIE model is sequenced so that information triggers decisions which trigger actions.

A = Assessment (COMPAS or other tool)

I = Interpretation of the results

P = Plan, create an action plan based on the information gathered

I = Implement the plan

E = Evaluate the results of the actions and outcomes

The AIPIE model is linear and cyclic, that is, the steps are sequential and inform ongoing practice.

Risk and need scales have been discussed at length in this document. The other element to consider for supervision is responsivity. An offender's responsivity, or any person who is considering making some kind of change, can be understood as their level of readiness and their skill set to make the changes. Responsivity to intervention includes the person's motivation for change and the type of intervention offered. If the intervention does not fit the need, then responsivity factors are lost. If there is good fit, then there is better chance for success.

2.6 Basic Descriptive Information for the Scales

The scales are divided into two categories:

1. The Need Scales provide measures of relatively simple constructs (e.g., financial problems). These scales are not meant to be predictive but aim simply and accurately to describe the offender.
2. The Risk Scales were developed using methods and strategies for predictive modeling. The purpose of the risk scales is prediction - the ability to discriminate between offenders who will and will not recidivate.

2.7 Conversion of Raw Scale Scores to Decile Scores

The COMPAS scale scores are transformed into decile scores. Deciles are obtained by ranking the scale scores of a normative group in ascending order and then dividing these scores into ten equal sized groups. Deciles range from 1 (lowest) to 10 (highest). These scores thus proceed in roughly 10% steps from lowest to highest (1 through 10). A decile rank of 1 indicates that the scale score is in the lowest 10% of all scores in the normative group. A decile rank of 2 places the scale score above 10% and below 20% of the scores, and so on, up to a decile of 10, which places the scale score in the top 10% of all scores in the normative group.

In general the decile rank has the following interpretation:

- 1 – 4: scale score is low relative to other offenders in norm group.
- 5 – 7: scale score is medium relative to other offenders in norm group.
- 8 – 10: scale score is high relative to other offenders in norm group.

Note, however, that the location of the decile cut-points vary depending on the type of COMPAS scale. Table 2.1 shows the cutting points for each type of COMPAS scale. Table 2.2 lists each COMPAS scale and its type.

Table 2.1: Cutting Points for COMPAS Scale Types.

Type 1	Low (1-4)	Medium (5-7)	High (8-10)
Type 2	Unlikely (1-2)	Probable (3-4)	Highly Probable (5-10)
Type 3	Unlikely (1-5)	Probable (6-7)	Highly Probable (8-10)
Type 4	Unlikely (1-4)	Probable (5-7)	Highly Probable (8-10)

The decile cutting points for the scale scores in the COMPAS Core composite norm group ($n=7381$) are shown in Table 2.3. The column labeled D1 contains the cut-off for the first decile, D2 the cut-off for the second decile, and so on. Thus, for the Criminal Personality Scale (CrimPers), roughly one-tenth of the offenders scored 23 and lower, another one-tenth scored 24 through 25, and so forth. If a score covers more than one decile, we use the convention of assigning it to the lower decile category. For instance, 30% of the composite sample have a score of 0 on the History of Noncompliance Scale (HistNonC), covering D1 through D3 in the table, but this score is assigned to the lower decile (D1). This characteristic is associated with the granularity of certain COMPAS Core scales, which is discussed in the next section.

Table 2.2: COMPAS Core Scales and Types.

Scale	Scale Type
Violent Recidivism Risk	1
General Recidivism Risk	1
Pretrial Release Risk	1
Criminal Involvement	1
History of Noncompliance	1
History of Violence	1
Current Violence	1
Criminal Associates/Peers	4
Substance Abuse	2
Financial Problems/Poverty	3
Vocational/Education Problems	3
Criminal Thinking	3
Family Criminality	3
Social Environment Problems	3
Leisure and Recreation	3
Residential Instability	3
Social Adjustment Problems	3
Socialization Failure	3
Criminal Opportunity	3
Criminal Personality	3
Social Isolation	3

Table 2.3: Decile Cut-Points for COMPAS Core Scales in the Composite Norm Group.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
CrimInv	1.0	3.0	6.0	7.0	9.0	11.0	12.0	13.0	15.0	19.0
HistNonC	0.0	0.0	0.0	1.0	2.0	2.0	3.0	5.0	7.0	21.0
HistViol	1.0	1.0	1.0	1.0	1.0	2.0	3.0	4.0	6.0	20.0
CurrViol	8.0	8.0	8.0	8.0	8.0	8.0	8.0	9.0	11.0	14.0
CassPeer	7.0	8.0	8.0	9.0	10.0	10.0	11.0	12.0	15.0	22.0
SubAbuse	10.0	10.0	11.0	12.0	13.0	14.0	14.0	15.0	16.0	20.0
Financ	5.0	6.0	7.0	8.0	9.0	9.0	10.0	11.0	12.0	15.0
VocEd	14.0	15.0	16.0	17.0	18.0	19.0	21.0	22.0	24.0	30.0
FamCrim	6.0	6.0	6.0	7.0	7.0	8.0	8.0	9.0	10.0	12.0
SocEnv	6.0	6.0	6.0	6.0	6.0	7.0	7.0	8.0	10.0	12.0
Leisure	5.0	5.0	6.0	7.0	8.0	9.0	10.0	12.0	14.0	17.0
ResInst	9.0	11.0	11.0	12.0	14.0	15.0	16.0	18.0	20.0	30.0
SocAdj	16.0	17.0	18.0	19.0	20.0	21.0	22.0	24.0	25.0	35.0
EJuvSoc	10.0	11.0	12.0	13.0	13.0	14.0	15.0	17.0	19.0	30.0
CrimOpp	15.0	17.0	18.0	20.0	21.0	22.0	24.0	25.0	28.0	40.0
Soc.Isol	11.0	13.0	15.0	16.0	18.0	19.0	21.0	23.0	26.0	40.0
CrimAttC	13.0	15.0	18.0	20.0	21.0	22.0	23.0	25.0	28.0	50.0
CrimPers	23.0	25.0	27.0	29.0	30.0	32.0	34.0	36.0	40.0	59.0
PretrialRisk	2.89	3.08	3.24	3.39	3.54	3.69	3.86	4.08	4.38	8.01
ViolRecidRisk	-2.90	-2.50	-2.20	-2.00	-1.70	-1.50	-1.20	-1.00	-0.60	1.90
GenRecidRisk	-1.30	-0.90	-0.70	-0.40	-0.20	0.00	0.20	0.40	0.60	1.90

2.8 Interpreting Decile Scores

It is important to note that decile scores can only be interpreted in a relative sense, and are always linked to the norm group. If, for example, the norm group that is referenced for decile scoring of the Violent Recidivism Risk Scale happens to consist of offenders at high risk of violent recidivism, then low decile scores would not necessarily indicate low risk of violent recidivism. Similarly, if the norm group happens to consist mainly of offenders with low risk of violent recidivism, the decile scores for Violent Recidivism Risk would be biased in the other direction – high scores could be associated with individuals who are actually not high risk for violent recidivism.

It is also important to note that for some scales, it is not always possible to break the sample into ten groups of exactly equal size. Hence, for some scales it was necessary to skip over some decile scores.

When it was not possible to divide the sample into ten groups, an algorithm was used to identify cutting points that divided the offenders into as many roughly equal-sized groups as possible and that used the full range of decile values (i.e., 1-10).

The issue of clumping affects a limited number of scales. Overall, the use of decile ranks has clear advantages over the use of raw scale scores in terms of interpretability. Low scores (e.g., 1 thru 4) directly reflect the lowest ends of the distribution, and high scores (e.g., 8 thru 10) reflect the highest ends of the distribution.

2.9 Norm Groups

The COMPAS Core normative data were sampled from over 30,000 COMPAS Core assessments conducted between January 2004 and November 2005 at prison, parole, jail and probation sites across the United States. The Core Norm Group was compiled to obtain proportions of prison, parole, jail, and probation assessment data that reflect proportions of adult correctional populations in the criminal justice system. Based on recent criminal justice statistics, 21.6% of persons under adult correctional supervision during 2011 were in prison, 12.2% were on parole, 10.5% were in jail, and 56.9% were on probation ([Bureau of Justice Statistics, 2012](#)). The Composite Norm Group consists of assessments from state prisons and parole agencies (33.8%); jails (13.6%); and probation agencies (52.6%). The Core Norm includes 7,381 offenders. Men represent 76.9% of the Core Norm Group ($n=5,681$), and women represent 23.1% of the Core Norm Group ($n=1,700$). The median age at assessment is 31.0 ($M = 32.6$) in the Core Norm Group. The racial composition of the Core Norm Group is 61.6% Caucasian, 24.9% Black, 10.3% Latino and 3.2% other racial groups.

In the current version of COMPAS Core, scale scores can be referenced to the scale distributions of eight normative subgroups: (1) male prison/parole, (2) male jail, (3) male probation, (4) male composite, (5) female prison/parole, (6) female jail, (7) female probation and (8) female composite.

COMPAS Core norm data are evaluated through client norm studies. Agency-specific norm groups are developed for some clients.

Chapter 3

COMPAS Validity and Reliability

In this section we summarize research findings from multiple studies that demonstrate COMPAS Core is reliable (test-retest and internal consistency), that its scales measuring needs have construct validity and behave consistently and that its risk scales have predictive validity.¹ An overall conclusion is that COMPAS Core was found to be reliable and has good predictive and construct validity.

Northpointe has an established history of working in partnership with our clients to advance knowledge and practice. From our early work in jail classification to our recent partnerships with the California Department of Corrections and Rehabilitation (CDCR) and the University of Cincinnati, Northpointe leverages the opportunity of public and private partnership to test and advance knowledge. Our research and evaluation findings are publicly shared through conference papers, technical reports, peer-reviewed articles and book chapters to advance the availability of current information for use in practice.

3.1 Predictive Validity of the COMPAS Risk Scales

COMPAS distinguishes between risk scales (designed to predict recidivism) and need scales (designed to measure needs, inform case plans and identify intervention targets). This approach of separating risk and needs aligns with current best practices in risk assessment (C. Baird, 2009; S. D. Gottfredson & Moriarty, 2006). The risk scales are used for classification and forecasting. The risk scales should have good discriminative ability and predictive ability (e.g., Singh, 2013). COMPAS has two main risk scales: General Recidivism Risk Scale (GRRS) and Violent Recidivism Risk Scale (VRRS). Some researchers believe risk scales should be dynamic (composed of dynamic, criminogenic needs) so that one can measure change in risk of recidivism over time. Others have argued that risk scales should be composed of static criminal history factors available in criminal justice management information systems, arguing that static risk scales are more objective, reliable, and efficient (Barnoski & Drake, 2007). Our risk scales make limited use of dynamic variables.

¹The General Recidivism Risk and Violent Recidivism Risk scales are used in both COMPAS Core and COMPAS Reentry. Identical linear equations are used to calculate the risk scales in the two applications.

There are different statistical approaches to predictive modeling. Machine learning methods are highly flexible and are usually preferred in applications where there is a complex relationship between predictors and outcomes (Berk, 2012; Berk & Bleich, 2013). Some methods are less flexible but the models they generate are easier to interpret. There are tradeoffs of predictive performance and interpretability between methods (James, Witten, Hastie, & Tibshirani, 2013; Brennan & Oliver, 2013). Our methods for developing and validating the GRRS were strongly influenced by the research of John Copas and colleagues who have developed an outcomes-based recidivism scale for England and Wales (Copas & Marshall, 1998). The methods used to develop both risk scales are described in various books on regression modeling and machine learning (e.g., Harrell, 2001; Hastie, Tibshirani, & Friedman, 2008; Kuhn & Johnson, 2013).

Northpointe is committed to testing, evaluating, and improving our risk scales. The General Recidivism Risk and Violent Recidivism Risk scales have been validated with prospective outcomes in new samples in several different studies since they were first developed.

When possible we include an outcomes component in the pilot test of COMPAS in new jurisdictions. This component is designed to evaluate the predictive validity of the risk scales. In 2006 we conducted pilot tests in the New York Office of Probation and Correctional Alternatives (OPCA), the New York State Division of Parole (NYSDP), and the Michigan Department of Corrections (MDOC). These three pilot studies all had outcomes studies built into them. In 2008 we conducted outcomes studies at all three sites using their pilot data. We also conducted separate studies in the California Department of Corrections and Rehabilitation (CDCR) and the OPCA. This latter study was published in the *Journal of Criminal Justice and Behavior* (Brennan, Dieterich, & Ehret, 2009).

Table 3.1 below shows the results of subsequent tests of the predictive validity of the COMPAS risk scales. These outcomes studies were conducted on large samples in the Michigan Department of Corrections (Brennan & Dieterich, 2008; Dieterich, Oliver, & Brennan, 2011; Dieterich, Brennan, & Oliver, 2011); New York State Office of Probation and Correctional Alternatives (Brennan & Dieterich, 2009; Brennan et al., 2009; Lansing, 2012); California Department of Corrections and Rehabilitation (Farabee, Zhang, Roberts, & Yang, 2010); Broward County Sheriff's Office (Flores, Bechtel, & Lowenkamp, 2016; Blomberg, Bates, Mann, Meldrum, & Nedelec, 2010); Santa Barbara County Probation Department (Dieterich, Mendoza, Hubbard, Ferro, & Brennan, 2017); and Riverside County Probation Department (Dieterich, Mendoza, Hubbard, Ferro, & Brennan, 2018).

Table 3.1 shows the area under the receiver operating characteristic curve (AUC) for the GRRS and VRRS from several outcomes studies. "The receiver operating characteristic (ROC) curve is currently the best-developed statistical tool for describing the performance" of a risk scale (Pepe, 2003, p. 66). The AUC is the most widely used measure of discrimination ability in criminal justice, psychology, medicine, and related fields. There are various conventions for interpreting the magnitude of the AUC. One of the more liberal grading scales is provided by Desmarais and Singh (2013): AUC values of 0.50 to 0.54 are poor, 0.55 to 0.63 are fair, 0.64 to 0.70 are good, and 0.71 to 1.00 are excellent. The consensus in the field of recidivism research seems to be that AUC values below 0.65 are poor, 0.65 to 0.69 are fair, 0.70 to 0.75 are good, and 0.76 and above are excellent. The sizes of AUC that

constitute poor, fair, good, or excellent discrimination depend on the area of study and the outcome (e.g., [Swets, 1988](#)). Note that for arrest, felony arrest, noncompliance and return to prison outcomes, the GRRS is tested. For person offense arrests the VRRS is tested.

The results of these studies indicate that the COMPAS risk scales generally fall into the moderate to good range of discrimination ability. They also indicate that COMPAS generally meets or exceeds the AUC values produced by competitive instruments such as the LSI-R (see p. [20](#)).

Table 3.1: Summary of AUC results for the General Recidivism Risk Scale (GRRS) and Violent Recidivism Risk Scale (VRRS) in several outcomes studies.

Study	N	Year	Any			Supervision
			Arrest	Felony	Person	Failure
NY Probation ^a	(n=2,328)	2009	0.680	0.700	0.710	
NY Probation ^b	(n=13,993)	2012	0.710			
MDOC Reentry ^c	(n=25,347)	2011		0.710	0.700	0.690
MDOC Probation ^d	(n=21,101)	2011		0.670	0.740	0.710
CDCR Reentry ^e	(n=25,009)	2010	0.700		0.650	
Broward Jail ^f	(n=6,172)	2016	0.710		0.710	
Mental Health Court ^g	(n=242)	2016	0.730			
Santa Barbara Probation ^h	(n=5,363)	2017	0.722		0.672	0.702
Riverside Probation ⁱ	(n=4,435)	2018	0.694		0.636	0.692

^a ([Brennan et al., 2009](#)).

^b ([Lansing, 2012](#)).

^c ([Dieterich, Brennan, & Oliver, 2011](#)).

^d ([Dieterich, Oliver, & Brennan, 2011](#)).

^e ([Farabee et al., 2010](#)).

^f ([Flores et al., 2016](#)).

^g ([Reich et al., 2016](#)).

^h ([Dieterich et al., 2017](#)).

ⁱ ([Dieterich et al., 2018](#)).

Differential Validity

A few independent outcomes studies have examined the predictive validity of the COMPAS risk scales for gender and racial groups. [Brennan et al. \(2009\)](#) found that the COMPAS risk scales performed equally well for African American and Anglo men at discriminating recidivists in a probation sample. A prior study examined the discriminative ability of the GRRS for different ethnic groups, and that study reported much weaker results for African American men ([Fass, Heilbrun, DeMatteo, & Fretz, 2008](#)). In predicting rearrest within 1 year of release, [Fass et al. \(2008\)](#) reported AUCs for the GRRS of 0.81 for Whites, 0.67 for Hispanics, 0.48 for African Americans, and 0.53 for the total sample assessed with COMPAS (N = 276). However, their study has at least one critical weakness that renders its findings unreliable. Their small overall sample size and base rates resulted in extremely small effective

sample sizes for the ethnic groups (African American = 36, Latino = 4, Anglo = 1). These effective sample sizes are too small for ROC analysis and unreliable results were obtained.

Angwin, Larson, Mattu, and Kirchner (2016) claimed to have found evidence that the COMPAS risk scales were biased against African Americans in a sample of defendants in Broward County, Florida. Results of subsequent secondary analyses of the Broward County study data conducted by Northpointe researchers (Dieterich, Mendoza, & Brennan, 2016) and independent researchers (Flores et al., 2016) completely refuted the findings of Angwin et al. (2016). Both of the secondary studies found that the GRRS and VRRS performed equally well for African American and Anglo defendants. Flores et al. (2016) found that the GRRS and VRRS were good predictors for arrests and violent arrests, respectively. They also determined that the risk scales predicted equally well for African American and Anglo defendants. Flores et al. obtained the following AUCs for the GRRS decile score predicting any arrest: 0.70 for African American, 0.69 for Anglo and 0.71 in the sample overall. Flores et al. obtained the following AUCs for the VRRS decile score predicting any violent arrest: 0.70 for African Americans, 0.68 for Anglos and 0.71 in the sample overall. Table 3.2 shows the results obtained by Dieterich et al. in the same data analyzed by Flores et al. and Angwin et al.

Table 3.2: AUC results for the General Recidivism Risk Scale (GRRS) decile scores and Violent Recidivism Risk Scale (VRRS) decile scores in the data analysis samples used by Angwin and colleagues.

Sample	n	events	base rate	AUC	Lower 95% CI	Upper 95% CI
GRRS						
Anglo	2103	822	0.39	0.69	0.67	0.72
African American	3175	1661	0.52	0.70	0.69	0.72
All	6172	2809	0.46	0.71	0.70	0.72
VRRS						
Anglo	1459	174	0.12	0.68	0.64	0.73
African American	1918	404	0.21	0.71	0.68	0.74
ALL	4020	652	0.16	0.72	0.70	0.74

Note. GRRS outcome is a misdemeanor or felony arrest. VRRS outcome is a violent misdemeanor or felony arrest.

Farabee et al. (2010) report separate findings for men and women in a California Department of Corrections and Rehabilitation sample of persons released onto parole with two years of follow-up. They present a matrix with bivariate correlation coefficients for the GRRS and any arrest separately for men and women. The Pearson product moment correlation between the General Recidivism Risk Score and any arrest is 0.32 for men and 0.32 for women, thus providing evidence that the risk scale has similar predictive validity for men and women.

Table 3.3 displays AUCs for the any arrest outcome for the data set used by Farabee et al. (2010). The AUCs in the table give an indication of how well the GRRS discriminates the offenders who were rearrested from those who were not rearrested. The results are for the

entire sample (All) and for Men, Women, Anglo, African American, and Latino groups. The values for the AUCs in the different groups are very nearly the same.

Table 3.3: AUCs for the General Recidivism Risk Scale (GRRS) for a California prison sample. The AUCs are calculated separately for the different subgroups defined by gender and ethnicity/race. The lower (Low) and upper bounds (High) of the 95 percent confidence interval are displayed along with the number of failures (Nfail) and the number of offenders in the sample (N).

	AUC	Low	High	Nfail	N
Men	0.71	0.70	0.71	14819	21015
Women	0.69	0.67	0.71	1595	2638
Anglo	0.70	0.69	0.71	4683	7268
African American	0.69	0.67	0.70	4813	6447
Latino	0.71	0.70	0.72	5980	8514
All	0.70	0.70	0.71	16414	23653

Table 3.4 displays AUCs for a large reentry sample from the Michigan Department of Corrections. The outcome was any arrest within three years following release from prison into the community. Offenders who did not have opportunity to fail in a three year period were excluded from the sample. As in the previous analysis, the results are for the entire sample (All) and for Men, Women, Anglo, African American, and Latino groups.

The AUCs in Table 3.4 vary from 0.71 (African American) to 0.78 (Latino). The effective sample size for the Latino group is relatively small, which results in a broad 95% confidence interval. The AUCs for Men (0.73) and Women (0.74) are nearly the same. The AUCs for Anglo (0.75) and African Americans (0.71) do noticeably differ but both values are reasonably high.

These results taken together are encouraging. They suggest that the predictive validity of the GRRS is good overall and nearly equivalent for men and women, and for Anglo, African American and Latino offenders.

Table 3.4: AUCs for the General Recidivism Risk Scale (GRRS) and any arrest outcome for a Michigan reentry sample. The AUCs are calculated separately for the different subgroups defined by gender and ethnicity/race. The lower (Low) and upper bounds (High) of the 95 percent confidence interval are displayed along with the number of failures (Nfail) and the number of offenders in the sample (N).

	AUC	Low	High	Nfail	N
Men	0.73	0.72	0.74	5427	13439
Women	0.74	0.71	0.77	341	961
Anglo	0.75	0.74	0.76	2807	7177
African American	0.71	0.69	0.72	2720	6571
Latino	0.78	0.73	0.84	89	289
All	0.73	0.72	0.74	5768	14400

Table 3.5 displays AUCs for the GRRS from a validation study conducted for the Santa Barbara County Probation Department (Dieterich et al., 2017). The outcome was any arrest within 3 years of the probation intake assessment. The results are for the entire sample (All) and for Men, Women, Anglos, and Latinos.

AUC results for the GRRS show good discriminative ability for women, men, Latinos, and Anglos. The AUCs for Men (0.72) and Women (0.72) are not statistically different. There are moderate and significant differences between the AUC for Latinos (0.74) and the AUC for Anglos (0.70).

Table 3.5: AUCs for the General Recidivism Risk Scale (GRRS) and any arrest outcome in the Santa Barbara County Probation outcomes study sample. The AUCs are calculated separately for the different subgroups defined by gender and ethnicity. The lower (Low) and upper bounds (High) of the 95 percent confidence interval are displayed along with the number of failures (Nfail) and the number of offenders in the sample (N).

	AUC	Low	High	Nfail	N
Men	0.72	0.71	0.74	2823	4277
Women	0.72	0.69	0.75	717	1086
Anglo	0.70	0.68	0.73	1440	2149
Latino	0.74	0.72	0.76	1759	2706
All	0.72	0.71	0.74	3543	5363

The validity of the GRRS has also been demonstrated in a specialty court setting. Reich et al. (2016) conducted a COMPAS validation study in a racially diverse sample of 242 Mental Health Court participants at three sites in New York City: Brooklyn Mental Health Court, Bronx Mental Health Court, and Queens Felony Mental Health Court. The study examined the ability of the COMPAS GRRS to accurately discriminate recidivists from non-recidivists at one-year and two-years. The GRRS Decile Score was found to have good discriminative ability at one-year (AUC = 0.70) and two-years (AUC=0.73). Serin and Lowenkamp (2015) identified the risk instruments that are best suited for use by Drug Courts on the basis of widely accepted validity criteria. The General Recidivism Risk Scale met all validity criteria and was one of only three instruments recommended for use by Drug Courts.

Differential Validity and Fairness Criteria

Several different fairness schemes based on classification statistics (true positive rate, false positive rate, positive predictive value, negative predictive value, and selection ratio) have been proposed in the criminal justice and computer science literature.

The true positive rate (tpr) is the percentage of persons that recidivated that have a high risk score. The false positive rate (fpr) is the percentage of persons that did not recidivate that have a high risk score. The selection ratio is the percentage of cases that fall into the High Level. The tpr and fpr are measures of diagnostic accuracy that assess discriminative ability.

The positive predictive value (PV+) is the probability that a person with high risk score will recidivate. The negative predictive value (PV-) is the probability that a person with a low risk score will not recidivate. The PV+ and PV- assess predictive ability.

Sensitivity (true positive rate) and Specificity (true negative rate) quantify the diagnostic accuracy of the risk scale and the predictive values quantify its clinical value (Pepe, 2003). A useful prediction will have a PV+ that is greater than the base rate and a PV- that is greater than 1 minus the base rate. A perfect test will predict the outcome perfectly with $PV+ = 1$ and $PV- = 1$. The predictive values depend on the accuracy of the test and the base rate of failure.

Practitioners in criminal justice settings are most interested in the probability that an individual with a high risk score will be arrested in the future (PV+), as opposed to the probability that an individual who has already been arrested has a high risk score (tpr). The purpose of administering a risk scale is to use the results to assess an individual's risk of re-offending at the time of assessment. The tpr and fpr are of no practical use to a practitioner in a criminal justice agency who is assessing an individual's probability of re-offending. The practitioner does not know at the time of the assessment if the individual is a recidivist or not. The tpr and fpr cannot be directly applied to an individual at the time of assessment (see Linn, 2004, for example).

Berk (2016) presented a primer that organized the different types of fairness that arise when risk scales are used in samples with different gender or ethnic groups. Three of those types are salient for most applications. The risk scale demonstrates *predictive fairness* if the selection ratio is the same for both groups, *use fairness* if the complements of the positive predictive values are the same in both groups, and *model fairness* if the false positive and false negative rates are the same for both groups.²

We can use the GRRS results from the Santa Barbara County Probation outcomes study for men and women and for Anglos and Latinos to demonstrate risk assessment fairness. The results for the GRRS show that the false positive rate at the High cut point is similar for women (0.16) and men (0.13) and for Anglos (0.14) and Latinos (0.14), providing evidence of *model error fairness*. The positive predictive value at the High cut point is similar for women (0.83) and men (0.86) and for Anglos (0.85) and Latinos (0.85), providing evidence of the salient fairness criterion in probation practice and termed variously as *use fairness* (Berk, 2016), *predictive parity* (Dieterich et al., 2016), or *calibration* (Kleinberg, Mullainathan, & Raghavan, 2016). The selection ratio at the High cut point is similar for women (0.32) and men (0.32) and for Anglos (0.31) and Latinos (0.33), providing evidence of *predictive fairness* (Berk, 2016). As reported in the previous section on ROC results, the AUC is similar for women (0.72) and men (0.72) and somewhat higher for Latinos (0.74) compared with Anglos (0.70). The combined results for the GRRS provide good evidence of fairness for women and men and for Anglos and Latinos.

²The false negative rate (fnr) is just the complement of the true positive rate (tpr). If the tpr is the same in both groups, then the fnr is the same.

Effect of Group-Specific Base Rates on Fairness Criteria

[Dieterich et al. \(2016\)](#) conducted a simulation analysis to assess the effects of differences in the risk scale distribution and base rate on the false positive and false negative rates. Results of their analysis indicate that larger differences in mean scores for two groups correspond to larger base rate differences as well as higher false positive rates and lower false negative rates for the group with the higher mean score (i.e., the group with the higher base rate). This is the same pattern of results reported by [Angwin et al. \(2016\)](#). [Dieterich et al. \(2016\)](#) stated that this pattern does not show evidence of bias, but rather is a natural consequence of using unbiased scoring rules for groups that happen to have different distributions of scores. These results help to explain the effects of the relatively higher risk scores and higher base rates of African Americans on the false positive and false negative rates in the [Angwin et al. \(2016\)](#) study.

Following the [Dieterich et al. \(2016\)](#) study, [Kleinberg et al. \(2016\)](#) put forward three fairness properties of risk scales: calibration (same predictive value) within groups, balance for the negative class (generalization of the false positive rate at the score level) within groups, and balance for the positive class (generalization of the false negative rate at the score level) within groups. They formally demonstrated that the only way these three properties can be achieved simultaneously is if the risk scale predicts perfectly or the two groups have equal base rates.

Risk scales may exhibit race and gender effects because race and gender are correlated with the outcomes that risk scales are designed to predict ([S. D. Gottfredson & Jarjoura, 1996](#)). Disadvantage in the domains of employment, education, and housing stems from structural inequalities in our society. Constructs within these domains correlate with criminal behavior. In some respects many of the widely accepted criminogenic needs are indirect measures of disadvantage. Risk scale scores use inputs (prior arrest, age at first arrest) and predict outcomes (arrests) that are impacted by intense police practices in some geographical areas ([Committee on Assessing Juvenile Justice Reform, 2013](#)). These effects are at the heart of methodological controversies in criminology related to risk assessment and racial bias that have emerged in different contexts over the years.

[Berk, Heidari, Jabbari, Kearns, and Roth \(2018\)](#) conducted a thorough examination of risk assessment fairness in criminal justice settings and concluded:

Except in trivial cases, it is impossible to maximize accuracy and fairness at the same time and impossible simultaneously to satisfy all kinds of fairness. In practice, a major complication is different base rates across different legally protected groups. There is a need to consider challenging trade-offs (p. 1).

[Mendoza, Dieterich, Oliver, and Brennan \(2016\)](#) developed such an approach that adjusts for the effects of intense police practices on recidivism risk scores and classification statistics when making decisions across thresholds of a recidivism risk scale. They use an example data set in which African American defendants have a higher base rate and higher risk scores relative to Anglo defendants. Their approach assumes that intense police practices increase arrest rates which shift the risk scores of African American defendants higher relative

to Anglos. With simulation analyses, they show that larger differences in mean scores for two groups correspond to larger base rate differences as well as higher false positive rates and lower false negative rates for the group with the higher mean score (i.e., the group with the higher base rate) when a single threshold is used. They demonstrate a principled approach using decision analysis that weighs in these prior effects of intense police practices to adjust the risk scale threshold for African Americans.

Examples of Validity Results for Different Tools and Outcomes

Here we provide examples of the AUCs obtained with other risk tools to help contextualize the findings of our studies. Perhaps the best known instruments are the Violence Risk Appraisal Guide [VRAG] (Quinsey et al., 1998); the Level of Services Inventory-Revised [LSI-R] (Andrews, Bonta, & Wormith, 2006); the Ohio Risk Assessment System [ORAS] (Latessa, Lemke, Makarios, Smith, & Lowenkamp, 2010); the Static Risk Offender Need Guide for Recidivism [STRONG-R] (Hamilton et al., 2017); and the Psychopathy Checklist-Revised [PCL-R] (Hare, 1991). The AUC values for these instruments in recent studies are quite varied depending on the populations, outcome periods, and dependent variables used in specific studies.

VRAG: Quinsey et al. (1998) found an AUC of 0.76 in a large scale, multiyear recidivism study. Barbaree, Seto, Langton, and Peacock (2001) reported AUCs of 0.69 in predicting serious reoffending and 0.77 when predicting any re-offense for sex offenders. Kroner, Stadtland, Eidt, and Nedopil (2007) obtained an AUC of 0.70 in a study of re-offending among mentally ill offenders.

LSI-R: The LSI-R has been tested more than any other risk assessment tool used in criminal justice settings. Results from several meta-analyses indicate that the LSI-R has good discriminative ability for general and violent recidivism. In their review, Andrews et al. (2006) reported an average r_{pb} value of 0.36 for general recidivism from 74 effect sizes. For violent recidivism, Andrews et al. reported an average r_{pb} value of 0.25 from 26 effect sizes. Note that a point-biserial correlation of 0.35 approximately corresponds to an AUC of 0.70 for base rates near 50% (Rice & Harris, 2005). Other meta-analyses have found similarly good results for the LSI and its variants (Gendreau, Goggin, & Little, 1996; Vose, Cullen, & Smith, 2008; Smith, Cullen, & Latessa, 2009). Barnoski and Aos (2003) found AUCs of 0.64 - 0.66 for the LSI-R in predicting felony and violent recidivism among Washington State prisoners. Flores, Lowenkamp, Smith, and Latessa (2006) reported an AUC of 0.69 using the LSI-R to predict re-incarceration among federal probationers. Dahle (2006) reported an AUC of 0.65 using the LSI-R to predict violent recidivism. Barnoski and Drake (2007) reported an AUC of 0.65 using the LSI-R to predict felony sex recidivism.

ORAS: (Latessa et al., 2017) conducted a re-validation of the ORAS tools in Ohio. From that study, we review the arrest outcomes for the Community Supervision Tool (CST), Prison Intake Tool (PIT), and Reentry Tool (RT). For the CST they obtained AUCs of 0.62 for men ($n=501$) and 0.65 for women ($n=492$). For the PIT they obtained AUCs of 0.61 for men ($n=246$) and 0.67 for women ($n=246$). For the RT they obtained AUCs of 0.60 for men ($n=255$) and 0.66 for women ($n=257$). In Indiana, Latessa, Lovins, and Makarios

(2013) conducted a validation of the CST in a community supervision sample ($n=626$) and a validation of the RT in a prison reentry sample ($n=362$). The outcome was arrest within two years. For the CST, Latessa et al. found moderate effects with men ($r_{pb} = 0.29$) and weak effects with women ($r_{pb} = 0.12$). Lovins, Latessa, May, and Lux (2017) conducted a validation study of the CST in a community corrections sample in Texas ($n=5,481$). They obtained AUCs of 0.67 for men and 0.68 for women. Latessa, Lux, Lugo, and Long (2016) conducted a validation study of the ORAS CST in a large Massachusetts Probation Service sample [MPS] ($n=10,548$). The outcome was a new arraignment. In the MPS study they obtained AUCs of 0.65 for men ($n=1,382$) and 0.63 for women ($n=9,076$). We could find no independent validation studies for the Ohio Risk Assessment System (ORAS).

STRONG-R: Hamilton et al. (2017) report AUC results for three offense-specific risk scales developed and internally validated using bootstrap re-sampling in a large Washington State Department of Correction sample. The recidivism follow-up was two years. For men, the AUCs for the Violent, Property, and Drug risk scales were 0.74, 0.78, and 0.76. For women the AUCs for the Violent, Property, and Drug risk scales were 0.74, 0.74, 0.73. We could find no independent validation studies of the STRONG-R.

PCL-R: Predictive accuracy varied across studies. For example, a Swedish study of mentally ill violent offenders (Grann, Belfrage, & Tengstrom, 2000) found AUC levels of 0.64 - 0.75 based on various follow-up time frames. Barbaree et al. (2001) reported AUCs of 0.61, 0.65, and 0.71 for the PCL-R in predicting various recidivism outcomes among sex offenders.

3.2 Validity of COMPAS Core Need Scales

3.2.1 Criterion Validity

In contrast to the COMPAS risk scales, the COMPAS need scales have a separate purpose and were developed using different methods. The risk scales were developed using methods and strategies for predictive modeling.

The need scales are not meant to be predictive but aim simply and accurately to describe the offender along dimensions relevant for correctional practice. Research findings indicate that individuals involved in the criminal justice system often have problems and deficits in the domains of education, housing, employment, substance abuse, relationships, and cognition. The need scales should be valid and reliable measures of constructs in these domains and other aspects of the person-in-environment that represent potential targets for interventions. The need scales guide individualized decisions for case planning, including identifying targets and choosing interventions. Within some theoretical frameworks, needs are expected to be criminogenic, suggesting that they cause recidivism and that recidivism can be reduced if the criminogenic need is effectively addressed. But research results indicate many constructs in these domains are only modestly correlated with recidivism, and evidence of a causal link between needs, treatment, and recidivism is lacking (e.g., Monahan & Skeem, 2014). Within the risk, need, and responsivity framework, high risk and high need individuals are targeted for the most intensive interventions (Andrews, Bonta, & Hoge, 1990). Here we focus only

on correlations to demonstrate that the COMPAS Core need scales are relevant and useful measures for correctional practice.

The following tables show measures of association between the COMPAS Core scales and recidivism in large samples from two COMPAS outcomes studies. The results obtained in the respective COMPAS outcomes studies provide evidence of the criterion validity of the COMPAS Core scales. The results demonstrate that in general the COMPAS Core need scales measure factors associated with recidivism, and hence, they are useful measures of potential intervention targets. The results can be compared with the results from published studies. For example [Barnoski and Aos \(2003\)](#) conducted an outcomes study in a sample of 22,533 offenders and provide a table with similar measures of association between the LSI-R subscales and recidivism.

Table 3.6 shows measures of association between the COMPAS Core scales and any arrest within two years in the study sample used by [Farabee et al. \(2010\)](#). The sample consists of 23,635 soon-to-be-released inmates assessed with COMPAS Core who were followed for two years after release from prison. The first column shows the correlation between each COMPAS Core scale and recidivism. For correlations between a continuous variable (e.g. Voced, Subabuse, etc.) and a dichotomous variable (recidivism), we estimate the point biserial correlation (r_{pb}).³ The point biserial correlation is mathematically equivalent to the Pearson product moment correlation (r). [J. Cohen and Cohen \(1983\)](#) provide the following conventions for interpreting r when both variables are continuous: 0.10 = small; 0.30 = medium; 0.50 = large. But r is sensitive to the base rate when one of the variables is dichotomous, and the conventions for small, medium, and large should be adjusted lower depending on the deviation from a 50% base rate (e.g., [Rice & Harris, 2005](#)). The base rate for arrest in the [Farabee et al.](#) study sample is 0.69, so the following interpretation for r_{pb} adjusted using the formulae in [Rice and Harris](#) can be used: 0.09 = small; 0.23 = medium; 0.35 = large. The next column shows the area under the receiver operating characteristic curve (AUC). The AUC is a rank measure indicating how well the respective scales discriminate recidivists from nonrecidivists. The AUC is more resistant to the base rate (e.g., [Babchishin & Helmus, 2016](#)). An AUC equal to 1 indicates that the scale discriminates perfectly. An AUC equal to 0.50 indicates that the scale does not discriminate any better than chance. By convention an AUC of 0.70 is regarded as good in criminal justice settings. The AUC is 0.60 for the Criminal Associates Scale - a modest result if this were a standalone risk scale, but for a need scale, the result indicates good criterion validity. The last column shows the odds ratio. The odds ratio indicates how much the odds of recidivating change for every one-unit increase in the respective COMPAS Core scale. The odds ratio for Criminal Associates is 1.09, which indicates that for every one-unit increase in the Criminal Associates raw score the odds of recidivism increases by 9%. There is solid evidence of criterion validity in this study sample for most of the COMPAS Core scales.

³In a previous version of the Practitioner's Guide, the biserial correlation was reported. The biserial coefficients are inferred estimates of what the Pearson correlation would be if both variables were continuous and normally distributed. We now use the Pearson product moment correlation (r), which is usually called the point biserial correlation (r_{pb}) when one of the variables is dichotomous.

Table 3.6: Measures of Association Between COMPAS Core Scales and Any Arrest Within Two Years in Farabee et al. Study Data.

COMPAS Scale	Point-Biserial Correlation	AUC	Odds Ratio
General Recidivism Risk	0.34	0.70	3.31
Criminal Involvement	0.20	0.61	1.10
Noncompliance History	0.16	0.61	1.11
Violence History	0.11	0.58	1.06
Current Violence	-0.05	0.52	0.92
Criminal Associates	0.14	0.60	1.09
Substance Abuse	0.02	0.51	1.02
Financial Problems	0.09	0.55	1.08
Voced Problems	0.17	0.61	1.11
Family Crime	0.07	0.54	1.11
Social Environment	0.10	0.56	1.12
Leisure	0.11	0.57	1.07
Residential Instability	0.08	0.55	1.04
Social Adjustment	0.15	0.60	1.10
Socialization Failure	0.18	0.62	1.13
Criminal Opportunity	0.19	0.62	1.10
Social Isolation	0.04	0.52	1.02
Criminal Thinking	0.11	0.57	1.04
Criminal Personality	0.13	0.58	1.05
Cognitive Behavioral	0.23	0.63	1.05

With $n=23,635$, a correlation of .013 is significant at $p < .05$ (2-tailed).

Table 3.7 shows the point biserial correlations between the COMPAS Core scales and any arrest within 1 year in the study sample from Brennan et al. (2009). The sample consists of 2,328 probation intakes assessed with COMPAS Core. The results in Table 3.7 can be compared to the results in Table 3 in Brennan et al. The sample and event of interest (any arrest) are identical, but here we fit a logistic regression model with a binary outcome (any arrest within one year), and in Brennan et al. we fit a Cox proportional hazards model in which the outcome is defined as failure over the entire follow-up which ranged out to 1,722 days. The base rate for arrest in the binary outcome sample is 0.17, so the following interpretation for r_{pb} adjusted using the formulae in Rice and Harris can be used: 0.08 = small; 0.19 = medium; 0.29 = large.

Table 3.7: Measures of Association Between the COMPAS Core Scales and Any Arrest Within 1 Year in the 2010 New York Probation Study Data.

COMPAS Scale	Point-Biserial Correlation	AUC	Odds Ratio
General Recidivism Risk	0.27	0.71	2.94
Criminal Involvement	0.08	0.56	1.05
Noncompliance History	0.13	0.59	1.15
Violence History	0.08	0.55	1.09
Current Violence	0.04	0.53	1.12
Criminal Associates	0.13	0.60	1.15
Substance Abuse	-0.07	0.55	0.93
Financial Problems	0.05	0.53	1.06
Voced Problems	0.17	0.63	1.12
Family Crime	0.12	0.57	1.22
Social Environment	0.09	0.57	1.18
Leisure	0.14	0.59	1.11
Residential Instability	0.08	0.56	1.06
Social Adjustment	0.17	0.63	1.12
Socialization Failure	0.18	0.64	1.15
Criminal Opportunity	0.22	0.66	1.14
Social Isolation	0.06	0.55	1.03
Criminal Thinking	0.09	0.57	1.04
Criminal Personality	0.15	0.62	1.06

With $n=2,328$, a correlation of .041 is significant at $p < .05$ (2-tailed).

3.2.2 Construct Validity

Construct validity refers to the extent to which a scale measures what it is supposed to measure. Construct validity is tested by observing correlations between measures of the same or divergent constructs. Construct validity is relevant only for the COMPAS need scales and refers in part to unidimensionality of the scale and to its factor structure. Construct validity additionally is based on establishing evidence that a scale correlates in an expected manner with similar scales, and to other relevant variables in theoretically expected ways. To demonstrate the construct validity of a measure requires the testing of different types of validity including convergent and divergent validity. Here we only address the convergent validity of the COMPAS Core need scales. A direct approach to convergent validity is to measure the correlation between matched scales of the LSI-R and COMPAS Core. The LSI-R is considered a gold standard because it is the current industry leader. This would be a good indication for how well the COMPAS Core scales are measuring the same concept. Results from a study conducted in the California Department of Corrections and Rehabilitation (Farabee et al., 2010) show a direct and high level of correlation between matching LSI-R and COMPAS Core scales. The findings shown in Table 3.8 offer strong evidence of the convergent validity of the COMPAS Core scales. Farabee et al. (2010) found high Pearson product moment correlations between the LSI-R and COMPAS Core measures of Criminal Involvement (0.64); Vocation/Education (0.51); Criminal Associates (0.48); Substance Abuse (0.53); Financial (0.49); and Residential Stability (0.57).

Table 3.8: Correlations between COMPAS Core and LSI-R scales in Farabee et al., 2010

COMPAS	LSI-R	Correlation
Criminal Involvement	Criminal History	0.64 ($p < .0001$)
Criminal Associates/Peers	Companions	0.48 ($p < .0001$)
Substance Abuse	Alcohol/Drug Problem	0.53 ($p < .0001$)
Financial	Financial	0.49 ($p < .0001$)
Vocation/Education	Education/Employment	0.51 ($p < .0001$)
Family Criminality	Family/Marital	0.16 ($p > .10$)
Leisure	Leisure/Recreation	0.05 ($p > .10$)
Residential Instability	Accommodation	0.57 ($p < .0001$)
Criminal Attitudes	Attitudes/Orientation	0.20 ($p = .08$)

Shifting to more general issues of convergent validity, we consider additional evidence to support the convergent validity of the COMPAS Core need scales. For example, the COMPAS Core Substance Abuse Scale correlates positively ($r = 0.44$) with the Substance Abuse Subtle Screening Inventory (SASSI) in the Michigan Department of Corrections pilot data ($n=769$). We also find the Core Substance Abuse Scale correlates with the Texas Christian University Drug Screen (TCU Drug Screen) (Knight, Simpson, & Morey, 2002) at 0.51 in a sample of offenders assessed with both scales in the Wyoming Department of Corrections ($n=4,874$). We find similar correlations between the Core Substance Abuse Scale and the TCU Drug Screen in a sample of 2,029 men assessed with both scales in the Massachusetts Department of Correction ($r = 0.54$).

Convergent validity is also demonstrated if a measure correlates in the predicted manner with other variables with which it theoretically should correlate. For example, research in developmental delinquency (longitudinal research in which anti-social behaviors and attitudes are studied over the life course) consistently finds that youth with early onset of delinquent behavior tend to have more serious delinquency trajectories and more negative emotionality, lower achievement, and problems in social adjustment (Moffitt, 1993). Thus, when we consistently find, over multiple studies, that our Criminal Personality, Criminal Attitudes, Social Adjustment and Vocational Educational scales correlate with age-at-first-arrest, just as developmental delinquency research predicts, we take this as evidence of convergent validity. Note that these correlations with age-at-first-arrest hold up when current age is statistically controlled.

Furthermore, age-at-first-arrest is a good external variable to demonstrate convergent validity of the COMPAS Core need scales. Although age-at-first-arrest is collected inside COMPAS, it comes from official records, while the need scales are scored using a different method (interview and self-report).

We have evidence of convergent validity of this type from psychometric studies in the Michigan Department of Corrections (MDOC), New York Office of Probation and Correctional Alternatives (OPCA), New York State Division of Parole, Virginia Department of Corrections, South Carolina Department of Probation, Parole, and Pardon Services, and many other sites. To illustrate our approach to demonstrating convergent validity, we present results in Table 3.9 from a sample in the Wisconsin Department of Corrections, Division of Community Corrections (DCC). The DCC sample consists of 25,773 Core COMPAS assessments conducted between July 1, 2012 and August 31, 2013. Men comprise 76.7% of the sample.

There are many notable correlation patterns in Table 3.9 that provide evidence of convergent validity for the COMPAS Core scales. For example, we see that age-at-first-arrest correlates negatively with the higher-order personality scales Criminal Thinking ($r = -.13$) and Criminal Personality ($r = -.24$). This comports with findings in developmental research that indicate offenders with early onset are more likely to have high scores on similar types of personality measures and more serious and persistent criminal involvement (Moffitt, 1993). Similarly, we see that offenders with earlier age-at-first-arrest are more likely to have higher scores on scales measuring factors that have been identified as criminogenic in longitudinal developmental studies. These scales include Criminal Associates ($r = -.28$), Family Crime ($r = -.22$), Vocational/Educational Problems ($r = -.24$), and Social Environment ($r = -.16$) (Farrington, Jolliffe, Loeber, Stouthamer-Loeber, & Kalb, 2001).

Another pattern in Table 3.9 is defined by the correlations between previous arrests and the scales Social Adjustment ($r = 0.22$), Criminal Personality ($r = 0.15$), Criminal Associates ($r = 0.23$) and Substance Abuse ($r = 0.22$) (Stouthamer-Loeber, Loeber, Wei, Farrington, & Wikstrom, 2002).

There are modest, significant correlations between the assault infractions item from COMPAS Core and the scales Criminal Associates and Peers ($r = .19$), Vocational Educational Problems ($r = 0.15$), Social Environment ($r = 0.13$), Social Adjustment ($r = 0.15$), and Criminal Personality ($r = 0.16$). In their meta-analysis, Gendreau, Goggin, and Law (1997)

Table 3.9: Concurrent correlations between COMPAS Core Scales and criminal history indicators in the Wisconsin Division of Community Corrections sample.

COMPAS Scale	Age-at-First	Prior Arrests	Parole Returns	Prior Prisons	Assault Infractions
Criminal Associates	-0.28	0.23	0.17	0.17	0.19
Substance Abuse	-0.07	0.22	0.14	0.15	0.06
Financial Problems	-0.07	0.08	0.06	0.05	0.04
Voced Problems	-0.24	0.16	0.13	0.11	0.15
Family Crime	-0.22	0.10	0.04	0.02	0.07
Social Environment	-0.16	0.10	0.11	0.13	0.13
Leisure	-0.13	0.04	0.02	0.00	0.05
Residential Instability	-0.09	0.10	0.11	0.09	0.11
Social Adjustment	-0.27	0.22	0.13	0.11	0.15
Social Isolation	-0.02	0.08	0.07	0.06	0.07
Criminal Thinking	-0.13	0.06	0.03	0.02	0.10
Criminal Personality	-0.24	0.15	0.11	0.09	0.16

With $n=25,773$, a correlation of .013 is significant at $p < .05$ (2-tailed).

found that antisocial attitudes and criminal peers were important individual level predictors of prison misconduct.

There are small, significant correlations between the number of returns to custody for a parole violation and the scales Criminal Associates and Peers ($r = 0.17$), Substance Abuse ($r = 0.14$), Vocational Educational Problems ($r = 0.13$), Residential Instability ($r = 0.11$), and Social Adjustment ($r = 0.13$). Substance abuse, residential stability, and employment and education have been identified in past research as important factors associated with reentry success (Nelson, Deess, & Allen, 1999; Petersilia, 2003; Solomon, Visher, La Vigne, & Osborne, 2006; Travis, 2005). At least one study using self-report and qualitative methods found that housing and employment problems did not distinguish between parole violators and successes (Bucklen & Zajac, 2009).

Overall, the observed relationships between the COMPAS Core scales and criminal history indicators in the Wisconsin DCC sample provide evidence of the convergent validity of the scales. These correlations comport with relationships between risk factors and serious and violent trajectories observed in developmental criminological research (Herrenkohl et al., 2000; Tolan & Gorman-Smith, 1998). The significant correlations we have pointed out are somewhat attenuated by variability in the base rates of the paired variables. These modest associations are typical of correlations between need scales and criminal involvement variables observed in many criminal justice research contexts.

3.2.3 Content Validity

Content validity refers to the coverage of key factors that are relevant in the criminogenic domain. COMPAS Core was designed to have greater coverage of relevant scales than the

LSI-R. Content validity has a major role in any assessment field. It refers to the extent to which an assessment comprehensively includes and assesses the key factors in a domain of interest. The LSI-R includes 10 important criminogenic factors that assess constructs supported in the literature.

A study conducted by [Farabee et al. \(2010\)](#) found that 9 out of these 10 LSI-R scales are clearly matched to a similar scale in COMPAS Core. Thus, in terms criminogenic scale coverage (content validity), COMPAS Core matches virtually all scales contained in the LSI-R. However, the COMPAS Core system additionally includes another 14 scales that can be utilized or turned on/off by an agency depending on its information needs. These additional scales are supported empirically and cover constructs such as anger/hostility, history of non-compliance, low social supports, and socialization failure.

3.3 Internal Consistency Reliability

For a scale to be useful it must be reliable. For example, if one were to carry out repeated testing of a given respondent with different questions or tests, approximately the same scale value should be obtained on each re-test. Generally, if the items entering a scale are highly correlated (internally consistent), then the summated scale will be reliable. Internal consistency reliability - typically assessed by Cronbach's Alpha Coefficient - is a widely used and popular reliability approach. It is often used as a counterpart to test-retest reliability. By convention alphas of 0.70 and above indicate acceptable internal consistency for most applications in the behavioral sciences. Low alphas indicate the scale has too few items or the items don't have much in common and possibly measure more than one construct ([Nunnally & Bernstein, 1994](#)).

Table 3.10 shows the summary statistics and alpha coefficients for the COMPAS Core scales in a sample of prison intake assessments in the Michigan Department of Corrections. We have consistently found similar results in prison and probation study samples across numerous jurisdictions.

The low alphas on Violence History (0.53) and Current Violence (0.52) reflect the fact that these are indexes composed of different types of offenses that do not necessarily correlate with each other. A low alpha does not indicate a problem because the items are not expected to be highly correlated as they are in a scale. Family Crime (0.62) is a similar type of index of problems experienced by family members.

Social Adjustment (0.54) and Criminal Opportunity (0.66) are higher order scales. They are not unidimensional. Low internal consistency is less of a concern for these scales. They are composed of two or three underlying constructs each. Cronbach's alpha is less useful for higher order scales, since the multidimensionality of the higher order scales makes it difficult to ascertain what low alpha coefficients indicate. Conversely high alphas do not necessarily indicate unidimensionality.

Table 3.10: Summary statistics and alpha coefficients for the COMPAS Core scales in a prison intake sample from the Michigan Department of Corrections .

	Items	N	Min	Max	Mean	SD	Alpha
Criminal Involvement	4	15,315	0.00	19.00	8.82	4.66	0.75
Noncompliance History	5	15,315	0.00	21.00	4.49	4.23	0.65
Violence History	9	15,315	0.00	16.00	2.13	2.37	0.52
Current Violence	7	15,315	7.00	13.00	8.21	1.28	0.53
Criminal Associates	7	15,315	7.00	22.00	9.75	2.66	0.71
Substance Abuse	10	15,315	10.00	20.00	12.81	2.40	0.76
Financial Problems	5	15,315	5.00	15.00	8.21	2.34	0.70
VocEd Problems	11	15,315	11.00	30.00	19.60	3.89	0.71
Family Crime	6	15,315	6.00	12.00	7.57	1.50	0.62
Social Environment	6	15,315	6.00	12.00	7.54	1.82	0.81
Leisure	5	15,315	5.00	17.00	7.86	3.52	0.86
Residential Instability	10	15,315	9.00	30.00	13.26	3.70	0.71
Social Adjustment	15	15,315	12.00	37.00	20.23	3.44	0.54
Socialization Failure	13	15,315	7.00	32.00	12.10	3.76	0.69
Criminal Opportunity	14	15,315	13.00	39.00	21.23	4.45	0.66
Social Isolation	8	15,315	8.00	40.00	16.90	4.85	0.83
Criminal Thinking	10	15,315	10.00	45.00	20.73	4.91	0.80
Criminal Personality	13	15,315	13.00	58.00	31.84	5.71	0.70

3.4 Test-Retest Reliability

In an independent study by [Farabee et al. \(2010\)](#) the COMPAS Core scales showed very high test-retest reliability, with correlations ranging from 0.70 to 1.00, and with an average correlation above 0.80. Thus, the various COMPAS Core sub-scales demonstrated good to excellent reliability over time. An important aspect of the Farabee study was a comparison against the well-known LSI-R. Overall, the average test-retest correlation coefficient for the COMPAS Core scales was 0.88; for LSI-R, the mean as measured in the same study was 0.64.

Chapter 4

Treatment Implications for Scales

Each COMPAS scale has been constructed based on a variety of behavioral and psychological constructs that are of very high relevance to recidivism and criminal careers. Included in this section is a brief description of the area of research/literature that supports the scale content and context. This material supplements the document “Measurement and Treatment Implications of the COMPAS Core Scales.”

Interpretation of the scale scores and how they relate to case planning and intervention is a key concept for COMPAS users. The information contained in this section is intended to assist you in your interpretation of the COMPAS scores as you plan for meaningful interventions and plot the course of behavioral change with the individual. Some brief examples of language for case planning are also offered with each need scale description as a means to generate thoughtful, individualized goals and tasks for a person under supervision. The language (not considered a full treatment plan or goal/task statement) in the case planning examples is action oriented in the goals and tasks. The concept of “how” is defined through behavioral statements. For example, how will the person find emergency housing, or how will the person find new, healthy friends.

4.1 Risk Scales

In this section we describe the Risk Scales in COMPAS. We have developed risks scales for general recidivism, violent recidivism, and pretrial misconduct. There are additional risk scales under development. Northpointe’s Research Department also conducts outcomes studies with clients and develops and validates customized risk assessment tools.

4.1.1 Pretrial Release Risk

The Pretrial Release Risk Scale (PRRS) was developed through a pretrial release outcomes study conducted in a large sample of felony defendants assessed with COMPAS in Kent County, Michigan Pretrial Services (Dieterich, 2010). The PRRS was constructed to predict failure to appear (FTA) and new felony arrest among defendants on pretrial release. The development sample included both supervised and unsupervised pretrial releases.

Prior pretrial risk assessment research has consistently identified a set of factors that are predictive of pretrial failure. The most common risk factors include current charges, pending charges, prior arrest history, previous pretrial failure, residential stability, employment status, community ties, and substance abuse (VanNostrand, 2003). We selected items from the COMPAS assessment and included them as candidates for risk model development on the basis of this prior research.

One purpose of pretrial release risk assessment is to sort a pretrial caseload into low-, moderate-, and high-risk groups based on the likelihood of failure to appear in court or commit a new crime pending trial. Use of the risk assessment tool by pretrial services agencies should result in more consistent and equitable decisions regarding release and conditions of release. The use of objective risk assessment tools is recommended by the National Association of Pretrial Services Agencies (2004). The risk assessment tool should be empirically derived and have demonstrated predictive validity in the jurisdiction in which it is deployed. The factors that enter into the risk assessment score should be consistent with applicable state statutes.¹ These and other guiding principles for pretrial risk assessment are outlined in Pretrial Services Legal and Evidence-based Practices (VanNostrand, 2007).

The current PRRS-II is a modified version of the PRRS. The PRRS-II includes eight risk factors (felony top charge, pending case, prior failure to appear, prior arrest on bail, prior jail sentence, drug abuse history, employment status, and length of residence).

4.1.2 General Recidivism

The recidivism risk scale was developed to predict new offenses subsequent to the COMPAS assessment date. The outcome used for the original scale construction was a new misdemeanor or felony offense within two years of the COMPAS administration date.

The scale inputs include criminal involvement (prior arrests and prior sentences to jail, prison, and probation), vocational/educational problems, drug history, age-at-assessment, and age-at-first-arrest. All of these risk factors are well known predictors of recidivism.

Decile scores 1 through 4 (Low Risk Level) may be regarded as low risk since they are clearly lower than "average." Decile Scores 5 through 7 (Medium Risk Level) may be regarded as medium risk since they are in the middle of the distribution and represent cases that are very close to "average" for the total population of the agency. Decile Scores of 8 and above (High Risk Level) may be regarded as high risk since they are in the top third of the distribution.

¹For example in New York a pretrial risk assessment instrument cannot be based on age, gender, or marital status (Division of Probation and Correctional Alternatives, 2007).

It is important to note that the risk scores are generally taken from static information and that current level of needs, for example, substance abuse or other issues, can influence a person's likelihood of acting out or recidivating. In a later discussion, the concept of Low risk/High needs will be covered. General recidivism refers to a broad range of potential acts, therefore, versatility is an element for consideration. The COMPAS Typologies document delineates the typologies that have been discovered through research at Northpointe. One trait that lends itself to recidivism is versatility.

4.1.3 Violent Recidivism

This scale was originally developed in COMPAS Core assessment data on a large sample of probation and presentence investigation (PSI) cases. The scale was subsequently added to COMPAS Reentry. The scale inputs include history of violence, history of non-compliance, vocational/educational problems, the person's age-at-assessment and the person's age-at-first-arrest. The strong association of these factors with future violence has been established in previous research and holds true for people who are considered "non-disordered" (Gendreau et al., 1996). Additionally, meta-analytic results from studies with disordered persons show that a history of violent crime is one of the more potent predictors of violent recidivism (Bonta, Law, & Hanson, 1998).

Decile scores 1 through 4 (Low Risk Level) may be regarded as low risk since they are clearly lower than "average." Decile Scores 5 through 7 (Medium Risk Level) may be regarded as medium risk since they are in the middle of the distribution and represent cases that are very close to "average" for the total population of the agency. Decile Scores of 8 and above (High Risk Level) may be regarded as high risk since they are in the top third of the distribution.

Some offenders, based on their past history of violent acts may score in the high range, yet, show low or medium needs areas. Consideration for the current status of the offender and the support network in place is, as always, recommended, yet in the case of a person who scores high on this scale, special supervision conditions may be deemed necessary.

4.1.4 Recidivism Risk Screen

The Recidivism Risk Screen (RRS) is a brief recidivism risk scale developed to predict a new misdemeanor or felony offense arrest within two years. The RRS consists of five salient risk factors (age, age at first arrest, number of prior arrests, employment status, and prior parole revocations). The RRS is particularly useful to agencies that apply a triage strategy as part of their risk and need assessment protocol to improve efficiency and reduce workload. The RRS is suitable as a prescreen in correctional facilities to select high risk cases for further assessment using a more comprehensive scale set from the Northpointe Suite. The RRS can also be used in community corrections settings to screen candidates for administrative supervision or lower supervision levels. The RRS is not intended as a substitute for the standard risk scales in the Northpointe Suite. The General Recidivism Risk and Violent Recidivism Risk scales measure aspects of risk (both general and violent recidivism) not covered by the

RRS. Used in combination with the Current Violence Scale, the General Recidivism Risk and Violent Recidivism Risk scales provide a complete recidivism risk profile.

4.1.5 On Counter-Intuitive Predictions

Sometimes the COMPAS risk score for a particular person does not match the practitioner's expectations or clinical judgment regarding the level of risk posed by that person. A case in point is when an offender with no prior violence history scores medium or high on the Violent Recidivism Risk Scale. Or, conversely, an offender with some violent history scores low on the Violent Recidivism Risk Scale. This section explains how this occurs and why it is not an indication that the risk scale has failed to work properly.

The COMPAS risk scales are actuarial risk assessment instruments. Actuarial risk assessment is an objective method of estimating the likelihood of reoffending. An individual's level of risk is estimated based on known recidivism rates of offenders with similar characteristics.

The Violent Recidivism Risk Scale is constructed from the following characteristics that we found to be predictive of new person offenses (misdemeanor or felony):

- History of Noncompliance Scale
- Vocational Education Scale
- Current age
- Age-at-first-arrest
- History of Violence Scale

Each item is multiplied by a weight (w). The size of the weight is determined by the strength of the item's relationship to person offense recidivism that we observed in our study data. The weighted items are then added together to calculate the risk score:

$$\text{Violent Recidivism Risk Score} = (\text{age} * -w) + (\text{age-at-first-arrest} * -w) + (\text{history of violence} * w) + (\text{vocation education} * w) + (\text{history of noncompliance} * w)$$

The strong association of each of these inputs with person offense recidivism that we observed in our studies has been established by many other researchers in criminal justice. Meta-analytic results show that violent criminal history, education and vocational problems, current age, and age-at-first-arrest are consistent predictors of violent recidivism. The Violent Recidivism Risk Scale has items in common with many risk assessment instruments in use in corrections, including the Level of Service Inventory-Revised (LSI-R); the General Statistical Information on Recidivism (GSIR); the Violence Risk Appraisal Guide (VRAG)

and the Sex Offender Risk Appraisal Guide (SORAG); and the Self-Appraisal Questionnaire (SAQ).

Your auto insurance company uses a similar risk prediction approach to estimate your risk of having an accident. Besides your age and accident history, the equation includes other characteristics such as credit rating and gender. If you are under 25, male, and have poor credit, you may be classified as high risk even though you have never had an accident.

In the context of Violent Recidivism Risk, if you are young, unemployed and have an early age-at-first-arrest and a history of supervision failure, you could score medium or high on the Violence Risk Scale even though you never had a violent offense arrest.

It is possible for a person's score on the Violent Recidivism Risk Scale to deviate considerably from what one would expect given the person's score on the History of Violence Scale. Consider a hypothetical person who scores high (D10) on History of Violence (2 prior misdemeanor assault offense arrests, 1 prior domestic violence offense arrest, 1 violent property offense arrest, and 1 prior weapons offense arrest); medium (D6) on vocation / education problems, and low on noncompliance history (D1). This person has a late age at onset (age at first arrest = 33 yrs) and he is 51 years old. He has no history of noncompliance (D1) and no vocation or education problems. All of these factors subtract substantially from his Violent Recidivism Risk score, which falls into decile 3 (D3). Note that age is one of the best predictors of violent recidivism, and it carries a lot of weight in the Violent Recidivism Risk Scale calculation. If our hypothetical person were 25 years old and his age at first arrest were 16 years old, his Violent Recidivism Risk score would jump to D8 (High).

Why Is the Current Offense Not Included in the Risk Score?

The Recidivism Risk Scale does not include current violent offense in its calculation. When an offender with a current violent offense obtains a Low Score on the Violent Recidivism Risk Scale, the Low Score may appear counterintuitive. The Violent Recidivism Risk Scale was trained to predict general violent recidivism (misdemeanor or felony person offense). During model development we generally find that violent current offense does not significantly improve the prediction of general violent recidivism. However, an appreciation of the nature and circumstances of the current offense remains essential for effective case management. Current violent offenses are captured by the Current Violence Scale.

What About Domestic Assault or Sex Assault Offenses?

For both domestic assault and sex assault, details about the current offense are important for understanding the risk of recidivism. If the current offense is domestic assault or sexual assault, then it is recommended to use an index-offense-specific risk tool to assess risk of recidivism. COMPAS includes secondary assessments for this purpose, including the Vermont Assessment of Sex Offender Risk-2 (VASOR-2) (McGrath & Hoke, 2001; McGrath, Lasher, Cumming, Langton, & Hoke, 2014) and the STATIC 99 (Hanson, 1997; Hanson & Thornton, 2000) for use with adult male sex assault offenders and the Revised Domestic Violence

Screening Instrument (DVSI-R) for use with adult domestic violence offenders ([Williams & Grant, 2006](#); [Stansfield & Williams, 2014](#)).

What Percent of the Assessments will have a Counterintuitive Pattern?

There are two counterintuitive patterns: (1) An offender with no prior violence history scores high on the Violent Recidivism Risk Scale and (2) An offender with high violent history scores low on the Violent Recidivism Risk Scale. The relative frequency of these patterns depends on the relative frequency of violent history in the agency population. If a large percent of the agency population has low violent history then pattern 1 is more likely. If a large percent of the agency population has high violent history then pattern 2 is more likely. The alignment between the agency data and the norm data will affect the proportion classified as high (or low) on the Violent Recidivism Risk Scale, which will also affect the likelihood of counterintuitive scores.

Cases that have a counterintuitive pattern of History of Violence and Violent Recidivism Risk should be examined closely and considered for an override. Persons who exhibit pattern 1 are more likely to have early age at onset and younger age at assessment, and possibly a history of noncompliance and vocational/educational problems. Persons who exhibit pattern 2 are more likely to have late age at onset and older age at assessment, with minimal history of noncompliance and few vocational/educational problems. In all cases a holistic framework to case formulation should be applied that takes into account the varied aspects of the offender as measured by the COMPAS risk and needs scales.

General Comments on Risk Prediction

Risk assessment is about predicting group behavior (identifying groups of higher risk offenders) - it is not about prediction at the individual level. Your risk score is estimated based on known outcomes of groups of offenders who have similar characteristics.

The Violent Recidivism Risk Scale could be constructed in such a way that a high (low) score can only be obtained for someone who has (doesn't have) a history of violent offense arrests. This could be accomplished for example by constructing the Violent Recidivism Risk Scale entirely (or almost entirely) of violent history items. However, based on our own research and that of many other researchers, a scale that depends too heavily on violent history items will not have good predictive power.

Our risk scales are able to identify groups of high-risk offenders - not a particular high-risk individual. We identify groups of offenders who score high, medium or low-risk. We expect that the high-risk group will have higher recidivism rates for violent offenses relative to the low-risk group - this, in fact, has been demonstrated in our outcomes studies.

It is also important to note that we would expect staff to disagree with an actuarial risk assessment (e.g. COMPAS) in about 10% of the cases due to mitigating or aggravating circumstances which the computer is not sensitive to. In those cases staff should be encouraged to use their professional judgment and override the computed risk as appropriate - documenting it in COMPAS with the Override Reason - for monitoring by supervisory staff.

4.2 Criminogenic Need Scales

Need scales measure a criminogenic need and help with case planning. In the following section we briefly describe each COMPAS Core need scale and give examples of the goals and tasks that might be put into a case-plan.

4.2.1 Cognitive Behavioral

This is a higher order scale that incorporates the concepts and items included in the Criminal Associates, Criminal Opportunity, Criminal Thinking, Early Socialization, and Social Adjustment scales.

This scale, as mentioned above, includes grouped items which represent areas of need that can best be addressed in settings that include cognitive restructuring approaches. Concurrent drug/alcohol treatment or other interventions that address immediate needs are recommended, a balanced approach is necessary to avoid overwhelming the person with interventions. For some people, implementing interventions before they are on community supervision is the best approach, as they will have the opportunity to focus on changing their thoughts, feelings and behavior in a controlled setting without the challenges of a community setting. When a person scores in the medium and high ranges of this scale, considerations for their world view must be made, beginning with the question, “does this person see a need for change?”.

Table 4.1: Case Planning example for Cognitive Behavior

Goal	Build new and increase healthy coping skills
Task	Immediate Needs: Identify sources/triggers of my anger, frustration, and feelings of being overwhelmed. Make separate lists for each feeling, include what was going on in my immediate surroundings at that moment, who else was there, stressful incidents, and any other information I think is significant.
Task	Ongoing Needs: Use my healthy coping skills (from my skills list/optional actions) to problem-solve in situations where I feel stressed, angry, overwhelmed or when I recognize my triggers to use old behavior to get through a situation.

4.2.2 Criminal Associates/Peers

An involvement with anti-social friends and associates is one of the “big five” risk factors for criminality to emerge in meta-analytic research (Gendreau et al., 1996). Affiliating with aggressive and criminal others is a significant risk factor for further violence and crime. This is consistent with both social learning theory and sub-cultural theories of crime (Andrews, Zinger, et al., 1990; Elliot, Huizinga, & Ageton, 1985).

This scale assesses the degree to which a person associates with other persons who are involved in drugs, criminal offenses or gangs, and determines whether they have a history of arrests and incarceration. A high score would identify persons who are involved in a network of highly delinquent friends and associates.

This domain is considered a strong area of influence for people in the criminal justice system. Interventions in this area can be difficult for the person as their identity with a group as well as a support system, albeit criminally involved, will be altered. Gang influence is particularly difficult as a real level of threat could exist for the person who, by leaving/taking a break from gang life, may be viewed as disrespecting those who have brought him/her to this point in life. Compliance, rather than change is likely for some people, yet, it is a step forward with respect to safety and recidivism.

Table 4.2: Case Planning example for Criminal Associates/Peers

Goal	Increase my association with pro-social, healthy friends
Task	Immediate Needs: Identify traits and behavior of positive, healthy friends and family members
Goal	Reduce interactions with anti-social, potentially harmful friends
Task	Identify friends and family who I tend to get into trouble with, include any co-defendants or criminally involved associates
Task	Create a plan to avoid interaction with criminally oriented friends/family, include statements regarding what my actions will be if I come into contact with the friends/family I have listed as “trouble” for me.

4.2.3 Criminal Involvement

The degree of criminal involvement has consistently emerged as a major risk factor for predicting ongoing criminal behavior. It is the most important of the major risk factors that have emerged in various meta-analysis studies ([Gendreau et al., 1996](#); [Andrews & Bonta, 1994](#)). Early juvenile delinquency involvement has also been linked to ongoing criminal behavior ([Moffitt, 1993](#)).

This scale is defined by the extent of the person’s involvement in the criminal justice system. A high score indicates a person who has had multiple arrests, multiple convictions, and prior incarcerations. The items centrally defining this scale are the number of arrests and number of convictions. A low score identifies the person who is either a first-time arrest or has minimal criminal history. Thus, the central meaning of this scale is the extensiveness of the criminal history.

Arrest history is useful here to see patterns (persons, places, things, time of year) and other related elements that could be antecedents to recidivism and perhaps causal factors (thoughts, feelings, beliefs, attitudes) that can be impacted by intervention. Cognitive behavioral approaches seem to work best in this life area to re-set a person’s response to triggers and patterned responses.

Case planning will be similar to criminal associates/peers, criminal personality and criminal opportunity and some cognitive behavioral goals. See the goals listed in Table 4.2, 4.4 and 4.3.

4.2.4 Criminal Opportunity

We have developed a higher order scale to assess the concept of criminal opportunity. This scale emerges from those criminological theories that stress the importance of routine daily activities and the importance of occupying certain social roles (marriage, parenting, being an employee). These roles tend to structure a person’s daily activities in a pro-social manner, fostering social bonds and associated local social controls. The theoretical background to this scale includes routine activities theory that emphasizes the importance of immediate local daily activities that place a person in high risk or high opportunity situations (L. E. Cohen & Felson, 1979). The second theoretical theme contributing to this scale is early social control theory (Hirschi, 1969) which emphasizes the importance of social bonds as inhibitors or constraints to crime. The third theoretical strand in which the concept of opportunity is important is the “life cycle” theory of Sampson et.al. (1994). This asserts that age related desistance from crime is linked to life cycle changes that increase both social bonds (wives, children, jobs) and the immediate social controls of associated roles.

This higher order scale assesses criminal opportunity by using items that represent a combination of the following: time in high crime situations, affiliation with high risk persons who often engage in illegal activities, an absence of pro-social or constructive activities (e.g. working, spending time with family, etc.), an absence of social ties, high boredom, high restlessness and being in a high risk age group. The central items include: being unemployed, living in a high crime area, having friends who engage in drug use, and having no constructive activities.

A variety of life areas are represented within this scale. Interventions can be put in place in concurrent waves—for example, seeking out new friends and activities that are pro-social and have positive elements such as learning new skills, helping others, gaining awareness and acting on the awareness at the same time. Structure is a key ingredient in reworking previously idle or non-constructive time. Performance measures as a means of accountability and tracking behavior are also useful tools in this area.

Table 4.3: Case Planning example for Criminal Opportunity

Goal	Increase positive activities
Task	Immediate Needs: Set a date and time for any new activities to help me follow through with the plans I make for new, positive activities.
Task	Ongoing Needs: Develop career aspirations, goals, and identify potential role models as a way to connect with others outside of my family as a means to move forward. Create a plan with each item listed, including dates, for behavioral actions on my part.

4.2.5 Criminal Personality

Several personality dimensions have emerged from recent research as significantly related to persistent criminality. These dimensions involve impulsivity, risk-taking, restlessness and boredom, absence of guilt (callousness), selfishness and narcissism, interpersonal dominance, anger and hostility, and a tendency to exploit others (Hare, 1991; Cooke, Forth, & Hare, 1998). Bonta (1996) reports that criminal personality was the second most important dynamic factor in predicting recidivism. Bandura (1996) also reports validating similar personality dimensions. Criminal personality was one of the "big five" risk factors for criminality in the meta-analysis of Gendreau (1996). The well known General Theory of Crime proposed by Gottfredson and Hirschi (1990) similarly invokes the personality concept of "low self-control," which includes similar dimensions of criminal personality. Prior research has demonstrated a modest but significant relationship between psychopathy, low self-control (variously defined) and both violence and general criminal behavior (Quinsey et al., 1998). Quinsey et al. (1998) include the PCL (Hare, 1991) within their violence risk predictive system – the VRAG.

The items in this scale cover the main dimensions identified as components of the criminal personality (e.g. impulsivity, no guilt, selfishness/narcissism, a tendency to dominate others, risk-taking, and a violent temper or aggression).

Personality is a complex concept and many social scientists believe personality is "set" in childhood/adolescence. Given that many factors come together to create personality, the idea of criminal personality is no less complicated. There are patterns seen in persons who exhibit criminal personality traits. Intervention then, is based on cognitive behavioral approaches that examine and offer alternatives to thoughts, feelings, beliefs and resultant criminal behavior. A specific diagnosis of anti-social personality disorder is not necessary when considering intervention, the area of focus is as listed above – what is the process the person undergoes while deciding to engage in criminal behavior, what is his/her rationale, and what is he/she willing to do about making changes?

Table 4.4: Case Planning example for Criminal Personality

Goal	Build new and increase positive coping and communication skills.
Task	Immediate Needs: Journal my behavior in the areas of thoughts, feelings, attitudes and resultant behavior when I feel stressed, angry, or that something unfair has happened to me. Do my journal entries daily for 5 days and bring to my next probation appointment.

4.2.6 Criminal Thinking Self-Report

Antisocial attitudes and beliefs are identified among the "big five" risk factors in meta-analysis studies of factors that predict crime (Gendreau et al., 1996). However, there is no agreement on the particular attitudinal dimensions or cognitions that are the most useful for predictive purposes. Various studies focus on aspects of thinking style, attitudes toward criminal

justice, neutralization and excuses, tolerance for law violation, cognitive justifications, etc. Clearly, this area could require a highly extensive inventory to map the full range of cognitive dimensions relative to crime. In the absence of such consensus, we adapted the approach of Bandura (1996). Bandura's approach assesses several key cognitive dimensions that justify, excuse, and minimize any damage caused by the person's behavior/crime.

This scale brings together several cognitions that serve to justify, support, or provide rationalizations for the person's criminal behavior. These dimensions include moral justification, refusal to accept responsibility, blaming the victim, and rationalizations (excuses) that minimize the seriousness and consequences of their criminal activity. These include rationalizations such as: drug use is harmless because it doesn't hurt anybody else, criminal behavior can be justified by social pressures, theft is harmless if those stolen from don't notice or don't need what was taken, etc.

The concepts discussed above as they relate to the Criminal Personality scale are also present in this scale, and have been identified in further detail through the person's own self-report. A distinct pattern of rationalizations for criminal and/or harmful behavior is present for those who score in the probable and highly probable categories. Interventions that focus primarily on cognitive behavioral approaches tend work best with those who evidence significant criminal thinking.

Table 4.5: Case Planning example for Criminal Thinking Self-Report

Goal	Modify criminal thinking, develop a positive attitude toward various life areas (see specific goals).
Task	Immediate Needs: Create a list of what works for me (positive thoughts and activities) and what doesn't (negative thoughts and activities) that keep me in the same cycle of getting into trouble.

4.2.7 Current Violence

This scale forms part of the general criminal history and measures the degree of violence in the present offense. The central item that defines the scale is the presence of an assaultive felony. Other key items involve whether or not a weapon was used, if there was injury to a person, etc.

Research has shown that the level of violence in the instant offense is not a good predictor of future crime. Keeping in mind the degree and type of violence in the instant offense as compared to the person's history of violence and current level of functioning/needs scores is good practice. One area for clear consideration is that of family violence and how this will affect any kind of living arrangement for community-based supervision.

Table 4.6: Case Planning example for Current Violence

Goal	Build new and increase healthy coping skills.
Task	Enroll in and successfully complete an Anger Management Program. Bring my homework and updates from the class to each probation appointment.
Task	Create a list of my healthy and unhealthy coping skills, then list next to each one the usual outcome when I use that reaction or response.

4.2.8 Family Criminality

From a social learning theory perspective, participation in criminal behavior may be facilitated by significant others who model such behavior. Research has consistently demonstrated that delinquency and adult crime are both associated with parent criminality (West, 1973; Lykken, 1995). Children may learn that violent and deviant behavior “work” in the context of their family. Aside from the social learning and role modeling perspective, other intergenerational mechanisms may operate to transmit values and behaviors from parent to child. Genetic influences, for example, may operate to transmit anti-social personality disorder and criminality (Lykken, 1995). COMPAS therefore includes a measure of family criminality focusing on the criminality and drug use history of the mother, father, and siblings.

This scale assesses the degree to which the person’s family members (mother, father, and siblings) have been involved in criminal activity, drugs, or alcohol abuse. The items cover: arrests of each family member, whether they have been in jail or prison, and whether the parent or parental figure has a history of alcohol or drug problems.

Families can be significant positive resources for any person in the criminal justice system. The presence of family criminality, however, can create a dichotomous situation in that, on the one hand the family is a source of support, comfort, and hope, and on the other hand, they may also be criminally involved and their support revolves around their criminal activity and belief systems.

Table 4.7: Case Planning example for Family Criminality

Goal	Eliminate criminal involvement with family members.
Task	Immediate Needs: List/identify family members (those who I have a relationship with and spend time with) who are criminally involved.
Task	Ongoing Needs: Create a time line of my involvement with these family members and the consequences/benefits of spending time with them, e.g. when did it happen and what happened while we were together.

4.2.9 Financial Problems

This concept appears as one of the more modest risk factors in the Gendreau et al. (1996) meta-analysis. It is linked to lower social class, poor housing, community disorganization, and other factors. Homicides, for example, are disproportionately found in high poverty areas. Numerous social dimensions related to poverty are linked to high crime, including residential mobility, family disruption, single parent families, crowded housing conditions, and higher opportunity for violence (Sampson & Lauritsen, 1994). The measure of poverty and financial problems in COMPAS focuses on the struggle to survive financially, problems paying bills and other issues related to a shortage of money.

This scale assesses the degree to which a person experiences poverty and financial problems. It assesses whether the person worries about financial survival, has trouble paying bills, and has conflicts with friends or family over money.

Unpredictable economic times may play a role in this area, however, a person's pattern of earning (or not) and spending money is an important element. Education on money management and fulfilling court ordered financial commitments is part of the necessary approach when considering interventions. Assuming someone knows how to manage their finances is an erroneous starting place, vocational training may also play a role in creating a successful change plan.

Table 4.8: Case Planning example for Financial Problem Scale

Goal	Gain financial stability/independence.
Task	Immediate Needs: Apply for financial assistance/emergency shelter and/or food stamps (use other resources as referred by PO).
Task	Immediate Needs: Inform my supervisor at work about my probation appointments and any terms and conditions that might impact my ability to do my job.

4.2.10 History of Non-Compliance

This scale focuses on the number of times a person has failed when he or she has been supervised in the community (probation or parole). The central defining items are the number of times that probation or parole has been violated or revoked. Related items include the number of times a new charge or arrest has occurred while the person was on probation and the number of returns to custody for parole violations.

This scale focuses on the number of times the person has failed when he or she has been placed on a community-based status. The central defining item is the number of times probation or parole has been suspended or revoked. Related items include the number of times the person has failed to appear for a court hearing, the number of times a new charge/arrest or technical rules violation has occurred while on probation, parole and prior community corrections program placement failures (i.e. electronic monitoring, community service work, day reporting, etc.) Thus, the scale involves the risk of technical rules violation failure leading to revocation of probation, pretrial release, or community corrections placement status.

Different states/agencies have different thresholds for supervision violation and suspension/revocation. While policy decisions do effect the person's history "on paper" it is also important to understand the person's willingness and ability to successfully complete community-based supervision. Clearly articulated expectations with terms and conditions of supervision and case planning are key factors in laying the groundwork for success. Behaviorally stated goals and a high degree of structure with room for individual differences and learning curves could enhance a person's success rate.

Table 4.9: Case Planning example for History of Non-Compliance

Goal	Attend all probation meetings as scheduled.
Task	Immediate Needs: Client and PO agree upon appointments for two week intervals including attendance at Cog/Behavioral group 1x week. Client to use pocket calendar for personal reminder of all appointments, during this two week period (March 10-24, 2010) client is to attend 2 scheduled appointments at this office (2/12 and 2/19 at 3pm) and the cog group on 2/15 and 2/22 at 6pm.
Note	All case planning activities should include tangible sanctions should the person fail to comply or engage in change behavior, and in the cases when a very high degree of structure is put in place, those sanctions may be stated on the case plan.

4.2.11 History of Violence

A history of violent behavior has been demonstrated to be one of the most powerful predictors of future violence (Farrington, 1991; Parker & Asher, 1987). The likelihood of future violence appears to steadily increase with each instance of a prior violent incident. Each prior arrest for violent behavior increases the likelihood of further violence. Similarly, a history of juvenile violence has been found to be a predictor of adult violence (Farrington, 1991).

The aim of this scale is to reflect the seriousness and extent of violence in an individual's criminal history. It focuses on the frequency with which violent felony offenses have occurred, the use of weapons, and the frequency of injuries to victims. The frequency of several specific violent offenses are also included in the scale (e.g., robbery, homicide, and assaultive offenses).

Multiple episodes of violence may suggest the need for further psychological evaluation. The accumulation of multiples (events, victims, types of crimes against persons/animals) creates a pattern of serious concern. Interventions may be targeted at cognitive behavioral constructs to manage behavior, and highly structured supervision may be preferred by the supervising agency.

While we are not going to change the past, we can teach people to intervene in old thought processes and put in place, new, healthier thoughts that lead to pro-social responses rather than reactions that always follow the same patterns.

Table 4.10: Case Planning example for History of Violence

Goal	Increase my healthy responses to events that trigger an angry reaction for me.
Task	Immediate Needs: List the way I have shown my thoughts and feelings in the past.
Task	Immediate Needs: Describe what happens when I lose self-control.
Task	Immediate Needs: Describe what happens when I use positive, self-control responses.

4.2.12 Leisure/Boredom

Aimlessness in the use of leisure time is linked to several theories of crime. For example, it is a component of Hirschi's early Social Control theory representing an aspect of weak external social bonding (Hirschi, 1969). Aimless use of leisure time is also included as a risk factor in the LSI (Andrews & Bonta, 1994). The General Theory of Crime (M. R. Gottfredson & Hirschi, 1990) includes aimlessness and the related concept of proneness to boredom within the dimension of low self-control or criminal personality. It is also linked to routine activities theory by the maxim of "Idle hands are the devil's workshop" (Osgood, Wilson, O'Malley, Bachman, & Johnston, 1996).

This scale assesses the degree to which the person experiences feelings of boredom, restlessness, or an inability to maintain interest in a single activity for any length of time. Thus, this scale may be regarded as reflecting a psychological dimension rather than representing the amount of constructive opportunities in the person's community environment.

As noted above, the issue is not necessarily time management, but the person's value of experiences and relationships. Creating an understanding of these elements may be a first step toward making changes for the individual. Some social or information processing issues may be identified through further assessment, and these issues can then be addressed accordingly.

Table 4.11: Case Planning example for Leisure/Boredom

Goal	Learn about the relationship between my level of participation with other people/events/interests and my ability to be involved in things outside of work or other required activities.
Task	Immediate Needs: Create a plan for getting involved with my friends who participate in the basketball league at the rec center. List the night and time of the league and the person who I can talk to get on a team. Ask my friend to go with me if I feel like I need support in joining the team.

4.2.13 Residential Instability

An unstable lifestyle is one aspect of the second factor of Hare's Psychopathy Checklist and this is an obvious risk factor for crime and violence (Hare, 1991). Additionally, low social ties and an unstable residential address are often used in pre-trial risk assessment instruments to predict risk of flight. The absence of social ties, and the presence of social isolation are also seen in Social Control theory as the absence of restraints on deviant behavior that result from weak social bonding. In addition, since change and stress are correlated, an unstable lifestyle may be stressful. Finally, personal stress/distress appears as a risk factor with modest predictive validity in meta-analysis studies (Gendreau et al., 1996).

The items in this scale measure the degree to which the individual has long term ties to the community. A low score on this scale indicates a person who has a stable and verifiable address, local telephone and long term local ties. A high score would indicate a person who has no regular living situation, has lived at the present address for a short time, is isolated from family, has no telephone, and frequently changes residences.

Community-based supervision requires a verifiable address. The reality is that some individuals end up in shelters right after release, or, they don't have the financial means to secure acceptable living quarters for months after sentencing/release. The historical nature of the person's residential stability is good information while the person is incarcerated in that planning can be put into place to avoid the pitfalls aforementioned. Renewing and/or creating family contacts and other potential support resources can be used as realistic goals in establishing residential stability.

Table 4.12: Case Planning example for Residential Instability

Goal	Seek and obtain sustainable living situation.
Task	Ongoing Needs: Develop a workable budget that includes housing costs that I did not list under my immediate needs such as pets, additional furnishings, any agreements that I can lawfully enter into to help reduce the cost of my rent.

4.2.14 Social Adjustment

Interpersonal problems may exist in each main social institution (family, school, work, etc.) A pattern of interpersonal problems may indicate poor social skills. The present higher order scale was constructed to assess the recurrence of interpersonal problems across various social contexts. Social skills training is often advocated as a treatment approach in preventing further violence and crime. Social adjustment problems are also implicated in several theoretical perspectives of criminal behavior (e.g., weak social bonding in social control theory (Hirschi, 1969), stress (Gendreau et al., 1996) social cognitive models of crime (Dodge, Pettit, McClaskey, & Brown, 1986; Dodge, 1998) and the erosion of social capital (Hagan, 1998)).

This scale is higher order in the sense that it uses items from other scales that crosscut several domains. It aims to capture the degree to which a person is unsuccessful and conflicted in his/her social adjustment in several of the main social institutions (school, work, family, marriage, relationships, financial.) A high score indicates a person who has been fired from jobs, had conflict at school, failed at school or work, has conflict with family, exhibits family violence, cannot pay bills, has conflicts over money, etc. Thus, the common theme is problematic social relationships across several key social institutions.

Areas for intervention will depend on the most pressing issue and need for support in that area. Creating a sense of connectedness and responsibility for self and to others is a foundational element of many cognitive behavioral approaches. Structuring communication expectations and methodologies for the individual may be a starting place, many programs provide sequenced awareness and practice options. The supervision professional may work with the individual in identifying other community-based pro-social activities, as well.

Table 4.13: Case Planning example for Social Adjustment

Goal	Increase positive social supports with family, friends, and community.
Task	Immediate Needs: Create a plan for increasing my time spent with positive, pro-social friends and family members.

4.2.15 Social Environment

Living in a high crime neighborhood is a well-established correlate of both delinquency and adult crime (Thornberry, Huizinga, & Loeber, 1995; Sampson & Lauritsen, 1994). This risk factor fits into several theoretical models of crime and delinquency (e.g., social disorganization, social learning, and sub-cultural theories). Disorganized and high crime communities are characterized by perceived high crime rates, gangs, easy access to drugs, and inadequate housing.

This scale focuses on the amount of crime, disorder, and victimization potential in the neighborhood in which a person lives. High crime is indicated by the presence of gangs, ease of obtaining drugs, the likelihood of being victimized, a belief that a weapon is needed for protection, and so on.

Few scales reflect areas where the person has no direct control over the identified issues, however, this scale is based on environmental factors that the individual has to cope with on a daily basis. Problem-solving around the possibility of relocating or finding a safer living arrangement may be paramount. Other risk factors come into play when considering the person's social environment (criminal opportunity, criminal peers, family criminality, residential instability, etc.) and these factors may become more of a primary focus should they be identified as active in the person's life.

The Social Environment and Social Isolation scales will typically use case planning language similarly. Increasing positive family and peer relationships, as we have seen in other scales is a primary focus, as well as involvement in specific activities.

4.2.16 Social Isolation

Positive social supports appear to serve several functions that may reduce crime and violence. Social support may act as a protective factor or mediator of stress, since stress and anxiety may predispose a person towards anger and violence. Positive social support has been shown in research to act as a protective factor against risk of violence even in high risk environments (Estroff & Zimmer, 1994). As described below, the COMPAS social isolation scale is bipolar in that it serves to identify social isolation/loner behavior on one pole and strong social supports at the other pole.

This scale assesses the degree to which the person has a supportive social network and is both accepted and well integrated into this network. The scale is scored such that a high score represents an absence of support, and the presence of feelings of social isolation and loneliness. The defining items include: feeling close to friends, feeling left out of things, the presence of companionship, having a close best friend, feeling lonely, etc.

As mentioned in other social support areas, intervention can be across many dimensions and impact the person on both the awareness and practice levels. Strategies might include finding a mentor, joining known pro-social or support groups, learning new skills/hobbies, and creating new social connections where the person's new, healthy behavior will be expected by those involved in the activities.

4.2.17 Socialization Failure

Socialization failure during childhood and adolescence has been consistently linked to crime and delinquency. Problems in the family and inadequate parenting are the critical background issues (Lykken, 1995). We have constructed a higher order factor in COMPAS that builds on the early onset of delinquency, problem behavior in school (dropout, suspensions, fighting, etc.), inadequate parental socialization, and early drug use. These are all well known risk factors for later criminality (Chaiken, Chaiken, & Rhodes, 1994; Lykken, 1995) and all represent early socialization problems. Lykken (1995) in particular, explores the link between socialization failure and criminal behavior in his concept of the sociopath.

This scale combines items reflecting family problems, early school problems, and early delinquency, all of which suggest socialization failure (how the person was socialized growing up). The intent is to examine socialization breakdown through its early indicators in school, delinquency, and family problems. A high score would represent a person whose parents were jailed or convicted or had alcohol or drug problems. In addition, a high score is associated with early behavior problems in school (being expelled, failing grades, skipping classes, fighting) and would also manifest serious delinquency problems.

This scale looks at the history or pathway that was involved in the person's upbringing that may have significantly affected his/her view of the world in terms of trust, respect for reasonable authority, value of others, and the development of beliefs and attitudes that are active and present today. High scoring individuals may need cognitive restructuring programs to assist in an awareness of, and change plan for, some of the beliefs and attitudes that lead to troublesome behavior for the person.

Table 4.14: Case Planning example for Early Socialization Failure

Goal	Build new and increase my positive coping skills and responses.
Task	Attend and successfully complete cognitive behavioral program.
Activity	Complete first exercise in workbook by 3-20-10 and bring the completed exercise to the next probation appointment. Participate in the cog group by engaging the exercise on My Thoughts, and participating in the role play discussion.
Note	In the case of a structured, sequenced program, case planning will often be stated as in the example above.

4.2.18 Substance Abuse

Numerous published research studies have established that substance abuse is a significant risk factor for both general criminal behavior and violent behavior. Substance abuse emerged as one of the major risk factors in the meta-analysis studies of Gendreau et al. (1996).

The present scale is a general indicator of substance abuse problems. A high score suggests a person has drug or alcohol problems and may need substance abuse intervention. The items in this scale cover prior treatment for alcohol or drug problems, drunk driving arrests, blaming drugs or alcohol for present problems, drug use as a juvenile, and so on.

The cut points on this scale are lower than the other needs scales due to the design of the scale. A person who scores in the Probable range (3-4) is considered a person who is in need of further evaluation (i.e. ASI, SASSI, etc.) and a person who scores in the Highly Probable range (5-10) may have a serious alcohol or drug problem requiring a structured treatment approach. Because of the high incidence of drug/alcohol abuse within the criminal justice population, a primary intervention for many individuals to impact recidivism is assisting the person to attain and maintain sobriety.

Substance abuse typically intersects every life area for a person. Therefore, cognitive behavioral restructuring and life skills planning may be needed following, or, in some cases during, treatment. Case planning language varies in this area between the example shown under the Socialization Failure (Table 4.14) scale regarding structured, sequenced steps, and, the use of supervision focused goals and tasks as listed in Table 4.15.

Table 4.15: Case Planning example for Substance Abuse

Goal	Maintain Sobriety
Task	Attend AA meetings 3 times per week and show my attendance card to my PO at each meeting.
Task	Call in for UA/BAC testing daily and report by 5pm on the day I am to do my testing.

4.2.19 Vocation/Education

Another of the “big five” risk factors for crime and recidivism prediction in the Gendreau et al. (1996) meta-analysis is labeled “social achievement.” This concept is an amalgam of educational attainment, vocational skills, job opportunities, a record of stable employment, good income, and, more generally, the level of legitimate economic opportunity. Basically, persons with more social capital have higher “life chances” than other persons who may have very restricted opportunities for success (Hagan, 1998; Coleman, 1990). The family is of critical importance in building social capital. Parents either transmit positive and substantial social capital to their child or fail in the socialization process. This scale is a higher order factor in COMPAS, using items from both educational and vocational domains. Individuals differ greatly in access to social capital or other resources. Social capital is somewhat dynamic. It can be built or destroyed. For example, a record of serious criminal behavior or high school dropout will clearly diminish life chances and social resources, whereas completing a job skills training course or obtaining a GED may increase these chances.

This higher order scale assesses the degree of success or failure in the areas of work and education. A high score represents a lack of resources. Those who score high will present a combination of failure to complete high school, suspension or expulsion from school, poor grades, no job skills, no current job, poor employment history, access only to minimum wage jobs, etc. Thus, the scale represents a lack of educational and/or vocational resources.

A score in the Probable range is significant in that a person may be struggling to seek and maintain employment that meets his/her skill set, ability, and interests. Vocational stability plays a significant role in success on community supervision. Intervention can therefore be initiated during incarceration or upon release. Education, or additional training may be the reasonable answer to assisting the person to maintain employment. Therefore, it is important to look at the whole picture in this domain when assessing paths and barriers to success.

Table 4.16: Case Planning example for Vocation/Education

Goal	Develop vocational skills
Task	Immediate Needs: Ask myself what it will take to meet the goals I am setting, identify barriers that come from others/situations, and those that I have put in place.
Task	Immediate Needs: Identify methods to break down the barriers that I have put in place, use my resources (supervisor, PO, instructor) to move forward with my plan.
Task	Enroll in vocational training program using the funding source I found when I contacted the instructor at the school.

4.2.20 The Lie Scale and Random Responding Test

These validity tests provide alerts that the person being assessed by COMPAS is possibly “faking good” or is responding randomly.

Items in the Lie Scale include questions about feeling unhappy or angry with the options across a Likert scale that include “never.” Since it is highly unlikely that a person has never felt unhappy or angry, the selection of “never” would suggest they are not telling the truth, or perhaps they are being careless with their responses. If several of the items on the Lie scale are given extreme answers, the criminal justice professional is then alerted to the possibility that the person is not responding truthfully.

The Random Responding scale is based on 37 highly correlated pairs of COMPAS scale items. Some items appear more than once in the pairs as they relate to more than one construct. Random responding has the effect of breaking these correlations. The cutting score was internally set up to detect the 5% of the respondents at the extreme end of the distribution who might be answering the questionnaire in a random fashion.

Chapter 5

Typology

The fact that people respond differently to different treatments has been labeled as responsivity and repeats the conventional wisdom that “one man’s meat is another man’s poison.” It indicates that the wrong treatment may make things worse and creates a need for careful matching of people to specific treatments. This is central to both “What Works” and to the Risk-Need-Responsivity (RNR) model. It also underlies Evidence-Based Practice (EBP), since incorrect matching of a person to treatment may sabotage the effectiveness of virtually any intervention. Thus, a challenge for treatment providers is to match intake assessments to service plans in order to achieve good outcomes. [Andrews et al. \(2006\)](#) recently acknowledge that specific responsivity or differential matching is the least explored of all the RNR principles. The traditional strategy for “matching” has been to develop treatment-relevant classifications to guide differential matching ([Warren, 1971](#); [Megargee & Bohn, 1979](#); [S. Baird, Heinz, & Bemus, 1979](#)). Most of these classification efforts failed because of a variety of technical problems ([Harris & Jones, 1999](#)).

However, we have developed risk and need typologies to facilitate the goals of specific responsivity and to guide the matching of interventions to client needs in the context of the COMPAS system. We have developed treatment-relevant typologies for both males and females. These are now included as a standard component of the COMPAS software. These typologies use advanced pattern recognition, cross-validation procedures and multiple methods to verify the stability of the typologies. Each person is now automatically classified on the basis of “best fit” to one of several standard and replicated needs profiles. The class profile of each person is automatically produced as part of the standard report to help treatment staff conceptualize the “kind” of client they are dealing with, and to develop a service plan to meet the specific responsivity needs of that unique individual. It is important to realize that no person is a perfect match to his/her class and will be unique in his/her overall pattern of risks and needs. However, his/her assigned prototype membership will suggest a beginning “framework” for a case plan that may then be customized according to the unique risk and need patterns of each person. Thus, the default treatment plans for each prototype will provide treatment staff a useful initial guide to the most likely kind of service plan for each individual.

The scales required to determine a type in the COMPAS Core typology are: Criminal As-

sociates, Substance Abuse, Financial Problems, Vocation/Education, Family Criminality, Social Environment, Leisure/Boredom, Residential Instability, Social Isolation, Criminal Attitudes, Criminal Personality, and Age at Assessment.

5.1 Interpretation

Questions may arise as to how to interpret the COMPAS typology assignment and how to integrate it into the case plan. Overall, we suggest that the typology results should be interpreted in the context of the other three key classification elements that are provided in the overall COMPAS Risk Assessment. These are as follows:

1. Risk Potential Scales (Predictive levels): These two (red) scales represent overall risk potential scales. They include separate risk scales for Violent Recidivism and General Recidivism.
2. Risk and Need Profiles (Prior history): Next, the profile chart provides the person's decile scores on all background scales (e.g., criminal history, drugs, peers, family, work/education, etc.). These provide the basic data elements that drive risk predictions, needs assessment and treatment plans.
3. Explanatory Typology: This provides the closest fit of each person to one of eight prototypical categories. The eight types represent different kinds of people. It is important to remember that the profile chart of any individual person will never be an exact match to his closest prototype. Many people are hybrids that may not fit well into any typology.

These three elements may be used collectively to guide case formulation and to understand what is "going on" with a case, and to select supervision levels and treatment interventions.

Other important elements that may influence case formulation are as follows:

Recommended Level of Supervision: The recommended level of supervision is found in the Assessment Summary section. The Violence and Recidivism risk potential factors are the main drivers of this recommendation.

Overrides of the supervision level: Overrides of the calculated recommended supervision level are clearly appropriate when it is felt that the automated procedure is either over- or under-estimating the risk level. This is especially true when the screener can identify the presence of mitigating or aggravating factors. Examples of mitigating factors are such things as your own street knowledge of the person, age and any extended periods of crime free behavior, etc. Aggravating factors are such things as severity of offense, gang membership, your knowledge of their street behavior, of non-apprehended crimes, or concerns on the Lie Scale or Random Response Score (as applicable).

Common Prototypes versus Anomalous cases: There are several things to understand about the typology label:

1. The typologies represent “Common Types” of people: We have found that there are eight common categories or prototypical offending and behavior patterns that often re-appear in criminal justice populations. These eight prototypes are described in the software and the software assigns each client to their nearest prototype. However, please remember that no individual is ever an exact match to his/her typology. In most cases there will be a good match to the closest fitting category, but will always have some differences to the ideal prototype. However, some cases will NOT be a good match to any prototype, or may straddle the boundaries between two prototypes. These boundary or hybrid cases are not given a prototype assignment and must be interpreted as unique cases.
2. What to do with the poor fitting/boundary cases: With boundary or hybrid cases, the typology should be ignored, or used as a starting point for a more individualized interpretation. Such boundary types are often harder to interpret and are more complex. If the screener’s judgment clearly disagrees with the computer-assigned prototype then an override is appropriate. The anomaly should be reported and the counselor will interpret the case using the individual’s case chart and other relevant information to determine processing and treatment plans.
3. Typology Purposes are explanatory and for treatment planning: A main purpose of the typology is to give an alert if a case belongs to one of the major case types (e.g., a young streetwise gang member; an older repeat drinking driver, etc). If a case is a good fit this may help in understanding the case and it’s treatment needs since such kinds of cases will have been seen before.
4. The Typology is not a risk classification! The typology emphasizes explanatory and need profiles and treatment: The typology prototypes represent diverse profiles of need factors, and are not designed as a predictive risk classification. Thus, the typology alone should not be used to determine risk levels but it may often help in risk and placement decisions if used in conjunction with the risk scales.

5.2 Male Typology

5.2.1 Type Descriptions

Category 1 - Chronic drug abusers – most non-violent

The central theme of this prototype is long-term substance abuse and non-violent offences. For example, serious substance abuse and use of alcohol/drugs at the current arrest. Problems often begin in adolescence, for example, with first arrests around age 16 or 17. Factors underlying this type may include mixtures of family criminality, family disorganization, out-of-home placements and some juvenile socialization problems. The profile appears in all ethnic groups, but especially young Anglos. The social context does not suggest total social exclusion. For example, some members have relatively few social risk factors and some strengths such as low poverty, educational-vocational resources, stable residence in good neighborhoods and are not isolated, bored or socially rejected. Anti-social personality and extreme criminal attitudes are mostly absent.

Official criminal histories support this profile. This type averages of 3 to 4 prior arrests mostly for drug use or trafficking. This category is mostly non-violent with relatively low current violence, low weapon offences and low victim injuries – although in some cases the current charge includes assault. There is little evidence of domestic violence and sex offences.

Category 2 - Low risk situational – fighting/domestic violence caution

This type has several economic and educational “strengths” suggesting an apparently normal citizen. They mostly avoid criminal associates and follow a low risk lifestyle. However, some members of this group are involved in serious violence, thus caution is warranted. These persons generally are not raised in high crime families, avoid drugs, have stable addresses in safe areas and few financial problems. Personality and criminal attitudes appear average. The profile offers no clear social or criminogenic explanation for offending or for violence. This pattern may reflect the well known accidental or situational event that unexpectedly occurs to create serious violence and an arrest situation.

The official criminal history reflects a low risk profile. The group, as a whole, has fewer official arrests, convictions or prior violence than other types. The official data shows lower violence history, lower weapons use, lower non-compliance, fewer probation episodes and almost no burglaries, robberies, The current offense often is for DUI, substance abuse or an assault (fight/no weapons). Many are incarcerated for the first time. However, as noted above, some members of this group have been charged with a serious assault and/or domestic violence. This category occurs in all ethnic or racial groups – a variant is found in Category 8.

Category 3 - Chronic alcohol problems – DUI, domestic violence

The dominant pattern of this category consists of older (40+), mostly relatively well-educated men who function fairly well with stable jobs, finances and residences, but with recurrent

alcohol problems and a history of DUI and/or domestic violence. They show the oldest age at first arrest (27) and are thus late starters. A generally low risk lifestyle is reflected by few criminal peers, educational-vocational and financial success, low crime families, stable and safe addresses and pro-social structured leisure. They mostly avoid high-risk situations and do not appear to hold anti-social attitudes or personalities. Thus, the explanation for their offending would appear to relate to alcohol proneness perhaps in a context of family stress, rather than social exclusion or environmental explanations.

The official data corroborates this pattern showing that this group has the highest score for current DUI arrest and using alcohol (but not drugs) at the current arrest. Overall, they have average criminal involvement and few violent offenses. However, domestic violence also occurs for some of these people. DUI and alcohol abuse are the major problems since the category has lower clusters arrest rates than other clusters for current violence, weapon arrests, assaults, juvenile felony arrests, fraud, property, burglary and robbery offenses. COMPAS risk scales assign this category to low risk, although this is influenced by their older age (since age lowers risk scores in the risk equations). Thus, they may be expected to have a moderate recidivism risk mainly for drug/alcohol related offenses or domestic violence.

Category 4 - Socially marginalized – poor, uneducated, stressed, habitual offenders

The central problem in this type is socio-economic marginalization (e.g., educational-vocational failure, poor job skills, poverty, unstable residence, poor social supports and social isolation). This category is older (average age 37) and occurs in all ethnic groups. The social resources for these men appear reasonable since they mostly do not have high crime families or antisocial peers, do not reside in high crime areas and do not hold extreme criminal attitudes – all of which argue against a social learning explanation and do not suggest a high-risk lifestyle. There is also little evidence of criminal personality.

Many of these cases are chronic repeaters with multiple arrests, probation terms and convictions. Their official criminal history coheres with the above profile in two main ways. First, they are mostly late starters with a late age at first arrest (21), few juvenile felonies and a relative absence of juvenile socialization problems. Second, their offense pattern of fraud larceny (and some drug trafficking) and low robbery, suggests instrumental crime for financial gain, or perhaps coping with poverty and unemployment. Finally, some of these men exhibit prior domestic violence that coheres with prior weapons use and victim injury. Substance abuse and criminal opportunity scores are about average.

Note: Mental health (MH) problems are often linked to social isolation and social adjustment problems. Thus, cases with MH and social withdrawal problems may enter this lonely marginalized category. A mental health assessment is recommended to clarify MH issues.

Category 5 - Criminally versatile – young marginalized persons often gang affiliated

This pattern exhibits multiple risk factors and several co-occurring causal processes linked to criminality. First, is extreme social exclusion/marginalization (e.g., educational-vocational failure, joblessness and poverty). Second is a lack of social control bonds, withdrawal from education and work, boredom and little constructive use of leisure. Third, their high-risk criminal opportunity lifestyle is reflected in weak pro-social bonds, boredom and higher than average gang affiliation. Fourth, social learning is suggested by a pattern of anti-social attitudes, gang membership (for some), early school failure and out-of-home placements, all implying affiliation with other rejected and weakly socialized peers. Finally, many of these cases reflect an anti-social personality that has been empirically linked to family disintegration, family crime, juvenile felonies and early onset shown by many of these cases. These themes reflect the sociopathic type of described by Lykken (1995) and Mealey (1995), and others.

The criminal history of this category coheres with the above high risk profile. This young group (22-23 average age) generally has an early age at first arrest (around 16), higher scores than other types for juvenile felonies, weapons arrests, current violence, current property and sex offense charges. However, there are two anomalies. First, they show relatively low substance abuse. Second they score only average for prior arrests and convictions, perhaps resulting from their youth (i.e., their early stage of a criminal career).

Category 6 - Socially isolated long term substance abuse – multiple minor and mostly non-violent offenses

This group reflects four major criminogenic problems. First, many members exhibit serious long-term substance abuse, suggesting addiction. Second, their extreme marginalization is shown by social isolation, poverty, unstable residence, poor social adjustment, boredom and a lack of pro-social leisure activities. Third, they appear embedded in a criminal drug culture and exhibit high criminal opportunity. Finally, a disposition for criminality is shown by high crime personality and antisocial attitudes. This type occurs in all ethnic groups.

The official criminal history matches this profile in several ways. Chronic criminality is shown by multiple arrests, convictions and probations. Chronic substance abuse is confirmed by alcohol and drug offenses, using hard drugs (heroin, cocaine) as juveniles, being high/intoxicated at current arrest and (in some cases) current drunk driving and/or drug possession charges (but rarely trafficking). This category is difficult to treat as shown by non-compliance, probation/parole revocations and FTA's. They also exhibit above average scores for current fraud, prior domestic violence and burglary/larceny (but, rarely robbery). Criminal violence (except for domestic violence) is rare as shown by relatively low arrests/convictions for weapons offenses and lower scores for assaultive felonies.

Category 7 - Serious versatile high risk individuals

This type has the most serious and violent profile. It may warrant referral for a test such as the Psychopathy Check List (PCL). This profile reflects a chronic, violent and versatile criminal career as well as multiple criminogenic risk factors.

This profile reflects four major causal processes linked to high criminality. 1) A strong personal disposition to crime is shown by anti-social personality, antisocial attitudes/thinking, early onset of crime, parental criminality and versatile criminal offences. 2) Social marginalization is shown by educational/vocational failure, unstable residence, poverty, boredom and weak pro-social ties. 3) Social learning as reflected by anti-social peers, anti-social neighborhood, parent criminal behavior and anti-social thinking. 4) Poor socialization is suggested by parental crime and family disorganization, early juvenile onset, early failure in school, criminal attitudes.

The official criminal history matches this extreme criminogenic profile. It has the most chronic and dangerous criminal career with the highest scores for criminal involvement, juvenile onset, non-compliance and violent and versatile offending. These people have the highest scores for arrests and convictions for robbery, burglary, weapon offenses, assaults, injury to victims, violent felonies, fraud, drug possession and domestic violence arrests.

Category 8 - Low risk situational accidental category

Like Category 2, this category reflects lower criminogenic risks and more pro-social strengths than most other categories. Thus, this profile offers no clear explanation for their engagement in the criminal justice system. Like Category 2, these persons reflect perhaps “normal” folks who became embroiled in a situational-accidental event that led to entry into the criminal justice system. Many members of this category will have less poverty, more adequate jobs and education, more stable residence in safer areas than most persons in this population. They appear mostly to avoid anti-social peers and criminal opportunities and may have pro-social ties. Their attitudes and personalities are not clearly anti-social. They report low drug use (compared to other groups), fewer criminal peers, lower family crime and positive use of leisure.

The criminal history of this category confirms its low risk, non-violent status. Most have few prior arrests and for many this may be their first incarceration. They generally have fewer felonies or weapons offenses, and less history of probation or probation failure. Most are assigned to the lowest risk category by the COMPAS risk models.

The current arrest pattern perhaps explains the situational nature of this category. Specifically, they have the lowest (mostly zero) scores for felony charges, assaultive felonies, weapons offenses, victim injury, family violence, burglary/larceny, robbery and drug offenses. In many cases their arrests are alcohol related, simple assault, drunk driving, non-felony fraud or minor property offense, or a sex offense. Thus, it is prudent to check the details (if available) of the current offense of persons in this category.

An important caution is that a small percentage of this type may be “faking good” as indicated by the Lie Test score. Thus, while many are truly low risk (as confirmed by official

history) a small percentage may be lying. Thus, it is still prudent to show caution with these persons.

5.3 Female Typology

5.3.1 Type Descriptions

Category 1 - Drug problems and anti-social sub-cultural influences – some with relationship conflicts

This group (average age 35) appears locked into a high-risk sub-culture e.g. anti-social peers, anti-social family and residence in a high-risk crime environment. Some reflect early onset of teenage delinquency and cocaine use as a juvenile. Chronic drug problems are suggested by above average scores for previous drug treatments and drug possession charges. Many of these women hold anti-social attitudes. This profile suggests a social learning process where these women are socialized within an anti-social drug sub-culture. However, some strengths are still present for some of these women, e.g., stable housing, adequate use of leisure time and apparently good social support. The group criminal history is about average and not noticeably violent – although the group is above average for jail and probation terms, prior convictions and non-compliance history. For some of these women their current domestic violence charges suggest relationship conflict.

Category 2 - Family disorganization and inadequate parenting – residential instability and minor non-violent offences

This younger group has an average age of 25 years. Early family disorganization, abuse and inadequate parents appear central. Their high scores for family criminality and juvenile out-of-home placements suggests inadequate parenting. Their high juvenile socialization score also suggests early onset of problems. Their adult life challenges include residential instability and social adjustment problems. However, several positive features emerge for some of these women, i.e., lower than average scores for criminal peers, below average scores for criminal attitudes and criminal personality. Many of these women appear to avoid drugs, with relatively few reporting drug treatment or use of drugs as juveniles. The profile suggests some positive social supports and fairly constructive use of leisure time. The criminal history is consistent with the above profile and is mostly non-violent and fairly low for non-compliance. The most common current charge is minor fraud. Mental health issues may be explored given the possibility of early family abuse and/or neglect.

Category 3 - Chronic substance abusers – women with higher social resources than other groups

This older (average age 38) category shows less poverty, more positive education and vocational skills and residence in an apparently safe low crime areas, than other categories. These positive features are consistent with lower than average scores for criminal associates, lower anti-social attitudes and a fairly positive use of leisure time. The group appears to have relatively fewer social adjustment problems, better social supports and a lifestyle that avoids high risks and criminal opportunity. They do not have high scores for criminal personality.

The official data matches this profile with a relatively late onset, mostly minor offenses and few juvenile problems.

DUI is the most frequent current offence among these mostly non-violent women – although some also have domestic a violence record. However, the presence of prior convictions, prior drug offences and frequency of prior treatments for drugs and/or alcohol underscores a clearly chronic substance abuse problem.

Category 4 - Marginalized poor and isolated older women – economic survival crimes

The average age of this group is 40 years. This group is characterized by poverty, social isolation and a lower than average constructive leisure activities. This group has a late onset with an average age at first arrest of 27 years. Their criminal history mainly involves minor fraud. Aside from poverty they show few other criminogenic factors. For example, they fall below average for criminal peers, antisocial attitudes, living in high crime areas or following high opportunity lifestyles. Their family of origin appears relatively law abiding. Their history exhibits few juvenile problems. It appears that their problems mostly emerge in adulthood from poverty and poor social support. Their instrumental crimes such as minor fraud and sex offences may be for economic survival. Their poor social adjustment and social isolation suggest screening for mental health problems. The risk assessment assigns most of these women to a low risk non-violent category.

Category 5 - Young antisocial poorly educated women with some violent offences and early delinquency onset

This younger category (average age is 25) has a limited adult criminal history - with relatively few adult arrests or convictions - but the highest score for a current violent offence, some involving felony and weapons charges. Their criminogenic factors include: early onset of delinquency, above average antisocial personality, antisocial attitudes, poor education/vocational resources, bored/unproductive use of leisure hours and pessimism about finding a good job. Early delinquency is reflected in higher than average juvenile marijuana and alcohol use (but fewer hard drugs), high school dropout and the earliest first arrest. Surprisingly, the group has relatively low affiliation with antisocial peers or gangs; no clear tendency to live in high crime areas, abuse drugs, or to have extreme poverty or a high crime family background. Their relatively low formal adult criminal histories, appear consistent with their average scores on COMPAS risk assessment scales. However, the presence of early onset delinquency and, in some cases, serious current violence suggests caution with this group.

Category 6 - Chronic long term criminal history A – multiple co-occurring social and psychological risk factors

Drugs, extreme socio-economic marginalization, teen onset of problems and extreme problems in social relations characterize this high risk category. The recidivism risk computation

identifies this group as high risk. Multiple criminogenic factors co-occur, including: antisocial peers, antisocial attitudes, antisocial personality, extreme substance abuse, high crime family, poverty, extreme vocational and educational deficits, inability to use leisure time constructively and a tendency to live a high risk life style. Problems started early and these women report the highest levels for out-of-home placements as juveniles, the worst school grades, the highest use of cocaine as a juvenile, the earliest first arrest and the highest number of juvenile felony arrests. This is a non-compliant group with multiple failures and extreme drug problems. Social isolation and social adjustment problems are high. This group commits a variety of offences, including: domestic violence, drug possession, and other assault.

Category 7 - Chronic long term criminal history B – multiple co-occurring problems and high risk

This rare and infrequent group is a more serious version of type 6. While both categories have multiple co-occurring risk and need factors group 7 is systematically higher than group 6. This category has the highest scores for: violence risk, recidivism risk, FTA risk and technical violation risk. They are highest for: overall criminal history, history of non-compliance, current violence and juvenile delinquency indicators. The multiple criminogenic factors include: residential instability, family crime, vocational-educational failures, antisocial attitudes, antisocial personality, social adjustment problems, social isolation/withdrawal, extreme drug use and so on. Compared to Category 6, this group has the highest scores for current violence, injuries to victims, current felony arrests and current robberies. They exhibit extreme poverty, live in higher risk areas and report more gang affiliations.

Category 8 - Late starters with multiple strengths and fewer risk factors – minor non-violent offence history

These women (like pattern 3) reflect higher resources than other groups for educational and vocational scores, jobs, completing high school, living in safer areas, stable housing, better social supports and fewer leisure problems. Their family background appears more pro-social and they report less poverty, antisocial attitudes or personality issues. This group appears to adopt safer lifestyles by avoiding anti-social persons, fewer drug problems and more pro-social leisure activities. While, we may be suspicious of this positive profile, their official criminal history is consistent with this low risk profile showing the lowest criminal involvement and incarcerations, the fewest arrests and convictions, the lowest arrest rate, the lowest felony charges, the lowest pending charges, less non-compliance and the oldest age at first arrest (average age is 27). Current charges reflect minor fraud and DUI. This official data therefore coheres with this low need/risk profile. However, some women in this category may be “faking good.” This was detected using the built-in COMPAS validity test for defensive faking-good responses and notice should be taken of this warning.

Bibliography

- Andrews, D. A., & Bonta, J. (1994). *The psychology of criminal conduct*. Cincinnati: Anderson Press.
- Andrews, D. A., Bonta, J., & Hoge, R. D. (1990). Classification for effective rehabilitation: Rediscovering psychology. *Criminal Justice and Behavior*, 17(1), 19-52.
- Andrews, D. A., Bonta, J., & Wormith, J. S. (2006). The recent past and near future of risk and/or needs assessment. *Crime and Delinquency*, 52(1), 7-27.
- Andrews, D. A., Zinger, I., Hoge, R. D., Bonta, J., Gendreau, P., & Cullen, F. T. (1990). Does correctional treatment work? A clinically relevant and psychologically informed meta-analysis. *Criminology*, 28(3), 369-403.
- Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016, May). Machine bias. ProPublica.
- Babchishin, K. M., & Helmus, L. M. (2016). The influence of base rates on correlations: An evaluation of proposed alternative effect sizes with real-world data. *Behavior Research Methods*, 48(3), 1021-1031.
- Baird, C. (2009). A question of evidence: A critique of risk assessment models used in the justice system. (Tech. Rep.). Madison, WI: National Council on Crime and Delinquency.
- Baird, S., Heinz, R., & Bemus, B. (1979). Project report 14: Two-year follow-up.
- Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (1996). Mechanisms of moral disengagement in the exercise of moral agency. *Journal of Personality and Social Psychology*, 71(2), 364-374.
- Barbaree, H. E., Seto, M., Langton, C. M., & Peacock, E. J. (2001). Evaluating the predictive accuracy of six risk assessment instruments for adult sex offenders. *Criminal Justice and Behavior*, 28(4), 490-521.
- Barnoski, R., & Aos, S. (2003). Washington's Offender Accountability Act: An analysis of the Department of Corrections' risk assessment (document no. 03-12-1202) (Tech. Rep.). Olympia, WA: Washington State Institute for Public Policy.
- Barnoski, R., & Drake, E. K. (2007). Washington's Offender Accountability Act: Department of Corrections' static risk assessment (Tech. Rep.). Olympia, WA: Washington State Institute for Public Policy.
- Berk, R. A. (2012). *Criminal justice forecasts of risk: A machine learning approach*. New York, NY: Springer.
- Berk, R. A. (2016). A primer on fairness in criminal justice risk assessments. *The Criminologist*, 41(6), 6 - 9.
- Berk, R. A., & Bleich, J. (2013). Statistical procedures for forecasting criminal behavior: A comparative assessment. *Criminology & Public Policy*, 12, 513-544.

- Berk, R. A., Heidari, H., Jabbari, S., Kearns, M., & Roth, A. (2018). Fairness in criminal justice risk assessment: The state of the art. *Sociological Methods & Research*. (Advance online publication. doi.org/10.1177/0049124118782533)
- Blomberg, T., Bates, W., Mann, K., Meldrum, R., & Nedelec, J. (2010). Validation of the COMPAS risk assessment classification instrument (Tech. Rep.). Tallahassee, Florida: Center for Criminology and Public Policy Research, College of Criminology and Criminal Justice, Florida State University.
- Bonta, J. (1996). Risk-needs assessment and treatment. Thousand Oaks, CA: Sage.
- Bonta, J., Law, M., & Hanson, K. (1998). The prediction of criminal and violent recidivism among mentally disordered offenders: A meta-analysis. *Psychological Bulletin*, 123(2), 123–142.
- Brennan, T., & Dieterich, W. (2008). Michigan Department of Corrections Core COMPAS pilot study: One-year follow-up (Tech. Rep.). Traverse City, MI: Northpointe Institute for Public Management.
- Brennan, T., & Dieterich, W. (2009). Testing the predictive validity of the DPCA COMPAS risk scales: Phase I (Tech. Rep.). Traverse City, MI: Northpointe Institute for Public Management.
- Brennan, T., Dieterich, W., & Ehret, B. (2009). Evaluating the predictive validity of the COMPAS risk and needs assessment system. *Criminal Justice and Behavior*, 36, 21-40.
- Brennan, T., & Oliver, W. L. (2013). The emergence of machine learning techniques in criminology. *Criminology and Public Policy*, 12, 551-562.
- Bucklen, K. B., & Zajac, G. (2009). But some of them don't come back (to prison!): Resource deprivation and thinking errors as determinants of parole success and failure. *The Prison Journal*, 89, 239-264.
- Bureau of Justice Statistics. (2012). Correctional populations in the United States, 2011. Washington, D.C.: U.S. Department of Justice, Office of Justice Programs.
- Chaiken, J., Chaiken, M., & Rhodes, W. (1994). Predicting violent behavior and classifying violent offenders. In A. Reiss & J. Roth (Eds.), *Understanding and preventing violence*, vol. 4: Consequences and control (pp. 217–295). Washington, D.C: National Academy Press.
- Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.
- Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 44, 588-608.
- Coleman, J. S. (1990). *Foundations of social theory*. Cambridge, Mass: Harvard University Press.
- Committee on Assessing Juvenile Justice Reform. (2013). *Reforming juvenile justice: A developmental approach* (R. J. Bonnie, R. L. Johnson, B. M. Chemers, & J. A. Schuck, Eds.). Washington, D.C.: The National Academies Press.
- Cooke, D. J., Forth, A. E., & Hare, R. D. (Eds.). (1998). *Psychopathy: Theory, research and implications for society*. Dordrecht, Netherlands: Kluwer Academic Publishers.
- Copas, J., & Marshall, P. (1998). The offender group reconviction scale: A statistical reconviction score for use by probation officers. *Applied Statistics*, 47, 159 - 171.
- Dahle, K. P. (2006). Strengths and limitations of actuarial prediction of criminal re-offence in a German prison sample: A comparative study of LSI-R, HCR-20 and PCL-R.

- International Journal of Law and Psychiatry, 29(5), 431-442.
- Desmarais, S. L., & Singh, J. P. (2013). Risk assessment instruments validated and implemented in correctional settings in the United States. (Tech. Rep.). Lexington, KY: Council of State Governments Justice Center.
- Dieterich, W. (2010). Kent County Pretrial Services outcomes study: Developing and testing the COMPAS pretrial release risk scale. (Tech. Rep.). Traverse City, MI: Northpointe.
- Dieterich, W., Brennan, T., & Oliver, W. L. (2011). Predictive validity of the COMPAS Core risk scales: A probation outcomes study conducted for the Michigan Department of Corrections (Tech. Rep.). Traverse City, MI: Northpointe Inc.
- Dieterich, W., Mendoza, C., & Brennan, T. (2016). Compas risk scales: Demonstrating accuracy equity and predictive parity: Performance of the COMPAS risk scales in Broward County (Tech. Rep.). Traverse City, MI: Northpointe Inc.
- Dieterich, W., Mendoza, C., Hubbard, D., Ferro, J., & Brennan, T. (2017). COMPAS risk scales validation study: An outcomes study conducted for the Santa Barbara County Probation Department (Tech. Rep.). Traverse City, MI: Northpointe.
- Dieterich, W., Mendoza, C., Hubbard, D., Ferro, J., & Brennan, T. (2018). COMPAS risk scales validation study: An outcomes study conducted for the Riverside County Probation Department (Tech. Rep.). Traverse City, MI: Northpointe.
- Dieterich, W., Oliver, W., & Brennan, T. (2011). Predictive validity of the Reentry COMPAS Risk scales: An outcomes study with extended follow-up conducted for the Michigan Department of Corrections. (Tech. Rep.). Traverse City, MI: Northpointe Inc.
- Division of Probation and Correctional Alternatives. (2007). New York State pretrial release services standards.
- Dodge, K. A. (1998). The structure and function of reactive and proactive aggression. In D. J. Pepler & K. H. Rubin (Eds.), *The development and treatment of childhood aggression* (pp. 201–218). Hillsdale, N.J.: Lawrence Erlbaum.
- Dodge, K. A., Pettit, G. S., McClaskey, C. L., & Brown, M. M. (1986). Social competence in children. *Monograph of the Society for Research in Child Development*, 51(2), 1–85.
- Elliot, D. S., Huizinga, D., & Ageton, S. (1985). *Explaining delinquency and drug use*. Beverly Hills, CA: Sage Publications.
- Estroff, S. E., & Zimmer, C. (1994). Social networks, social support, and violence among persons with severe, persistent mental illness. In J. Monahan & H. J. Steadman (Eds.), *Violence and mental disorder: Developments in risk assessment* (pp. 259–295). Chicago: University of Chicago Press.
- Farabee, D., Zhang, S., Roberts, R. E., & Yang, J. (2010). COMPAS validation study: Final report (Tech. Rep.). UCLA Integrated Substance Abuse Programs.
- Farrington, D. P. (1991). Childhood aggression and adult violence: Early precursors and later life outcomes. In D. J. Pepler & K. H. Rubin (Eds.), *The development and treatment of childhood aggression* (pp. 5–29). Hillsdale, NJ: Lawrence Erlbaum.
- Farrington, D. P., Jolliffe, D., Loeber, R., Stouthamer-Loeber, M., & Kalb, L. M. (2001). The concentration of offenders in families, and family criminality in the prediction of boys' delinquency. *Journal of Adolescence*, 24, 579–596.
- Fass, T., Heilbrun, K., DeMatteo, D., & Fretz, R. (2008). The LSI-R and the COMPAS. *Criminal Justice and Behavior*, 35, 1095–1108.

- Fischer, C. (1995). The subcultural theory of urbanism: A twentieth year assessment. *American Journal of Sociology*, 101, 543 - 577.
- Flores, A. W., Bechtel, K., & Lowenkamp, C. (2016). False positives, false negatives, and false analyses: A rejoinder to Machine bias: There's software used across the country to predict future criminals. And it's biased against Blacks. *Federal Probation*, 80(2), 38-46.
- Flores, A. W., Lowenkamp, C. T., Smith, P., & Latessa, E. J. (2006). Validating the Level of Service Inventory-Revised on a sample of federal probationers. *Federal Probation*, 70(2), 44-78.
- Gendreau, P., Goggin, C., & Little, T. (1996). A meta-analysis of the predictors of adult offender recidivism: What works! *Criminology*, 34, 575-607.
- Gendreau, P., Goggin, C. E., & Law, M. A. (1997). Predicting prison misconducts. *Criminal Justice and Behavior*, 24(4), p414 - 431.
- Gottfredson, M. R., & Hirschi, T. (1990). *A general theory of crime*. Stanford: CA: Stanford University Press.
- Gottfredson, S. D., & Jarjoura, G. R. (1996). Race, gender, and guidelines-based decision making. *Journal of Research in Crime and Delinquency*, 33, 49-69.
- Gottfredson, S. D., & Moriarty, L. J. (2006). Statistical risk assessment: Old problems and new applications. *Crime & Delinquency*, 52, 178-200.
- Grann, M., Belfrage, H., & Tengstrom, A. (2000). Actuarial assessment of risk for violence: Predictive validity of the VRAG and the historical part of the HCR-20. *Criminal Justice and Behavior*, 27, 97-114.
- Grove, W. M., Zald, D. H., Lebow, B. S., Snitz, B. E., & Nelson, C. (2000). Clinical versus mechanical prediction: A meta-analysis. *Psychological Assessment*, 12(1), 19-30.
- Hagan, J. (1998). Life course capitalization and adolescent development. In R. Jessor (Ed.), *New perspectives on adolescent risk behavior* (pp. 499-517). New York: Cambridge University Press.
- Hamilton, Z., Kigerl, A., Campagna, M., Barnoski, R., Lee, S., van Wormer, J., & Block, L. (2017). Designed to fit: The development and validation of the STRONG-R recidivism risk assessment. *Criminal Justice and Behavior*, 43, 230-263.
- Hanson, R. K. (1997). The development of a brief actuarial risk scale for sexual offense recidivism. (User Report 97-04). Ottawa, Ontario: Department of the Solicitor General of Canada.
- Hanson, R. K., & Thornton, D. (2000). Improving risk assessments for sex offenders: A comparison of three actuarial scales. *Law and Human Behavior*, 24, 119-136.
- Hare, R. D. (1991). *Manual for the Hare Psychopathy Checklist-Revised*. Toronto, Canada: Multi-Health Systems.
- Harrell, F. E., Jr. (2001). *Regression modeling strategies*. New York: Springer.
- Harris, P., & Jones, P. R. (1999). Differentiating delinquent youths for program planning and evaluation. *Criminal Justice & Behavior*, 26(4), 403-434.
- Hastie, T., Tibshirani, R., & Friedman, J. (2008). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). New York: Springer.
- Herrenkohl, T. I., Maguin, E., Hill, K. G., Hawkins, J. D., Abbott, R. D., & Catalano, R. F. (2000). Developmental risk factors for youth violence. *Journal of Adolescent Health*, 26, 176-186.

- Hirschi, T. (1969). *Causes of delinquency*. Berkeley, CA: University of California Press.
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning with applications in R*. New York: Springer.
- Kleinberg, J., Mullainathan, S., & Raghavan, M. (2016, November). Inherent trade-offs in the fair determination of risk scores. *StatML Papers*. Retrieved from <https://arxiv.org/abs/1609.05807v2>
- Knight, K., Simpson, D. D., & Morey, J. T. (2002). *Evaluation of the TCU Drug Screen (Tech. Rep.)*. Fort Worth, TX: Institute of Behavioral Research Texas Christian University.
- Kroner, C., Stadtland, C., Eidt, M., & Nedopil, N. (2007). The validity of the violence risk appraisal guide (VRAG) in predicting criminal recidivism. *Criminal Behaviour and Mental Health*, 17(2), 89 - 100.
- Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling*. New York: Springer.
- Lansing, S. (2012). *New York State COMPAS-Probation Risk and Needs Assessment Study: Evaluating predictive accuracy (Tech. Rep.)*. Albany, New York: New York State Division of Criminal Justice Services, Office of Justice Research and Performance.
- Latessa, E. J., Lemke, R., Makarios, M., Smith, P., & Lowenkamp, C. T. (2010). The creation and validation of the Ohio Risk Assessment System (ORAS). *Federal Probation*, 74(1), 16-22.
- Latessa, E. J., Lovins, B., & Makarios, M. (2013). *Validation of the indiana risk assessment system: Final Report (Tech. Rep.)*. University of Cincinnati School of Criminal Justice.
- Latessa, E. J., Lux, J. L., Lugo, M., & Long, J. (2016). *Examining the validity and reliability of the Ohio Risk Assessment System Community Supervision Tool and Community Supervision Screening Tool (Tech. Rep.)*. University of Cincinnati.
- Latessa, E. J., Machak, S., Lux, J., Newsome, J., Lugo, M., & Papp, J. (2017). *The Ohio Risk Assessment System (ORAS): A re-validation & inter-rater reliability study (Tech. Rep.)*. Cincinnati, OH: The University of Cincinnati Corrections Institute. (Prepared for the Ohio Department of Rehabilitation and Correction)
- Linn, S. (2004). A new conceptual approach to teaching the interpretation of clinical tests. *Journal of Statistics Education*, 12, 1 - 9.
- Lovins, B. K., Latessa, E. J., May, T., & Lux, J. (2017). Validating the ohio risk assessment system community supervision tool with a diverse sample from texas. *Corrections*, 0(0), 1-17. Retrieved from <https://doi.org/10.1080/23774657.2017.1361798> doi: 10.1080/23774657.2017.1361798
- Lykken, D. (1995). *The antisocial personalities*. Hillsdale, N.J.: Lawrence Erlbaum.
- McGrath, R. J., & Hoke, S. E. (2001). *Vermont Assessment of Sex Offender Risk*. Waterbury, VT: Author
- McGrath, R. J., Lasher, M. P., Cumming, G. F., Langton, C. M., & Hoke, S. E. (2014). Development of the Vermont Assessment of Sex Offender Risk-2 (VASOR-2) Reoffense Risk Scale. *Sexual Abuse: A Journal of Research and Treatment*, 26, 271-290.
- Mealey, L. (1995). The sociobiology of sociopathy: An integrated evolutionary model. *Behavioral and Brain Sciences*, 18(3), 523-599.
- Megargee, E., & Bohn, M. (1979). *Classifying criminal offenders: A new system based on the MMPI*. Beverly Hills, CA: Sage.

- Mendoza, C., Dieterich, W., Oliver, W. L., & Brennan, T. (2016, November). Decision analysis and equity. Paper presented at the Annual Meeting of the American Society of Criminology. Philadelphia, PA.
- Moffitt, T. E. (1993). Adolescence-limited and life-course persistent antisocial behavior: A developmental taxonomy. *Psychological Review*, 100, 674–701.
- Monahan, J., & Skeem, J. (2014). Risk redux: The resurgence of risk assessment in criminal sanctioning. *Federal Sentencing Reporter*, 26, 158-166.
- National Association of Pretrial Services Agencies. (2004). National Association of Pretrial Services Agencies standards on pretrial release (3rd edition) (Tech. Rep.). National Association of Pretrial Services Agencies.
- Nelson, M., Deess, P., & Allen, C. (1999). *The first month out: Post-incarceration experiences in New York City*. New York: Vera Institute.
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). New York: McGraw-Hill.
- Osgood, D. W., Wilson, J. K., O'Malley, P. M., Bachman, J. G., & Johnston, L. D. (1996). Routine activities and individual deviant behavior. *American Sociological Review*, 61(4), 635-655.
- Palmer, T. (1994). *A profile of correctional effectiveness and new directions for research*. Albany, NY: SUNY Press.
- Parker, J. G., & Asher, S. R. (1987). Peer relations and later personal adjustment: Are low-accepted children at risk. *Psychological Bulletin*, 102(3), 357–389.
- Pepe, M. S. (2003). *The statistical evaluation of medical tests for classification and prediction*. New York: Oxford University Press.
- Petersilia, J. (2003). *When prisoners come home: Parole and prisoner reentry*. New York: Oxford University Press.
- Quinsey, V. L., Harris, G. T., Rice, M. E., & Cormier, C. A. (1998). *Violent offenders: Appraising and managing risk*. Washington, DC: American Psychological Association.
- Reich, W. A., Picard-Fritsche, S., Barber Rioja, V., & Rotter, M. (2016). *Evidence-based risk assessment in a mental health court: A validation study of the COMPAS risk assessment* (Tech. Rep.). New York: Center for Court Innovation.
- Rice, M. E., & Harris, G. T. (2005). Comparing effect sizes in follow-up studies: ROC area, Cohen's d, and r. *Law and Human Behavior*, 29(615-620).
- Sampson, R., & Lauritsen, J. (1994). Deviant lifestyles proximity to crime and the offender-victim link in personal violence. *Journal of Research in Crime and Delinquency*, 27, 7–40.
- Serin, R. C., & Lowenkamp, C. T. (2015). *Selecting and using risk and need assessments* (Vol. X) (No. I). Alexandria, VA: National Drug Court Institute.
- Singh, J. P. (2013). Predictive validity performance indicators in violence risk assessment: A methodological primer. *Behavioral Sciences and the Law*, 31, 8-22.
- Smith, P., Cullen, F. T., & Latessa, E. J. (2009). Can 14,737 women be wrong? A meta-analysis of the LSI-R and recidivism for female offenders. *Criminology and Public Policy*, 8, 183-208.
- Solomon, A. L., Visher, C., La Vigne, N. G., & Osborne, J. (2006). *Understanding the challenges of prisoner reentry: Research findings from the Urban Institute's prisoner reentry portfolio*. Washington, DC: Urban Institute Press.

- Stansfield, R., & Williams, K. R. (2014). Predicting family violence recidivism using the DVSI-R. *Criminal Justice and Behavior*, 41, 163-180.
- Stouthamer-Loeber, M., Loeber, R., Wei, E., Farrington, D. P., & Wikstrom, P.-O. H. (2002). Risk and promotive effects in the explanation of persistent serious delinquency in boys. *Journal of Consulting and Clinical Psychology*, 70, 111-123.
- Swets, J. A. (1988). Measuring the accuracy of diagnostic systems. *Science*, 240, 1285-1293.
- Swets, J. A., Dawes, R. M., & Monahan, J. (2000). Psychological science can improve diagnostic decisions. *Psychological Science in the Public Interest*, 1, 1-26.
- Thornberry, T. P., Huizinga, D., & Loeber, R. (1995). The prevention of serious delinquency and violence: Implications from the program of research on the causes and correlates of delinquency. In J. C. Howell, B. Krisberg, J. D. Hawkins, & J. J. Wilson (Eds.), *Sourcebook on serious, violent and chronic juvenile offenders* (pp. 213-237). Thousand Oaks, CA: Sage.
- Tolan, P. H., & Gorman-Smith, D. (1998). Development of serious and violent offending careers. In R. Loeber & D. P. Farrington (Eds.), *Serious and violent juvenile offenders: Risk factors and successful interventions* (pp. 68-85). Thousand Oaks, CA: Sage.
- Travis, J. (2005). *But they all come back: Facing the challenges of prisoner reentry*. Washington, DC: Urban Institute Press.
- VanNostrand, M. (2003). *Assessing risk among pretrial defendants in Virginia: The Virginia pretrial risk assessment instrument* (Tech. Rep.). Virginia Department of Criminal Justice Services.
- VanNostrand, M. (2007). *Legal and evidence-based practices: Application of legal principles, laws, and research to the field of pretrial services* (Tech. Rep.). National Institute of Corrections and Crime and Justice Institute.
- Van Voorhis, P., Wright, E., Salisbury, E., & Bauman, A. (2010). Women's risk factors and their contributions to existing risk/needs assessment: The current status of a gender-responsive supplement. *Criminal Justice And Behavior*, 37, 261-288.
- Vose, B., Cullen, F. T., & Smith, P. (2008). Empirical status of the Level of Service Inventory. *Federal Probation*, 72, 22-29.
- Warren, M. Q. (1971). Classification of offenders as an aid to efficient management and effective treatment. *Journal of Criminal Law, Criminology, and Police Science*, 62, 239-258.
- West, D. J. (1973). *Who becomes delinquent?* London: Heinemann.
- Williams, K. R., & Grant, S. R. (2006). Empirically examining the risk of intimate partner violence: The Revised Domestic Violence Screening Instrument (DVSI-R). *Public Health Reports*, 121, 400-408.

RISK ASSESSMENT FACTSHEET

Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) Pretrial Release Risk Scale - II (PRRS-II)

LAST UPDATED: June 20, 2019

REVIEWED BY: Northpointe, Inc. Research Department: Dr. William Dieterich, Dr. Eugenie Jackson, Christina Mendoza

Note: The PRRS-II is a modified version of the PRRS-I that does not include age at assessment as a factor. This factsheet discusses the PRRS-II.

Separately, according to Equivant, “The Northpointe, Inc. Research division designed a new Pretrial Assessment in 2018: the California Pretrial Assessment (CAPA). The CAPA was designed based on SB10 and is intended to serve the state of California’s pretrial reform efforts. This new assessment utilizes a point scoring system which can be administered, scored and interpreted with ease, addressing the need for full transparency in the pretrial process.

The CAPA was constructed and automated for testing purposes, and the Northpointe Research division is currently finishing a validation study on the new assessment. The CAPA validation study is being completed using a dataset provided by a California jurisdiction interested in using a state-specific tool that is validated on a California-based population. Study results are expected to be compiled and published August, 2019. Once Northpointe Research has completed the study, the CAPA will replace the PRRS-II within the Northpointe Suite software application for California jurisdictions.”

Once the CAPA is released and available, a new Factsheet will be prepared with information specific to the CAPA.

Who created the risk assessment?

The Pretrial Release Risk Scale (PRRS-II) was created by researchers at Northpointe, Inc. (now Equivant), a private company.

How large was the training data set?

The PRRS-II was developed using a sample of 2,831 felony defendants (Source 1).

How was the training data set collected and assembled (i.e., what jurisdiction(s) is it from)?

The training data came from a study in Kent County, Michigan. The data was selected from felony defendants who were assessed with the full COMPAS suite at pretrial and subsequently released. Most of the defendants had been released under supervision of pretrial services in Kent County, while the remainder of the data set was comprised of a random sampling (stratified by gender) of defendants who had been released (but not under supervision) in the relevant time frame. This random sample was drawn because of the “cost associated with manual searches” in Kent County’s system to observe outcomes for defendants not released under supervision (Source 1).

Over what time frame was the data collected?

The data collected pertained to defendants who were assessed with the full COMPAS suite between January 2005 and December 2008 (Source 1).

What factors (i.e., defendant characteristics) were included in the data set? This question pertains to all the factors that were available about defendants, not necessarily all the factors that were used to train or develop the model.

The information included the factors from the full COMPAS assessment, the Objective Point Scale (OPS) Kent County used to make bond recommendations for felony cases, dates pertaining to arrest and release, and outcomes (failure to appear (FTA) and new felony arrest) (Source 1).

Does the dataset include instances of defendants who were detained? If so, does the data include outcomes for those people (i.e., did the data account for counterfactual estimation; if so, how)?

No - the samples that were used contained defendants who had been released at some point in the observed pretrial process (Source 1).

Are there any known issues or errors with the data?

Criminal justice data sets, in general, often suffer from measurement error and sample bias. The researchers noted that, "As is the case in all pretrial release samples, the Kent County pretrial study sample is affected by selection mechanisms that determine which defendants are released and included in the estimation sample" (Source 1). They further note that "The results that we obtain in the study sample of felony defendants may not generalize to other settings or other types of pretrial defendant" (Source 1). In addition, one issue of note pertaining to measurement of outcomes is that "felony offenses committed by defendants in the unsupervised group may go undetected if they occur outside of Kent County" (Source 1). Beyond that, according to Equivant, there are no known issues or errors with the data used in the study.

In what year was the risk assessment created?

The risk assessment was created in 2009-2010.

What factors, among all the factors in the training data, were considered in the development of the risk assessment? If not all factors were considered, how were those that were considered chosen?

Using "subject matter knowledge," the researchers identified 38 variables in the full COMPAS assessment data as "potential candidates for model development" (Source 1). These variables pertained to criminal history, employment, education, housing, substance abuse and gang affiliation (Source 1).

How were factors that were considered ultimately chosen for exclusion or inclusion in the final model (the risk assessment itself)?

To construct the model after selecting the "candidate pool," the researchers took the following steps: "examine correlation structure and reduce the candidate pool by eliminating collinear candidate variables; examine nonlinear relationships and select variables using penalized (shrinkage) backward elimination; check the stability of the model selection procedure using bootstrap replications" (Source 1; see Source 1 for more information).

Does the final model include as a factor(s) arrests that did not lead to convictions?

Yes - the final model includes "number of times arrested/charges with a new crime while on pretrial release" (Source 3).

Does the final model include socioeconomic factors such as housing and employment status? Does the final model include personal health factors such as mental health or substance abuse?

Yes - the final model includes “history of drug abuse,” “employment status” and “length of time in current community or neighborhood” (Source 1).

How were weights assigned to each factor included in the final model? (rounding correlation coefficients, Burgess Method, etc.)

The risk assessment “is a weighted linear combination of risk factors (regression equation) derived through survival analysis with shrinkage applied to the weights to compensate for how the risk scale will perform when applied to a different sample” (Source 1).

How does the final model define outcomes (i.e., during the model development process, was there a distinct outcome defined for each type of failure (flight risk, new crime, new violent crime, etc.) or were outcomes compounded?

“We define pretrial misconduct as failure to appear (FTA) or arrest for a new felony offense while on pretrial release” (Source 1).

What does the output of the model look like (i.e. a score on a scale of 1-10, etc.)?

According to Equivant, “The output of the PRRS II is a risk score (1-10) and a corresponding risk level (Low, Medium, High)” (Source 1).

Does the model output risk level designations or convert raw scores into risk level designations such as “low risk,” “moderate risk,” and “high risk”?

Yes, the model outputs risk levels Low, Medium, and High. These risk levels were determined by transforming risk scores into deciles scores, analyzing the trends in probability of failure, and then cutting the deciles into groups. As a result, 50% of the cases fell into the medium risk level (Source 1). The Kent County report states that “When the Pretrial Release Risk Scale is deployed in a different jurisdiction, new deciles and cutting points should be set and tested” (Source 1).

What proportion of samples in the training data set failed at each risk score and/or level (i.e., what percentage of people with a score of 5 or a label of “moderate risk” actually failed to appear)?

See Source 1, page 45 for more detail on failure rates at each decile score.

Did the model developers assess the predictive validity of the model? If so, how (reported AUC, FPR, TPR, etc.)?

Yes - the model developers “evaluated the predictive accuracy of the Pretrial Release Risk Scale using Receiver Operating Characteristic (ROC) methods. We estimated the area under the ROC curve (AUC) in the training data and in the bootstrap samples to compensate for over-optimistic results obtained in the training data. The Pretrial Release Risk Scale achieved an apparent AUC of .711 in the training data and an AUC adjusted for over-optimism of .688. The model with age removed had somewhat lower predictive accuracy with an apparent AUC of .694 and adjusted AUC of .673” (Source 1).

Where is the risk assessment used?

According to Equivant, “two counties in California use the PRRS-II. Customer contracts include language that prohibits the dissemination of agency names” (Source 3). Also according to Equivant, “We cannot provide detailed jurisdiction information, per our customer license agreements.”

Are the factors and weights of the risk assessment publicly available?

According to Equivant, “The PRRS-II factors are publicly available; the PRRS-II weights are available to licensed users and stakeholders. The new CAPA calculation is point driven and will be transparent to users, defendants, judges, attorneys, and other stakeholders.”

Does the risk assessment cost money for a jurisdiction to adopt? Does the risk assessment come with any sort of software or software package?

According to Equivant, “Yes. It is accessible only through the purchase of a Northpointe Suite software license; however, there is no additional fee to use the PRRS-II once using the Northpointe Suite. The software provides multiple pretrial assessments for risk assessing, as well as pretrial supervision functionality. This allows an agency to track release/detain data and to manage ongoing community supervision needs if needed” (Source 3).

Does the adoption of the risk assessment require training? If so, by who?

According to Equivant, “Yes, training is needed. Northpointe requires and provides training to its licensees. All assessments available to an agency require an implementation process that includes training. For a single pretrial assessment, the implementation process takes approximately 4-5 hours” (Source 3).

Does the risk assessment involve or require an in-person interview?

According to Equivant, “Two items require an interview: Employment status & How long have you been living at your current residence? Court records and case file information can be used to answer the other items” (Source 3).

How does the risk assessment account for missing information?

According to Equivant, “It doesn’t” (Source 3).

Has the risk assessment been analyzed on non-training data for predictive validity? Has the risk assessment been analyzed with training data or non-training data with regard to performance for different race groups? Has the risk assessment been analyzed with training data or non-training data with regard to performance for different genders? If so, by who, when, and using what data?

According to Equivant, “Outside of our internal development work, there have been no published studies on the performance of the PRRS-II that we are aware of.”

Information retrieved from:

[1] Research and Development Department, Northpointe, Inc. Kent County Pretrial Services Outcomes Study: Developing and Testing the COMPAS Pretrial Release Risk Scale (April 23, 2010).

[2] Equivant. Practitioner’s Guide to COMPAS Core (April 4, 2019).

[3] Information about the CAPA and PRRS-II provided by Equivant (d/b/a Northpointe, Inc.) File attached.

[4] Email correspondences with Equivant, Inc.

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Questions about the COMPAS pretrial risk assessment tool: PRRS-II.		
1	Are there any known issues or errors with the data?	No.
2	Where is the risk assessment used?	Two counties in California use the PRRS-II. Customer contracts include language that prohibits the dissemination of agency names.
3	Are the factors and weights of the risk assessment publicly available?	The PRRS-II factors are available, the weights are not. Please see attachment.
4	Does the risk assessment cost money for a jurisdiction to adopt?	Yes. It is accessible only through purchase of a <i>Northpointe Suite</i> software license; however, there is no additional fee to use the PRRS-II once using the <i>Northpointe Suite</i> . The software provides multiple pretrial assessments for risk assessing, as well as pretrial supervision functionality. This allows an agency to track release/detain data and to manage ongoing community supervision needs if needed.
5	Does the adoption of the risk assessment require training? If so, by who?	Yes, training is needed. Northpointe requires and provides training to its licensees. All assessments available to an agency require an implementation process that includes training. For a single pretrial assessment, the implementation process takes approximately 4-5 hours.
6	Does the risk assessment come with any sort of software or software package?	Yes; please see response to question 4.
7	Does the risk assessment involve or require an in-person interview?	Two items require an interview: Employment status & How long have you been living at your current residence? Court records and case file information can be used to answer the other items.
8	How does the risk assessment account for missing information?	It doesn't.

California Pretrial Reform: New Pretrial Assessment

The Northpointe, Inc. Research division designed a new Pretrial Assessment in 2018: the *California Pretrial Assessment (CAPA)*. The CAPA was designed based on SB10 and is intended to serve the state of California's pretrial reform efforts. This new assessment utilizes a point scoring system which can be administered, scored and interpreted with ease, addressing the need for full transparency in the pretrial process.

The CAPA was constructed and automated for testing purposes, and the Northpointe Research division is currently finishing a validation study on the new assessment. The CAPA validation study is being completed using a dataset provided by a California jurisdiction interested in using a state-specific tool that is validated on a California-based population. Study results are expected to be compiled and published August, 2019. Once Northpointe Research has completed the study, the CAPA will replace the PRRS-II within the *Northpointe Suite* software application for California jurisdictions.

Documentation on the CAPA is included in the attached file along with documentation for the PRRS-II.

COMPAS Pretrial Scale Documentation

The Northpointe Suite is an automated decision-support software package of risk and needs assessments and case management tools that have been developed for specific decision points within the criminal justice system. These decision points include pretrial, supervision, and rehabilitative treatment planning.

Below is a description of the COMPAS Pretrial tools either currently available or soon to be available in the Northpointe Suite.

Pretrial Release Risk Scale (PRRS) II

Table 1 shows the items that enter the COMPAS Core Pretrial Release Scale II. A lasso survival model was fit to obtain regression weights for the variables.

Table 1: Model Elements and their corresponding descriptions for the PRRS II Raw Score model.

PRRS II Model Element	Description
a	Intercept (constant)
w_i	Coefficient (weight) for i th variable
n.pending	Number of pending charges or holds
crime.category	Which offense category represents the most serious current offense
n.jail	Number of times sentenced to jail for more than 30 days
n.fta	Number of times failed to appear for scheduled court hearing
n.arrest.on.bail	Number of times arrested/charged with a new crime while on pretrial release
drug.hx	History of drug abuse (dichotomous variable)
month.local	Length of time in current community or neighborhood
have.employment.school	Employment Status (Full Time; Part Time; Unemployed; Not in labor force)

Equation ?? calculates the raw score for the PRRS II. Cut points are used to convert raw scores to decile scores. Decile scores are then collapsed into risk levels or text scores: Low, Medium, High.

$$\begin{aligned}
 \text{PRRS II Raw Score} = & a + w_1 \times \text{n.pending} \\
 & + w_2 \times \text{crime.category} \\
 & + w_3 \times \text{n.jail} \\
 & + w_4 \times \text{n.fta} \\
 & + w_5 \times \text{n.arrest.on.bail} \\
 & + w_6 \times \text{drug.hx} \\
 & + w_7 \times \text{month.local} \\
 & + w_8 \times \text{have.employment.school}
 \end{aligned}$$

California Pretrial Assessment (CAPA)

The CAPA is a 7-item Test Instrument that is SB10 compliant. It is a modified version of the 8-item PRRS II. Table 2 depicts the items used in calculating a CAPA raw score. The CAPA is a summative scale. There are no weights or an intercept term.

Table 2: CAPA Scale items & corresponding descriptions.

Item	Description
n.pending	Number of pending charges or holds
larceny	Top charge is a felony property or fraud offense
n.jail	Number of times sentenced to jail 30 days or more
n.fta	Number of times failed to appear for scheduled court hearing
any.arrest.on.bail	Arrested/charged with a new crime that resulted in conviction while on pretrial release
drug.hx	History of drug abuse (dichotomous variable)
probpar	On probation or parole at time of current offense

VIRGINIA PRETRIAL RISK ASSESSMENT INSTRUMENT - (VPRAI)

Instruction Manual – Version 4.3



Virginia Department of Criminal Justice Services

4/2/2018 Amended

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Virginia Pretrial Risk Assessment Instrument (VPRAI) Instruction Manual

DETERMINING ELIGIBILITY

A Virginia Pretrial Risk Assessment Instrument (VPRAI) examines a defendant's status at the time of the arrest related to any active community criminal justice supervision, current charges, pending charges, criminal history, history of failure to appear, history of violent convictions, employment, and history of drug abuse. For this reason, the instrument is primarily intended to be completed after arrest and presented at the first court appearance. Completing the instrument soon after arrest increases the likelihood of capturing the most accurate information as it relates to the defendant's status at the time of arrest. This instrument is also used to determine the supervision level for those defendants placed on pretrial supervision. This is discussed in more detail in the Pretrial Placement Module Section, beginning on page 21 of this manual.

A pretrial investigation must be conducted prior to completing the VPRAI. A VPRAI is required for all eligible defendants and should be completed by using the instructions provided in this manual. Defendants who do not meet all of the criteria listed below are not eligible for instrument completion as part of the pretrial investigation.

1. The defendant must be an adult – 18 years or older or a juvenile previously certified as an adult by the court.
2. The defendant must not be incarcerated for unrelated charges at the time of the arrest or when the new warrants were served.
3. The defendant must have been arrested for one or moreailable offense(s) – Class 1 and 2 misdemeanors (M1 and M2), unclassified misdemeanors (M9) that carry a penalty of jail time, or any felony. Class 3 misdemeanors, Class 4 misdemeanors, and Class 9 misdemeanors, which carry a maximum penalty of a fine, are not eligible for instrument completion.
4. The defendant must have been arrested for a criminal offense (includes criminal traffic charges but NOT traffic infractions). Defendants charged solely with the following are not eligible:
 - ✓ Civil offense
 - ✓ FTA or capias due to an underlying charge from a civil court
 - ✓ Fugitive warrant/warrant of extradition

The VPRAI is automated and contained in the Pretrial and Community Corrections Case Management System (PTCC). The appendix contains a sample of a completed instrument created using sample data. The VPRAI can only be created after completing the Screening, VPRAI (Step 1), VPRAI (Step 2), and VPRAI (Step 3) tabs contained in the Jail Admission Event Module (JAE) of PTCC.

THE JAIL ADMISSION EVENT (JAE) MODULE

Screening Tab

This tab will be completed to determine whether a defendant will be investigated. Based on the information gathered, the defendant will be “screened in” or “screened out.”

Screened

In

Out - Reason: [Dropdown]

Other Desc.: [Text Field]

Selecting “screened out” indicates the defendant is not eligible for a VPRAI for one of the following reasons: Detainer(s), Drunk in Public, Federal / U.S. Marshall’s Office Hold(s), J&DR Court Juvenile Defendant, Parole Violation, or PB-15. Selecting “screened in” indicates the defendant is awaiting bail and eligible for a VPRAI. For any defendant who is eligible but is NOT investigated, select a reason from the dropdown. If “Other” is selected, enter a description in the appropriate field.

Investigated

Yes

No - Reason: [Dropdown]

Other Desc.: Behavior Not Conducive To Interview

By: Debilitated Due To Drugs/Alcohol/Medical Conditions At Time

Criminal Record: Declined Interview

Released On Bond Before Interview

In the Screening tab, the following information is required for the VPRAI: First Name, Last Name, Race, Social Security Number (SSN), Sex, Date of Birth (DOB), Primary Charge Classification (PCC), Jail Admission Date, Jail, Screened, and Investigated (see Figure 1).

The defendant is eligible for a VPRAI when “Screened” = “in” and “Investigated” = “yes.” If “yes” is selected, a VPRAI must be completed.

FIGURE 1. SCREENING TAB IN JAIL ADMISSION EVENT MODULE (JAE)

Pretrial and Community Corrections Case Management System (PTCC) - [Screening - Screening]

File Edit Modules Reports Administration Window Help

Screening VPRAI Charges Court Assignment Court Reports Recommendation Charge Update Court Update

Name: Case, Sample; SSN: 555555555; DOB: 07/25/1988 Screening ID: 201707240001

Scr. Date	Jail Name	PCC	Scr. In	Reason Screened Out	Investigated
07/24/2017	Chesapeake City Jail	F6	Yes		Yes

Existing Defendant New Defendant

First Name: Sample
 Middle Name: Suffix:
 Last Name: Case

Race: White SSN: 555-55-5555
 Sex: Male Age: 28 DOB: 07/25/1988
 PCC: F6
 Jail Admission Date: 07/22/2017
 Jail: Chesapeake City Jail

Screened
 In Out - Reason:
 Other Desc.:
 By: Collins, Kirk - PTCC Date: 07/24/2017

Investigated
 Yes No - Reason:
 Other Desc.:
 By: Collins, Kirk - PTCC Date: 07/24/2017
 Criminal Record Check: ABC

Staff: Shiflett, Donna
 Date Edited: 07/24/2017 05:43 AM

Exit << Previous Save Undo New Delete Next >>

VPRAI (Step 1) Tab

All of the information on VPRAI (Step 1) tab is required: Instrument Completion Date, Arrest Information, Research Factors, and Risk Factors (see Figure 2). The Risk Level is a calculated field, which resides on this tab.

FIGURE 2. VPRAI (STEP 1) TAB IN THE JAE MODULE

Pretrial and Community Corrections Case Management System (PTCC) - [Screening - VPRAI]

File Edit Modules Reports Administration Window Help

Screening **VPRAI** Charges Court Assignment Court Reports Recommendation Charge Update Court Update

Name: Case, Test; SSN: 999999999; DOB: 07/12/1993 Screening ID: 2017071200002

VPRAI (Step 1) VPRAI (Step 2) VPRAI (Step 3) VPRAI (Step 4)

Instrument Completion Date: 07/12/2017

Arrest Information

Court Date: 07/12/2017

Charge(s): Possession of Stolen Property
Bond Type and Amount: \$10,000 Secured
Court: Arlington County GDC

Research Factors

Prior Misdemeanor Conviction: Yes
Prior Felony Conviction: Yes
Prior Violent Convictions: 0
Prior FTAs in Past 2 Years: 0
Prior FTAs Older Than 2 Years: No
Prior Sentence to Incarceration: Yes

Risk Factors

Active Community Supervision: Yes
Charge is Felony Drug, Theft or Fraud: Yes
Pending Charge(s): No
Criminal History: Yes
Two or More FTAs: No
Two or More Violent Convictions: No
History of Drug Abuse: No
Employed at Time of Arrest: Full-Time Student

Calculate Risk

Risk Level: 4

Staff: Rose, Ken
Date Edited: 07/12/2017 10:45 AM

Exit << Previous Save Undo New Delete Next >>

Research Factors

Research factors are collected for ongoing VPRAI validation and research. Responses to these research factors are entered in the appropriate sections on the VPRAI (Step 1) Tab (see Figure 2) in the JAE Module. Guidance for selecting accurate responses to the factors is provided below.

1. Prior Misdemeanor Conviction

- ✓ Select “Yes” if the defendant has at least one adult misdemeanor conviction in the past.
- ✓ Select “No” if the defendant has no misdemeanor conviction in the past.

2. Prior Felony Conviction
 - ✓ Select “Yes” if the defendant has at least one adult felony conviction in the past.
 - ✓ Select “No” if the defendant has no felony conviction in the past

3. Prior Violent Convictions – Enter the number of adult convictions of violent offenses (count each conviction). For the purpose of the VPRAI, an act of violence is defined by [§19-2.297.1](#) and includes any act that causes or intends to cause physical injury to another person. The type of violent offenses include, but are not limited to, Murder, Manslaughter, Mob related felonies, Kidnapping, Abduction, Malicious Wounding, Robbery, Carjacking, Arson, Assault, or Sex Offenses (Rape, Sexual Assault / Battery, Carnal Knowledge of a Child, Forcible Sodomy). Violent convictions for the purpose of the VPRAI also include misdemeanor charges of Simple Assault or Assault and Battery and Violation of Protective Orders.

A conviction for **attempt** or being an **accessory before the fact** to commit any of the offenses listed above **is** counted. A conviction for **conspiring** or being an **accessory after the fact** to commit any of the offenses listed above is **not** counted.

 - ✓ Select “0”
 - ✓ Select “1”
 - ✓ Select “2”
 - ✓ Select “3”
 - ✓ Select “More”

4. Prior Failure to Appear in Past 2 Years – Enter the number of Failures to Appear, as an adult, within the past two years of the current arrest date. See the definition for failure to appear on page 10.
 - ✓ Select “0”
 - ✓ Select “1”
 - ✓ Select “2”
 - ✓ Select “3”
 - ✓ Select “More”

5. Prior Failure to Appear Older than 2 Years
 - ✓ Select “Yes” if the defendant has a Failure to Appear, as an adult, from two or more years from the current arrest date.
 - ✓ Select “No” if the defendant does not have a Failure to Appear, as an adult, from two or more years from the current arrest date.

6. Prior Sentence to Incarceration as an Adult
 - ✓ Select “Yes” if the defendant was sentenced to an active period of incarceration prior to the current arrest date.
 - ✓ Select “No” if the defendant has not been previously sentenced to an active period of incarceration.

Risk Factors

The VPRAI calculates a defendant’s level of risk based on eight (8) risk factors listed below. Responses to these risk factors are entered in the appropriate sections on the VPRAI (Step 1) Tab (see Figure 2) in JAE Module. Note that there are verifications for data accuracy on this screen. Responses entered for the research factors - Prior Misdemeanor or Felony Conviction, Prior Violent Convictions, and Prior Failure to Appear Pretrial in Past 2 Years and Older than 2 Years - are repeated in the corresponding risk factors - Criminal History, Two or More Failures to Appear and Two or More Violent Convictions. Guidance for selecting accurate responses to the risk factors is provided below.

1. Active Community Criminal Justice Supervision
 - ✓ Select “Yes” if the defendant was under any active community criminal justice supervision including state or local probation, parole, pretrial services, the alcohol safety action program (ASAP), drug court, day reporting, or any other form of active criminal justice supervision at the time of the arrest. Active supervision does NOT include unsupervised probation, a term of good behavior, or release on bail without pretrial supervision.
 - ✓ Select “No” if the defendant was not on active community criminal justice supervision at the time of the arrest.
2. The charge is a felony drug, theft or fraud
 - ✓ Select “Yes” if any of the current charges are in any of the following felony categories: drug, theft or fraud.
 - ✓ Select “No” for all other felony and misdemeanor charges.
3. Pending Charge(s) – The defendant has a pending charge(s) when there is an open criminal case that carries the possibility of a period of incarceration, and the pending charge has an offense date that is before the offense date of the current charge. (A charge with a disposition of “deferred” is NOT counted as a pending charge.)

EXCEPTION: If the current arrest is solely for a failure to appear, the underlying charge related to the failure to appear does not constitute a pending charge. In addition, if a defendant is arrested, remains incarcerated pending trial, and is served with new warrants, this does not constitute a pending charge.

- ✓ Select “Yes” if the defendant had one or more charges for jailable offenses pending in a criminal or traffic (not civil) court at the time of arrest.
 - ✓ Select “No” if the defendant had no pending charge(s) at the time of arrest.
4. Criminal History – A conviction for a criminal offense that carries the possibility of incarceration is counted as a prior criminal history. NOTE: A charge with a disposition of “deferred” is NOT counted as a conviction.
- ✓ Select “Yes” if the defendant has at least one adult misdemeanor or felony conviction in the past.
 - ✓ Select “No” if the defendant has no misdemeanor or felony conviction in the past.
5. Two or More Failures to Appear – For the purposes of scoring the VPRAI, a failure to appear means any prior failure to appear for a criminal charge that (a) carries the possibility of incarceration, and (b) as a result of the failure to appear, the court issued a *capias* or equivalent. A failure to appear for a single court appearance is counted once regardless of the number of failure to appear charges related to the one court appearance. A failure to appear is not counted if there is confirmation that the defendant was in custody (jail or prison) when the failure to appear occurred. NOTE: FTA is counted regardless of the disposition.
- ✓ Select “Yes” if the defendant has failed to appear in court two or more times as an adult.
 - ✓ Select “No” if the defendant has not failed to appear two or more times as an adult.
6. Two or More Violent Convictions – For the purpose of the VPRAI, an act of violence is defined by [§19.2-297.1](#) and includes any act that causes or intends to cause physical injury to another person. This includes, but is not limited to, Murder, Manslaughter, Mob related felonies, Kidnapping, Abduction, Malicious Wounding, Robbery, Carjacking, Arson, Assault, or Sex Offenses (Rape, Sexual Assault / Battery, Carnal Knowledge of a Child, Forcible Sodomy). Violent convictions for the purpose of the VPRAI also include misdemeanor charges of Simple Assault or Assault and Battery and Violation of Protective Orders.

A conviction for attempt or being an accessory *before* the fact to commit any of the offenses above **is** counted. A conviction for conspiring or being an accessory *after* the fact to commit any of the offenses is **not** counted.

- ✓ Select “Yes” if the defendant has two or more prior violent convictions as an adult.

- ✓ Select “No” if the defendant does not have two or more prior violent convictions.

7. Employed at the Time of Arrest – Enter the employment status at the time of arrest. *Employment* includes part- or full-time as long as the defendant worked regularly and consistently for a minimum of 20 hours per week. A defendant who is not employed but is enrolled in high school or is attending college fulltime is considered a *student*. A defendant who is not employed but is considered a *primary caregiver* if he or she is responsible for, and consistently cares for, at least one dependent child (under the age of 18) or disabled or elderly family member, living with the defendant at the time of arrest. A defendant who is not employed but is receiving retirement benefits or retirement savings is considered *retired*.

Select the appropriate status from the following dropdown items:

- ✓ Employed
- ✓ Full-time Student
- ✓ Primary Caregiver
- ✓ Retired
- ✓ None

8. History of Drug Abuse – For the purpose of the risk assessment, drug abuse includes any illegal or prescription drugs and does not include alcohol. Consideration should be given to the information provided by the defendant, criminal history, information contained in supervision records, and any information provided by references regarding drug abuse (**excluding alcohol**).

Examples: Indications of history of drug abuse could include (a) previously used illegal substance(s) repeatedly, distinguishing from short-term experimental use; (b) admits to previously abusing illegal or prescription drugs; (c) the criminal history contains drug related convictions; and (d) the defendant received drug treatment in the past.

Any one or a combination of the factors above can be used to determine whether or not the defendant has a history of drug abuse.

- ✓ Select “Yes” to indicate the defendant has a history of drug abuse.
- ✓ Select “No” if the defendant does not have a history of drug abuse.

Scoring and Risk Level

After selecting responses to the eight risk factors, the risk level will be automatically calculated in PTCC by selecting the *Calculate Risk* button. The defendant's Risk Level is identified as one of the following six levels: 1, 2, 3, 4, 5 and 6. See Figure 3 below.

FIGURE 3. VPRAI (STEP 1) TAB IN THE JAE MODULE: CALCULATE RISK

Pretrial and Community Corrections Case Management System (PTCC) - [Screening - VPRAI]

File Edit Modules Reports Administration Window Help

Screening **VPRAI** Charges Court Assignment Court Reports Recommendation Charge Update Court Update

Name: Case, Test; SSN: 999999999; DOB: 07/12/1993 Screening ID: 2017071200002

VPRAI (Step 1) VPRAI (Step 2) VPRAI (Step 3) VPRAI (Step 4)

Instrument Completion Date: 07/12/2017

Arrest Information

Court Date: 07/12/2017

Charge(s): Possession of Stolen Property
Bond Type: \$10,000 Secured
and Amount: Arlington County GDC
Court:

Research Factors

Prior Misdemeanor Conviction: Yes
Prior Felony Conviction: Yes
Prior Violent Convictions: 0
Prior FTAs in Past 2 Years: 0
Prior FTAs Older Than 2 Years: No
Prior Sentence to Incarceration: Yes

Risk Factors

Active Community Supervision: Yes
Charge is Felony Drug, Theft or Fraud: Yes
Pending Charge(s): No
Criminal History: Yes
Two or More FTAs: No
Two or More Violent Convictions: No
History of Drug Abuse: No
Employed at Time of Arrest: Full-Time Student

Calculate Risk

Risk Level: 4

Staff: Rose, Ken
Date Edited: 07/12/2017 10:45 AM

Exit << Previous Save Undo New Delete Next >>

TABLE 1. VPRAI: WEIGHTED RISK FACTORS

Based on the odds ratio of each risk factor's ability to independently predict the likelihood of any pretrial failure, each risk factor has been weighed to maximize predictive value of the VPRAI.

Risk Factor	Points
Active community criminal justice supervision	2
Charge is felony drug, felony theft, or felony fraud	3
Pending charge(s)	2
Criminal history	2
Two or more failure to appear	1
Two or more violent convictions	1
Unemployed at time of arrest	1
History of drug abuse	2
Total Possible Score	14

TABLE 2. VPRAI: RISK LEVEL BASED ON CALCULATED SCORE

The defendant's total score on the VPRAI will identify their level of risk.

VPRAI-R Score	Risk Level
0 - 2	Level 1
3 - 4	Level 2
5 - 6	Level 3
7 - 8	Level 4
9 - 10	Level 5
11 - 14	Level 6

VPRAI (Step 2) Tab

The following information, described below, will be entered in the VPRAI (Step 2) tab to apply the pretrial decision-making matrix, the Praxis. See Figure 4 below.

FIGURE 4. VPRAI (STEP 2) TAB IN THE JAE MODULE

Pretrial and Community Corrections Case Management System (PTCC) - [Screening - VPRAI]

File Edit Modules Reports Administration Window Help

Screening **VPRAI** Charges Court Assignment Court Reports Recommendation Charge Update Court Update

Name: Case, Sample; SSN: 555555555; DOB: 07/25/1988 Screening ID: 2017072400001

VPRAI (Step 1) **VPRAI (Step 2)** VPRAI (Step 3) VPRAI (Step 4)

Praxis Applies: Yes

Most Serious Charge Cat: Non-Violent Felony

FTA Underlying Charge:

Praxis Recommendation:

Release: Yes

Pretrial Supervision: Level II

Staff Recommendation:

Recommendation: Release

Pretrial Supervision: Yes

No Rec Reason:

Consistent With Praxis: Yes

If No Reason:

Staff Making Rec: Collins, Kirk - PTCC Staff

Recommendation Date: 07/24/2017

Save

Staff: Shiflett, Donna

Date Edited: 07/24/2017 05:55 AM

Exit Previous Save Undo New Delete Next >>

Praxis Recommendation

Section 1

The defendant's current charge(s) will determine whether the Praxis applies. The Praxis applies to the following charge categories: Violent Felony or Firearm, Violent Misdemeanor, Non-Violent Felony, Driving under the Influence, and Non-Violent Misdemeanor. It does not apply to Murder, Homicide, Manslaughter or an attempt to commit any of these crimes. Other charges that are not Praxis eligible are Probation Violation, Contempt of Court, and Escape.

- ✓ Select "Yes" if the Praxis does apply.
- ✓ Select "No" if the Praxis does not apply.

If the Praxis does apply, determine the most serious charge category and select from the following dropdown options:

- ✓ Violent Felony / Firearm¹
- ✓ Violent Misdemeanor
- ✓ Non-Violent Felony
- ✓ Driving Under the Influence
- ✓ Non-Violent Misdemeanor
- ✓ Failure To Appear² – If selected, indicate the primary charge category for the underlying charge:
 - Violent Felony / Firearm
 - Violent Misdemeanor
 - Non-Violent Felony
 - Driving Under the Influence
 - Non-Violent Misdemeanor

Section 2

The Praxis Recommendation will automatically fill based on the pretrial decision-making matrix. Based on the information entered into PTCC, a recommendation about release and pretrial supervision will be auto-filled. The recommendation in the “Release” field is either “yes” or “no.” If release is recommended, the appropriate level of supervision will be displayed in the “Pretrial Supervision” field. If release is not recommended, the “Pretrial Supervision” field is “no.”

Staff Recommendation

After a review of this information, complete this section by selecting on of the following options:

- ✓ Release
- ✓ Detain
- ✓ No Recommendation

If “Release” is recommended, select whether pretrial supervision is recommended. If the value in the dropdown “no recommendation” is selected, list the reason(s) in the “No Rec Reason” field.

“Consistent with Praxis” is an automatic fill (yes or no) based on whether the Praxis Recommendation and the Staff Recommendation are in agreement. If the answer is “no,” enter the reason for the override to the Praxis.

Note that the Praxis recommendation concurrence rate for each agency must be 85% or higher.

¹ Firearm offenses include any charge relating to possession, use, or manufacturing a firearm. Examples include shooting at a vehicle, discharging a weapon in a public place, brandishing, illegally carrying a concealed weapon, or removing or altering the serial number or other identification number on a firearm.

² If “Failure to Appear” is selected, identify the primary charge category for the underlying charge, and increase the preliminary risk level by one risk level.

Officer and Recommendation Date

After completing this tab and making a recommendation. The officer will:

1. Select their name from the dropdown list.
2. Enter the date the recommendation was made.

VPRAI (Step 3) Tab

The VPRAI (Step 3) tab provides a list of seven (7) common conditions of release. This screen contains a text box to enter other conditions as permitted by §19.2-123 of the *Code of Virginia*, and a text box to enter information relevant to the staff recommendation. See Figure 5 below.

FIGURE 5. VPRAI (STEP 3) TAB IN THE JAE MODULE

Pretrial and Community Corrections Case Management System (PTCC) - [Screening - VPRAI]

File Edit Modules Reports Administration Window Help

Screening **VPRAI** Charges Court Assignment Court Reports Recommendation Charge Update Court Update

Name: Case, Sample; SSN: 55555555; DOB: 07/25/1988 Screening ID: 2017072400001

VPRAI (Step 1) VPRAI (Step 2) **VPRAI (Step 3)** VPRAI (Step 4)

Conditions of Release:

Refrain from excessive use of alcohol or use of drugs No contact with victim or potential witness

Submit to testing for drugs and alcohol Maintain or seek employment

Refrain from possessing a firearm, destructive device, or other dangerous weapon Maintain or commence educational program

Comply with a curfew

Additional Conditions of Release:

this space is for any additional conditions permitted by the Code of Virginia

Mitigating/Aggravating Considerations:

Include information related to risk that is deemed important.

Case Meets Rebuttable Presumption

Print VPRAI

Exit << Previous Save Undo New Delete Next >>

Staff: Shifflett, Donna
Date Edited: 07/24/2017 05:55 AM

Conditions of Release

Conditions of release can be recommended if the bail recommendation entered in the Staff Recommendation section is Release with or without pretrial supervision. There are seven (7) common conditions that can be recommended by selecting the box next to recommended condition (see Figure 5: VPRAI (Step 3) Tab in Jail Admission Event Module). The seven (7) common conditions include:

- ✓ Refrain from excessive use of alcohol or use of drugs;
- ✓ Submit to testing for drugs and alcohol;
- ✓ Refrain from possessing a firearm, destructive device, or other dangerous weapon;
- ✓ No contact with victim or potential witness;
- ✓ Maintain or seek employment;
- ✓ Maintain or commence educational program; and
- ✓ Comply with a curfew.

Additional Conditions of Release

Other conditions of release permitted by the *Code of Virginia* can be entered in this section of the VPRAI (Step 2) tab. These other conditions should be written with detailed specificity.

Mitigating / Aggravating Considerations

Include additional information related to risk that is deemed as important and should be considered by the judicial officer when making the bail decision is entered in the “Mitigating / Aggravating Considerations” section of this tab. Comments entered are intended to focus on risk, making note of any mitigating or aggravating factors that may not be reflected in the risk factors. Mitigating factors would be any information that may lessen the seriousness of any of the eight (8) primary risk factors that were identified for the defendant and any positive factors that are relevant to the bail decision. For example: “Although the defendant has a criminal history, it was 20 years ago.” Aggravating factors would be any additional information identified during the pretrial investigation that may increase the level of risk and was not accounted for in the eight (8) primary risk factors. For example: “Although the defendant does not have a history of drug abuse, he has a long history of alcohol abuse.”

Create VPRAI

The VPRAI Report is created by the PTCC software and uses information entered into the four tabs contained in the Jail Admission Event module of PTCC including the Screening, VPRAI (Step 1), VPRAI (Step 2), and VPRAI (Step 3) tabs. Select the “Print VPRAI” button to view and print the VPRAI Report.

TABLE 3. PRETRIAL PRAXIS (MANUAL VERSION)

Risk Level	Recommendation	VPRAI: Charge Category				
		Non-Violent Misd.	Driving Under the Influence	Non-Violent Felony	Violent Misd.	Violent Felony or Firearm
Level 1	Bail Status	Release	Release	Release	Release	Release
	Pretrial Supervision	No	No	No	No	Level II
	Special Conditions	No	No	No	No	As Needed
Level 2	Bail Status	Release	Release	Release	Release	Release
	Pretrial Supervision	No	Monitor	Monitor	Monitor	Level III
	Special Conditions	No	No	No	No	As Needed
Level 3	Bail Status	Release	Release	Release	Release	Detain
	Pretrial Supervision	Monitor	Monitor	Level I	Level I	No
	Special Conditions	No	No	No	As Needed	N/A
Level 4	Bail Status	Release	Release	Release	Release	Detain
	Pretrial Supervision	Level I	Level I	Level II	Level II	No
	Special Conditions	No	As Needed	As Needed	As Needed	N/A
Level 5	Bail Status	Release	Release	Release	Detain	Detain
	Pretrial Supervision	Level II	Level II	Level III	No	No
	Special Conditions	As Needed	As Needed	As Needed	N/A	N/A
Level 6	Bail Status	Detain	Detain	Detain	Detain	Detain
	Pretrial Supervision	No	No	No	No	No
	Special Conditions	N/A	N/A	N/A	N/A	N/A

VPRAI (Step 4) Tab

Details about the court decision are entered in the VPRAI (Step 4) tab. See Figure 6 below.

FIGURE 6. VPRAI (STEP 4) TAB IN THE JAE MODULE

Screening | **VPRAI** | Charges | Court Assignment | Court Reports | Recommendation | Charge Update | Court Update

Name: Case, Sample; SSN: 555555555; DOB: 07/25/1988 Screening ID: 2017072400001

VPRAI (Step 1) | VPRAI (Step 2) | VPRAI (Step 3) | **VPRAI (Step 4)**

Court Decision

Decision: Unsecured Bond

Pretrial Supervision: Yes

Consistent With Staff Rec: Yes

If no, reason: _____

Judicial Officer: _____

Substitute Officer: _____

JAE Outcome

Pretrial Release Date: ____/____/____

Disposition Date: ____/____/____

Length of time in Jail: _____

ABC

Exit | << Previous | Save | Undo | New | Delete | Next >>

Staff: Shiflett, Donna
Date Edited: 07/24/2017 05:50 AM

Court Decision

Select from the options provided in the dropdown:

1. Decision – Select one from the following dropdown options:
 - ✓ Recognizance
 - ✓ Unsecured Bond
 - ✓ Secured Bond
 - ✓ Denied Bail
 - ✓ Bonded Out After Investigation, but Before Court
 - ✓ Case Disposed

2. Pretrial Supervision – Select one from the following dropdown options:
 - ✓ Select “Yes” if the judicial officer ordered pretrial supervision.
 - ✓ Select “No” if pretrial supervision is not ordered.

3. The field “Consistent with Staff Recommendation” is auto-filled based on the staff recommendation entered in VPRAI Step 2 and the Court Decision entered on this tab. See Table 4 for details on how it is determined whether the court decision is consistent with the staff recommendation.
 - ✓ If the field “Consistent with Staff Recommendation” is “no,” enter the reason the judge did not follow the recommendation in the following field: “If no, reason.”

TABLE 4. GRID FOR “CONSISTENT WITH STAFF RECOMMENDATION”

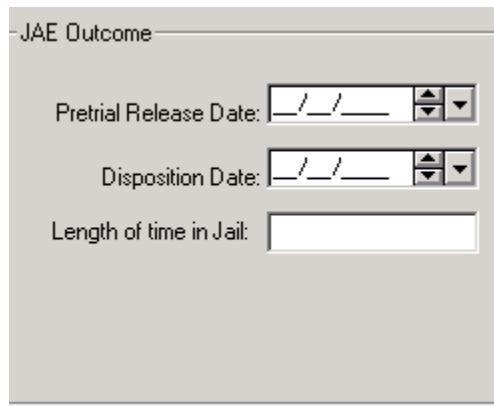
Consistent with Staff Recommendation Chart			
Staff Recommendation	Court Decision		Consistent with Staff Recommendation
	Decision	PTS	
Release without PTS	Recognizance, Unsecured, or Secured	No	Yes
Release without PTS	Recognizance, Unsecured, or Secured	Yes	No
Release without PTS	Denied Bail	N/A	No
Release with PTS	Recognizance, Unsecured, or Secured	No	No
Release with PTS	Recognizance, Unsecured, or Secured	Yes	Yes
Release with PTS	Denied Bail	N/A	No
Detain	Denied Bail	N/A	Yes
Detain	Recognizance, Unsecured, or Secured	No	No
Detain	Recognizance, Unsecured, or Secured	Yes	No

4. Select the name of the Judicial Officer from the dropdown or
5. List the name of the Substitute Judicial Officer.

JAE Outcome

Information contained in the JAE Outcome section of this tab is for the purpose of tracking the outcome of the case. Following is an overview for completing these fields:

1. If the defendant was released from jail before trial, enter the release date.
2. If the defendant remained in jail until trial, enter the disposition date.
3. The “Length of Time in Jail” field will auto-fill based on the jail admission date entered on the Screening tab and the release date or disposition date entered on this tab.



The screenshot shows a form titled "JAE Outcome" with three input fields:

- Pretrial Release Date: A date field with a format of __/__/__ and a dropdown arrow.
- Disposition Date: A date field with a format of __/__/__ and a dropdown arrow.
- Length of time in Jail: A text input field.

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THE PRETRIAL PLACEMENT MODULE

Information is entered in the Pretrial Placement Module for defendants ordered to pretrial supervision. If a risk assessment was not completed prior to the placement, a risk assessment must be completed under the VPRAI tab located in the Pretrial Placement Module.

Step 1: Setup / Intake

Once a defendant is ordered to pretrial supervision, an intake must be completed in the Setup Module in PTCC. All information must be entered under each tab in the Setup Module before a placement is made “active.” See Figure 7 below for the tabs included in the Setup Module.

FIGURE 7. SETUP MODULE

Pretrial and Community Corrections Case Management System (PTCC) - [Setup - Demographics]

File Edit Modules Reports Administration Window Help

Demographics Aliases Residence Family/Reference Employment Other Income Education Military
UNCOPE/Substance Use Substance Treatment Health Issues Other Ed/Tx Programs Assessment Tests Criminal Events

Name: Case, Sample; SSN: 555555555; DOB: 07/25/1988 Interview/Pending Investigation Intake ...

Demographics Demographics (contd.)

First Name: Sample SSN: 555-55-5555
Middle Name: Suffix: DOB: 07/25/1988
Last Name: Case Age: 28
Maiden Name: Race: White
Marital Status: Sex: Male
Height (in): Eye Color: Dependents:
Weight (lbs): Hair Color: No. of Dependents: 0
No. Living w/Defendant: 0
Language:
Primary Language: Virginia SID No:
Other Description: FBI No:
English Literate: Interpreter Needed: Local Tracking No:
Date Last Reviewed: / /

Exit << Previous Save Undo New Delete Next >> Staff: Shiflett, Donna
Date Edited: 07/24/2017 05:46 AM

Check the “Intake” box if you are completing an intake.

Interview/Pending Investigation Intake ...

Step 2: Placement Submodule

Information about the referral is entered under the Placement Tab in the Pretrial Placement Module. If a screening for this placement was previously completed, link the completed VPRAI to the corresponding screening by selecting it from the pop up box. If there is no screening related to this placement, select “no screening for this placement” from the pop up box. See Figure 8 below.

FIGURE 8. PLACEMENT TAB IN PT PLACEMENT MODULE

Scr. Date	Jail Name	PCC	Scr. In	Reason Screened Out	Investigated	VPRAI Date	VPRAI Risk
No Screening For This Placement							
06/01/2017	Alexandria City Adult Detention Center	F9	Yes		Yes	06/01/2017	High
06/01/2017	Allegheny County Jail	F2	Yes		Yes	06/01/2017	High
06/02/2017	Accomack County Jail	F1	Yes		Yes	06/02/2017	Above Average
06/03/2017	Albermarle/Charlottesville Regional Jail	F2	Yes		Yes	06/03/2017	High
06/04/2017	Accomack County Jail	F1	Yes		Yes	12/31/9999	
07/19/2017	Allegheny Regional Jail	F2	Yes		Yes	12/31/9999	

Step 3: VPRAI

If a risk assessment was not completed prior to the placement, it must be completed under the VPRAI tab located in the Pretrial Placement Module. See Figure 9 below. Completion of the risk assessment for all defendants placed on pretrial supervision is required. The VPRAI provides important information related to risk level and the appropriate level of supervision.

Do not enter any information in the Jail Admission Event Module for direct placements.

FIGURE 9. VPRAI TAB IN PT PLACEMENT MODULE

Pretrial and Community Corrections Case Management System (PTCC) - [Pretrial - VPRAI]

File Edit Modules Reports Administration Window Help

Placement **VPRAI** Charges Conditions Payment Obligations Court Dates Attorney

Name: Case, Test; SSN: 999999999; DOB: 07/12/1993 Placement Number: 2017071200001

VPRAI

Instrument Completion Date: 07/27/2017

Research Factors

Prior Misdemeanor Conviction: No Prior Felony Conviction: No

Prior Violent Convictions: 0

Prior FTAs in Past 2 Years: 0

Prior FTAs Older Than 2 Years: No

Prior Sentence to Incarceration: No

Risk Factors

Active Community Supervision: No

Charge is Felony Drug, Theft or Fraud: No

Pending Charge(s): No

Criminal History: No

Two or More FTAs: No

Two or More Violent Convictions: No

History of Drug Abuse: Yes

Employed at Time of Arrest: None

Calculate Risk

Risk Level: 2

Print VPRAI

Praxis

Praxis Applies: Yes

Charge Category: Non-Violent Felony

FTA Underlying Charge:

Praxis Sup Level: Monitoring Assigned Sup Level: Level I

Consistent With Praxis: No

// No Reason: sdfsdaf

Staff: Rose, Ken

Date Edited: 07/27/2017 10:23 AM

Exit << Previous Save Undo New Delete Next >>

Research Factors

For further explanation on completing these fields, see the research factors under the Jail Admission Event Module section found on pages 7 - 9 of this manual.

Risk Factors

For further explanation on completing these fields, see the risk factors under the Jail Admission Event Module section found on pages 9 - 11 of this manual.

Praxis

The purpose of this section is to identify the supervision level for those defendants ordered to pretrial supervision. To determine whether the Praxis applies and an explanation on selecting the charge category, see the “Praxis Recommendation” section on pages 14 - 15 of this manual.

After selecting the charge category, the “Praxis Supervision Level” field will auto-fill with the supervision level. The officer will then select the “Assigned Supervision Level” from the following dropdown:

- ✓ Level I
- ✓ Level II
- ✓ Level III
- ✓ Monitoring

After selecting the “Assigned Supervision Level” the “Consistent with Praxis” field will auto-fill with a “yes” or “no” based on the officer selection and the displayed “Praxis Supervision Level.” If the assigned supervision level is different than the Praxis supervision level, enter the justification for the override in the “If no, reason” field. Note that the Praxis supervision concurrence rate for each agency must be 85% or higher. In addition, the supervision level must not be adjusted up or down by more than one level. For example, a Praxis Level I could only be overridden to Monitoring or Supervision Level II.

Praxis – Supervision Levels

The defendant’s calculated risk level and the current most serious charge category will determine the level of supervision for those ordered to pretrial supervision. Using the risk level identified by the VPRAI and selecting the current most serious charge category, defendants released with pretrial supervision will be assigned to one of four levels of supervision: Pretrial Monitoring, Level I, Level II, or Level III. See Table 5.

TABLE 5. PRETRIAL PRAXIS – SUPERVISION LEVELS (MANUAL VERSION)

Risk Level	Recommendation	VPRAI: Charge Category				
		Non-Violent Misd.	Driving Under the Influence	Non-Violent Felony	Violent Misd.	Violent Felony or Firearm
Level 1	Pretrial Supervision Level	Monitor	Monitor	Monitor	Monitor	Level II
Level 2	Pretrial Supervision Level	Monitor	Monitor	Monitor	Monitor	Level III
Level 3	Pretrial Supervision Level	Monitor	Monitor	Level I	Level I	Level III
Level 4	Pretrial Supervision Level	Level I	Level I	Level II	Level II	Level III
Level 5	Pretrial Supervision Level	Level II	Level II	Level III	Level III	Level III
Level 6	Pretrial Supervision Level	Level III	Level III	Level III	Level III	Level III

Based on the pretrial supervision level identified by the Praxis, defendants will be assigned to one of the following differential supervision strategies. See Table 6.

TABLE 6. DIFFERENTIAL SUPERVISION LEVEL OF THE PRAXIS

Level	Supervision Strategy
Pretrial Monitoring	<ul style="list-style-type: none"> ✓ Court date reminder for every court date ✓ Criminal history check before court date
Pretrial Supervision Level I	<ul style="list-style-type: none"> ✓ Court date reminder for every court date ✓ Criminal history check before court date ✓ Face-to-face contact once a month ✓ Special conditions compliance verification
Pretrial Supervision Level II	<ul style="list-style-type: none"> ✓ Court date reminder for every court date ✓ Criminal history check before court date ✓ Face-to-face contact every other week ✓ Special conditions compliance verification
Pretrial Supervision Level III	<ul style="list-style-type: none"> ✓ Court date reminder for every court date ✓ Criminal history check before court date ✓ Face-to-face contact every week ✓ Special condition compliance verification

VIRGINIA PRETRIAL RISK ASSESSMENT INSTRUMENT (SAMPLE)

Virginia Pretrial Risk Assessment Instrument

Instrument Completion Date: 04/03/2018

Court Date: 04/03/2018

First Name: John

Last Name: Test

Race: White

SSN: 568-15-2469

Sex: Male

DOB: 06/30/1972

Charge(s): Grand Larceny, Possession of Cocaine
\$5,000 Secured Bond
General District Court

Recommendation	Primary Charge Category	Risk Level
Release With Pretrial Supervision	Non-Violent Felony	5

Pretrial services recommendation is consistent with the Praxis

Conditions of Release

- Refrain from excessive use of alcohol or use of drugs
- Submit to testing for drugs and alcohol
- Maintain or seek employment

Risk Assessment

- The defendant was on active criminal justice supervision at the time of arrest.
- The defendant has a current charge of felony drug, theft or fraud.
- The defendant did not have pending charges at the time of arrest.
- The defendant has prior criminal convictions.
- The defendant does not have 2 or more failure to appears.
- The defendant does not have 2 or more violent convictions.
- The defendant has a history of drug abuse.
- The defendant did not meet employment stability requirements at the time of arrest.

Mitigating/Aggravating Considerations

Although the defendant was not employed at the time of arrest, he will begin employment next week at American Auto Repair as a mechanic. This information was verified by the owner of American Auto Repair, John Sullivan.

Confidential - Further disclosure prohibited by law pursuant to §2.2-3706 and §19.2-152.42 of the Code of Virginia.

This recommendation is based on information available to the pretrial officer at the time the report was compiled. The Court may have additional information available to it when a bail/bond hearing is held, such as the nature and circumstances of the alleged offense, the number of charges that are pending, any juvenile criminal history, or the potential risk the defendant may pose to the alleged victim(s) or witness(es).

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VPRAI – MANUAL SCORING SHEET

Virginia Pretrial Risk Assessment Instrument (Manual Scoring Sheet)

Instrument completion Date: _____ Court Date: _____
 First Name: _____ Last Name: _____
 SSN: _____ DOB: _____ Race: _____ Sex: _____

Charge(s): _____

Research Factors:

1. Prior Adult Misdemeanor Conviction: Yes No
2. Prior Adult Felony Conviction: Yes No
3. Prior Violent Conviction: 0 1 2 3 or More
4. Prior Failures to Appear in Past 2 Years: 0 1 2 3 or More
5. Prior Failures to Appear Older than 2 Years: Yes No
6. Prior Sentence to Incarceration: Yes No

Risk Factors:

#	Risk Factors	# Points	Yes ✓	No ✓	Score	
1	Active Community Criminal Justice Supervision	2 points				
2	Current Charge is Felony Drug, Felony Theft or Felony Fraud	3 points				
3	Pending Charge at Time of Arrest	2 points				
4	One or More Adult Criminal Convictions	2 points				
5	Two or more Failures to Appear	1 point				
6	Two or more Violent Convictions	1 point				
7	Unemployed at the Time of Arrest	1 point				
8	History of Drug Abuse	2 points				
Total Score						
Score	0 - 2	3 - 4	5 - 6	7 - 8	9 - 10	11 - 14
Risk Level	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6

The pretrial risk assessment identifies the defendant's risk level as _____

Praxis Recommendation:

1. Does the Praxis apply: Yes No
2. If yes, determine the most serious charge category:
 - Violent Felony / Firearm
 - Violent Misdemeanor
 - Non-Violent Felony
 - Driving Under the Influence
 - Non-Violent Misdemeanor
 - Failure to Appear (If selected, choose the primary charge category for the underlying charge.)
 - Violent Felony / Firearm (If selected, Risk Level = Current Risk Level + 1)
 - Violent Misdemeanor (If selected, Risk Level = Current Risk Level + 1)
 - Non-Violent Felony (If selected, Risk Level = Current Risk Level + 1)
 - Driving under the Influence (If selected, Risk Level = Current Risk Level + 1)
 - Non-Violent Misdemeanor (If selected, Risk Level = Current Risk Level + 1)

Confidential- Further disclosure prohibited by law pursuant to §2.2-3706FB and §19.2-152.4:2 of the Code of Virginia

Risk Level	Recommendation	VPRAI: Charge Category				
		Non-Violent Misdemeanor	Driving Under the Influence	Non-Violent Felony	Violent Misdemeanor	Violent Felony or Firearm
Level 1	Bail Status	Release	Release	Release	Release	Release
	Pretrial Supervision	No	No	No	No	Level II
	Special Conditions	No	No	No	No	As Needed
Level 2	Bail Status	Release	Release	Release	Release	Release
	Pretrial Supervision	No	Monitor	Monitor	Monitor	Level III
	Special Conditions	No	No	No	No	As Needed
Level 3	Bail Status	Release	Release	Release	Release	Detain
	Pretrial Supervision	Monitor	Monitor	Level I	Level I	No
	Special Conditions	No	No	No	As Needed	N/A
Level 4	Bail Status	Release	Release	Release	Release	Detain
	Pretrial Supervision	Level I	Level I	Level II	Level II	No
	Special Conditions	No	As Needed	As Needed	As Needed	N/A
Level 5	Bail Status	Release	Release	Release	Detain	Detain
	Pretrial Supervision	Level II	Level II	Level III	No	No
	Special Conditions	As Needed	As Needed	As Needed	N/A	N/A
Level 6	Bail Status	Detain	Detain	Detain	Detain	Detain
	Pretrial Supervision	No	No	No	No	No
	Special Conditions	N/A	N/A	N/A	N/A	N/A

Recommendation: ✓ the box below to indicate your recommendation

<input type="checkbox"/> Release without Pretrial Supervision	<input type="checkbox"/> Release with Pretrial Supervision	<input type="checkbox"/> Detain	<input type="checkbox"/> No Recommendation
---	--	---------------------------------	--

Conditions of Release:

- _____
- _____

Mitigating / Aggravating Considerations:

RISK ASSESSMENT FACTSHEET

Virginia Pretrial Risk Assessment Instrument (VPRAI)

LAST UPDATED: June 19, 2019

REVIEWED BY: Kenneth Rose, Virginia Department of Criminal Justice Services

Note: Though the VPRAI was first developed in 2003, the tool was revised in 2007 to remove the “Outstanding Warrants” factor and was further revised in 2016. Though we describe both the original tool (referred to as “VPRAI”) and the 2016 revised tool (referred to as “VPRAI-Revised”) in this factsheet, our focus is on the 2016 revised tool. More information about the 2003 tool can be found in Source 1.

Who created the risk assessment?

The VPRAI was created by the Virginia Department of Criminal Justice Services, led by Marie VanNostrand, Ph.D. The VPRAI-Revised was developed by Luminosity, Inc. (a private company) and was supported by the Virginia Department of Criminal Justice Services. The researchers who worked on the VPRAI-Revised were Mona J.E. Danner, Ph.D. (Old Dominion University), Marie VanNostrand, Ph.D. (Luminosity, Inc.), and Lisa M. Spruance, M.S. (Independent Consultant).

How large was the training data set?

The training data set for the VPRAI had 1,971 cases. The training data set for the VPRAI-Revised had 14,383 cases.

How was the training data set collected and assembled (i.e., what jurisdiction(s) is it from)?

The training data set for the VPRAI was collected by the Virginia Department of Criminal Justice Services from a sample of defendants arrested in one of seven different Virginia localities. The localities “varied substantially in community characteristics,” including, community type, population, sex, race, and socioeconomic status. (See Source 1, page 4). Data was collected from personal interviews, by consulting various criminal and state records, and by contacting defendant references. The researchers used a sampling procedure for interviewing defendants “to account for variances in arrest due to time of day, day of week, month, and season” (See source 1, page 4).

The training data set for the VPRAI-Revised was a subset of data collected and used for another study about pretrial release in Virginia (See Source 4). The training data set for the VPRAI-revised came from Virginia localities using the VPRAI. (Source 5).

Over what time frame was the data collected?

For the VPRAI, data was collected from a “sample of defendants arrested in select Virginia localities between July 1, 1998 and June 30, 1999..The cases were tracked until final disposition through the use of court and other official records to determine the pretrial outcome” (Source 1).

For the VPRAI-Revised, the data collection process occurred from October 2012 through December 2014 (Source 4).

What factors (i.e., defendant characteristics) were included in the data set? This question pertains to all the factors that were available about defendants, not necessarily all the factors that were used to train or develop the model.

The VPRAI training data set had 50 factors that had to do with “demographic characteristics, physical and mental health, substance abuse, residence, transportation, employment and school status, income, the charge(s) against the defendant, and criminal history” (Source 1; see Source 1 for full list).

For the VPRAI-Revised training data set, “each case contain[ed] a VPRAI and data on charge category, demographics, supervision and outcome” (Source 5) as well as information on 20 additional alternative risk factors pertaining to charge type, failure to appear, violent convictions, employment, and drug abuse (Source 5).

Does the dataset include instances of defendants who were detained? If so, does the data include outcomes for those people (i.e., did the data account for counterfactual estimation; if so, how)?

No - defendants who were detained were filtered out of both the VPRAI and VPRAI-Revised training data sets; the samples that were used contained defendants who had been released at some point in the observed pretrial process (Source 1; Source 4).

Are there any known issues or errors with the data?

Criminal justice data sets, in general, often suffer from measurement error and sample bias. The tool creators did not note any more specific issues in their development reports.

In what year was the risk assessment created?

The VPRAI was created in 2002 and fully implemented in 2005. The VPRAI-Revised was developed in 2015-2016.

What factors, among all the factors in the training data, were considered in the development of the risk assessment? If not all factors were considered, how were those that were considered chosen?

For the VPRAI, all factors were considered. The VPRAI-Revised was built by examining the VPRAI and exploring whether alternative or additional factors could improve the tool (Source 1). Thus, the development of the VPRAI-Revised considered the factors on the VPRAI as well as 20 additional or alternative risk factors (Source 5).

How were factors that were considered ultimately chosen for exclusion or inclusion in the final model (the risk assessment itself)?

For the VPRAI, researchers used a variety of bivariate analysis techniques to “identify the statistically significant variables (risk factors) related to pretrial outcome (success or failure pending trial).” The researchers used the results of the bivariate analyses to build a binary logistic regression model (see Source 1 for more).

The original VPRAI had nine factors. However, in a validation study conducted in 2007, Luminosity, Inc. and the Virginia Department of Criminal Justice Services decided to alter the VPRAI by removing the factor “Outstanding Warrants.” They did so after determining that the factor “was not a statistically significant predictor of pretrial outcome” and that the risk assessment without “Outstanding Warrants” “was a slightly better predictor of pretrial outcome when compared to the original 9 factor model” (Source 2).

For the VPRAI-Revised, a variety of statistical techniques were used to examine the eight factors in the VPRAI (the one without “Outstanding Warrants”) and test whether alternatives would improve the tool’s performance in any way. This analysis led to alterations to two factors, the addition of one factor, and the removal of one factor (Source 5).

Does the final model include as a factor(s) arrests that did not lead to convictions?

The VPRAI considered “Charge Type” and “Pending Charge(s)” (Source 1). The VPRAI-Revised includes “Charge is felony drug, theft, or fraud” and “Pending charge” (Source 5). It is important to note that such current or pending charges may or may not have ultimately lead to a conviction.

Does the final model include socioeconomic factors such as housing and employment status? Does the final model include personal health factors such as mental health or substance abuse?

Yes - the VPRAI included “Length at Current Residence,” “Employed/Primary Child Caregiver,” and “History of Drug Abuse” (Source 1). The VPRAI-Revised includes “Unemployed at time of arrest” and “History of drug abuse” (Source 5).

How were weights assigned to each factor included in the final model? (rounding correlation coefficients, Burgess Method, etc.)

For the VPRAI, weights were assigned by applying a transformation to the coefficients from the binary logistic regression model and then rounding to the nearest whole number (Source 1). For the VPRAI-Revised, weights were assigned by rounding the odds ratios from the logistic regression model for the VPRAI-revised (See Source 5 for more information).

How does the final model define outcomes (i.e., during the model development process, was there a distinct outcome defined for each type of failure (flight risk, new crime, new violent crime, etc.) or were outcomes compounded?

Both the VPRAI and VPRAI-Revised compound outcomes into a single outcome. This was the “pretrial outcome, defined as success or failure pending trial” where “a defendant was classified as a ‘failure’ pending trial if he failed to appear for a scheduled court appearance or was arrested for a new offense pending trial” (Source 1).

According to Kenneth Rose, “Future plans are to separate failure by risk of failure to appear in court and new alleged criminal offenses. In addition to new alleged criminal offenses, distinguishing between violent and non-violent may be another future consideration.”

What does the output of the model look like (i.e. a score on a scale of 1-10, etc.)?

The output of the VPRAI-Revised is a score between 0 and 14.

Does the model output risk level designations or convert raw scores into risk level designations such as “low risk,” “moderate risk,” and “high risk”?

For the VPRAI-Revised, numerical scores are collapsed into six different risk levels (see Source 5 for more information on the risk levels).

What proportion of samples in the training data set failed at each risk score and/or level (i.e., what percentage of people with a score of 5 or a label of “moderate risk” actually failed to appear)?

For the VPRAI-Revised, we present failure rates by risk level in the training data below. (Source 5; see source 5 for failure rates by risk score).

Risk Level	Score Range	Any Failure Rate
1	(0-2)	6.1%
2	(3-4)	9.8%
3	(5-6)	14.9%
4	(7-8)	21.4%
5	(9-10)	29.3%
6	(11-14)	37.1%

Did the model developers assess the predictive validity of the model? If so, how (reported AUC, FPR, TPR, etc.)?

Yes - the predictive validity for both the VPRAI and the VPRAI-Revised were assessed by the tool developers using a variety of statistical techniques, including calculating AUC values, tests of statistical significance, and plotting failure rates in the training data as a function of risk scores (See sources 1, 2, and 5 for more information).

Where is the risk assessment used?

There is no definitive list of where the VPRAI or VPRAI-R are used. The risk assessment is used statewide in Virginia and in a number of counties in California. According to Dr. VanNostrand, "It was...adopted in Summit County, Ohio in 2004 and later independently validated by Dr. Chris Lowenkamp through the University of Chicago. A couple of years later it was adopted in Lake County, Illinois and later independently validated by Court researchers. It was then implemented in 10 counties in Michigan. After that the use of the tool spread rapidly. A survey...in 2012...revealed it was being used in counties in at least 12 states."

Are the factors and weights of the risk assessment publicly available?

Yes, the factors and weights for both the VPRAI and the VPRAI-Revised are publicly available.

Does the risk assessment cost money for a jurisdiction to adopt? Does the adoption of the risk assessment require training? If so, by who?

According to Dr. Marie VanNostrand, "The VPRAI is public domain and free. There are some consultants who offer training and implementation TA for a fee."

According to Kenneth Rose of the Virginia Department of Criminal Justice Services, "Implementation and training outside of Virginia is up to the other outside agency to determine."

Does the risk assessment come with any sort of software or software package?

In Virginia, "The VPRAI is automated and contained in the Pretrial and Community Corrections Case Management System (PTCC)" (Source 7).

However, according to Kenneth Rose, "The software/database used in Virginia is for Virginia agencies only. Software implementation is up to the outside agency to determine." According to Dr. Marie VanNostrand, the VPRAI may also be included in some off the shelf software applications.

Does the risk assessment involve or require an in-person interview?

Yes, the risk assessment requires an in-person interview.

How does the risk assessment account for missing information?

If information is missing, the risk assessment cannot be completed.

Has the risk assessment been analyzed on non-training data for predictive validity? Has the risk assessment been analyzed with training data or non-training data with regard to performance for different race groups? Has the risk assessment been analyzed with training data or non-training data with regard to performance for different genders? If so, by who, when, and using what data?

Yes. Numerous validation studies have been completed for the VPRAI, including ones with a focus on the VPRAI's predictive power across race and gender groups. The VPRAI-Revised was created as a result of a validation study intending to improve the original VPRAI.

Validation studies have been performed in the state of Virginia and elsewhere, including in Mecklenburg County, North Carolina, Oakland County, Michigan, Summit County, Ohio, Lake County, Illinois, and Mecklenburg, NC. A number of these studies are included in the “Information retrieved from” section; others can be found online.

In Riverside County, California, a validation study that modified the VPRAI led to the creation of the Riverside Pretrial Risk Assessment Instrument (RPRAI). See source 9.

Information retrieved from:

[1] Marie VanNostrand Ph.D., *Assessing Risk Among Pretrial Defendants in Virginia: The Virginia Pretrial Risk Assessment Instrument* (April 2003)

[2] Marie VanNostrand, Ph.D. and Kenneth J. Rose (Luminosity, Inc.), *Pretrial Risk Assessment in Virginia* (May 1, 2009)

[3] Marie VanNostrand, Ph.D. (Luminosity, Inc.), Kenneth J. Rose (Luminosity, Inc.), and Kimberly Weibrecht, J.D. (Crime and Justice Institute at CRJ), *In Pursuit of Legal and Evidence-Based Pretrial Release Recommendations and Supervision* (March 2011)

[4] Mona J.E. Danner, Ph.D. (Old Dominion University), Marie VanNostrand, Ph.D. (Luminosity, Inc.), Lisa M. Spruance, M.S. (Independent Consultant), *Risk-Based Pretrial Release Recommendations and Supervision Guidelines* (August 2015)

[5] Mona J.E. Danner, Ph.D. (Old Dominion University), Marie VanNostrand, Ph.D. (Luminosity, Inc.), Lisa M. Spruance, M.S. (Independent Consultant), *Race and Gender Neutral Pretrial Risk Assessment, Release Recommendations, and Supervision: VPRAI and Praxis Revised* (November 2016)

[6] Kenneth Rose, *Virginia Pretrial Risk Assessment Instrument (VPRAI) & Praxis Overview*, Pretrial Services Stakeholder Group: Workgroup B (June 11, 2018)

[7] Virginia Department of Criminal Justice Services, *Virginia Pretrial Risk Assessment Instrument (VPRAI) Instruction Manual 4.3* (April 2018)

[8] Information from Dr. Marie VanNostrand and Kenneth Rose.

[9] Brian Lovins and Lori Lovins, Correctional Consultants Inc. *Riverside Pretrial Assistance to California Counties (PACC) Project: Validation of a Pretrial Risk Assessment Tool*.

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PRETRIAL RISK ASSESSMENT TOOLS

A Primer for Judges, Prosecutors,
and Defense Attorneys

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This report was prepared following a meeting convened by the John D. and Catherine T. MacArthur Foundation as part of the Safety and Justice Challenge, which seeks to reduce over-incarceration by changing the way America thinks about and uses jails. Core to the Challenge is a competition designed to support efforts to improve local criminal justice systems across the country that are working to safely reduce over-reliance on jails, with a particular focus on addressing disproportionate impact on low-income individuals and communities of color.

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A vibrant national debate is occurring as to what role, if any, pretrial risk assessment tools can or should play in bail reform. This critical issue brief is intended to inform this ongoing debate by describing pretrial risk assessment tools and what they are designed to do. This primer is not intended to guide the selection, validation, or implementation of a specific pretrial risk assessment tool; resources to support these decisions are available elsewhere.¹ Instead, our goal is to provide foundational knowledge about pretrial risk assessment tools to contextualize and support further discussion regarding the use and evaluation of these tools in practice.

RISK AND REFORM IN PRETRIAL JURISPRUDENCE

In the past several years, every state has enacted legal reforms governing pretrial release and detention.² These reform efforts reflect widespread recognition that jails in much of the country are overused, and that many people who could succeed in the community on pretrial release are incarcerated due to their inability to post even modest financial bonds. “The overarching reform vision is to shift from the ‘resource-based’ system of money bail to a ‘risk-based’ system, in which pretrial interventions are tied to risk rather than wealth.”³ Accordingly, jurisdictions across the United States are exploring alternatives to money bail that center on the likelihood that a defendant *will appear in court without a new arrest*, rather than on a defendant’s ability to pay bail. One strategy involves the implementation of pretrial risk assessment tools — empirically based tools that aim to estimate the likelihood of appearance in court with no new arrest, thereby providing information that can support objective and transparent decision-making.

In this context, the results of pretrial risk assessment tools may enhance the fair administration of justice *if* the information they produce leads to more equitable and less carceral decisions. Specifically, **pretrial risk assessment tools could provide some objective, empirical evidence to inform decisions** to release defendants who pose low risk of failure to appear and threat to public safety with minimal or no conditions; to release other defendants with conditions and strategies to maximize the likelihood they will appear at future court dates and avoid rearrest (e.g., community supervision, electronic monitoring); and to consider detention only for those defendants whose risk of failure

to appear and threat to public safety cannot be managed in the community. However, the results of pretrial risk assessment tools should never result in detention without a due process hearing with a higher burden of proof on the state to show that there are no conditions that would reasonably assure appearance in court with no new arrest.

Pretrial risk assessment tools are designed to *inform* not *replace* the exercise of judicial decision-making and discretion. The results produced by pretrial risk assessment tools should be considered transparently and on the record within a range of pretrial release guidelines. At a detention hearing, judges also should consider other relevant information, including the nature and circumstances of the offense(s) charged, the weight of the evidence, factors required by state statute that are not captured in the risk assessment, and input from prosecutors and defense attorneys. Thus, pretrial risk assessment tools provide group-based information that may support pretrial decisions, while still allowing for judicial discretion that accounts for the facts and circumstances of an individual case.

RISK ASSESSMENT DEFINED

Risk assessment can be defined as the process through which *risk factors* and *protective factors* are used to estimate the *likelihood* that an outcome will occur. **In the context of pretrial risk assessment, the outcome of legal interest is *appearance in court with no new arrest during the pretrial period*.** Inherent in this definition is that there is still uncertainty regarding whether or not the defendant will be successful. Indeed, it is not possible to predict human behavior with 100% certainty. Yet, the Supreme Court does not require that we know the likelihood of success with 100% certainty, and in fact, used “reasonable assurance” in its ruling that detention should be the “carefully limited exception.” To that end, a preponderance of research shows

Pretrial risk assessment tools are designed to inform not replace the exercise of judicial decision-making and discretion.

that the use of a validated risk assessment tool can improve the accuracy with which these likelihoods are estimated, compared to decisions that rely solely on subjective judgment.⁴

RISK AND PROTECTIVE FACTORS

Items included in pretrial risk assessment tools describe characteristics of the defendant, their social environments, or their circumstances. A review of the myriad of available pretrial risk assessment tools shows that they typically include some combination of the following:

- Defendant age
- Substance use
- Criminal history, including violence and failure to appear
- Active community supervision
- Pending/current charge(s)
- Employment stability
- Education
- Housing/residential stability
- Family/peer relationships
- Community ties

Risk factors are characteristics of a defendant, their environment, or their circumstances that are associated with *increased* likelihood of failure to appear and/or rearrest, whereas *protective factors* are characteristics that are associated with *decreased* likelihood of failure to appear and/or rearrest. Although protective factors are not included in many pretrial risk assessment tools, there is more and more research showing the value they add to the risk assessment process. In particular, studies show that protective factors are not just the absence of a risk factor, but rather that they reduce the likelihood of recidivism among offenders exposed to risk factors.⁵ In this way, consideration of protective factors can increase the accuracy with which we estimate the likelihood of pretrial outcomes.

ESTIMATING THE LIKELIHOOD OF FAILURE TO APPEAR AND REARREST

The estimated likelihood produced by a pretrial risk assessment tool, known as a *risk estimate*, will usually be described as a probability or category of risk, such as low, moderate, or high. The risk estimate produced

The ultimate description of a defendant's risk as low, moderate, or high in a given jurisdiction is a policy decision, not a scientific one.

by a pretrial risk assessment tool will typically be based on the defendant's score in relation to a reference or norming population. That is, the defendant's score will be compared to the scores of defendants studied during the tool's development or validation process and their rate of failure to appear and/or rearrest. The process through which information regarding risk and protective factors is used to estimate risk for failure to appear and/or rearrest is an empirical one. Specifically, numeric item ratings are transformed into a score, which in turn represents an estimate of the likelihood of failure to appear and/or rearrest. Most pretrial risk assessment tools produce one score that is used to estimate different pretrial outcomes, while some tools produce separate scores for each pretrial outcome of interest.

The ultimate description of a defendant's risk as low, moderate, or high in a given jurisdiction is a policy decision, not a scientific one. A pretrial risk assessment tool can describe a defendant's likelihood of failure to appear and/or rearrest as a function of the rates of those outcomes among other defendants with a score in the same range. However, the pretrial risk assessment tool cannot speak to how these rates of failure to appear and/or rearrest are viewed within a given jurisdiction. Instead, the acceptability and tolerability of those rates should be determined by stakeholders before implementation. For instance, a defendant may receive a score that indicates a 20% likelihood of failure to appear. Stakeholders must decide what this 20% likelihood means for pretrial decision-making in that jurisdiction.

Further, that 20% likelihood reflects the rate of failure to appear in the population of defendants used to develop or "norm" the pretrial risk assessment tool, which may not represent the rate of failure to appear among defendants who receive that score in other jurisdictions. For this reason, a pretrial risk assessment tool, no matter how well

validated in other jurisdictions, should be subjected to local evaluation, ideally in the form of a pilot study, before full-scale implementation. Doing so provides information regarding rates of failure to appear and rearrest for a new crime associated with the different scores in that jurisdiction. It also provides the opportunity to tailor pretrial release guidelines to these jurisdiction-specific failure rates.

RISK ASSESSMENT APPROACHES AND TOOLS

Approaches to Risk Assessment

There are several different approaches to risk assessment that range from subjective and qualitative to objective and empirical, or some combination thereof. Historically, the process of risk assessment — in the context of pretrial decision-making or otherwise — was qualitative and subjective, often referred to as *unstructured professional judgment*. That is, the decision maker, such as a judge, would rely on their professional training, their experience, and information gathered from the defendant, official records, or other sources to inform their subjective evaluation of risk for failure to appear and/or rearrest. This approach is “unstructured” insofar as it does not rely on a standardized checklist or protocol, although a decision maker may have a handful of factors they consider or set questions they ask defendants to inform their decisions.

This unstructured professional judgment was the standard of practice in risk assessment through the 1970s. However, on average, unstructured professional judgments of public safety risks have repeatedly been shown to be less accurate than empirically based risk assessment approaches.⁶ Why?

Human judgment is inherently influenced by personal beliefs. In some cases, these beliefs are accurate and relevant to the decision at hand. In other cases, including in the context of bail decisions, these beliefs can reflect inaccurate stereotypes that contribute to biased and erroneous decisions.⁷

Empirically based approaches, often referred to as *structured risk assessment*, are the accepted state-of-the-science when it comes to pretrial risk assessment, as well as risk assessment in other public safety domains.

Structured risk assessment tools were informed by more than 65 years of rigorous research studying factors that are statistically associated with public safety risks.

There are two overarching approaches to structured risk assessment: (1) actuarial risk assessment, and (2) structured professional judgment. While proponents of each approach have debated their relative merits, research reviews show that they estimate the likelihood of public safety risks with comparable reliability (i.e., consistency between assessors) and predictive validity (i.e., accuracy in forecasting the outcome of interest).⁸

Actuarial risk assessment is the most prominent form of structured risk assessment in pretrial settings. Actuarial risk assessment tools assign numerical values to each risk and protective factor and then weight and combine the item ratings to produce risk scores. The methods through which item ratings are weighted and combined differ, but generally reflect the degree to which the items are related to the outcome of interest and the statistical association between the items in the development sample(s). The estimated likelihood of failure to appear and/or rearrest are then determined as a function of the rate of failure to appear and/or rearrest among defendants in the development sample(s) who received that same risk scores.

Whereas the actuarial risk assessment approach automates the scoring of the assessment, the *structured professional judgment* approach provides a framework for estimating risk, without removing professional judgment from the assessment process altogether. These tools guide assessors to consider a set list of evidence-based risk and protective factors. Although assessors rate the presence, severity, and/or relevance of the risk and protective factors, the item ratings are not summed to produce a numerical score that represents a likelihood or probability. Instead, assessors consider the item ratings as they relate to an individual's case and circumstances to inform their final, *professional judgment* of risk as low, moderate, or high. Widely used in other domains, the structured professional judgment approach is uncommon in pretrial risk assessment.

Structured risk assessment tools were informed by more than 65 years of rigorous research studying factors that are statistically associated with public safety risks.

Finally, some pretrial risk assessment tools use a hybrid approach that combines features of actuarial risk assessment and structured professional judgment, through the inclusion of a *clinical or professional override*. These instruments typically use the actuarial risk assessment approach to produce the risk estimate, but they also provide the individual completing the assessment with the opportunity to “override” the actuarial risk estimate; that is, they can assign a higher or lower risk estimate before the results of the pretrial risk assessment are shared with the judicial decision-maker. **This professional override exists within the structure of the risk assessment tool itself and is separate and distinct from the exercise of judicial discretion.**

Pretrial Risk Assessment Tools

Recent reviews have identified more than two dozen different pretrial risk assessment tools in various jurisdictions across the United States. These tools differ not only in how they estimate risk, but also in the factors they assess and the source(s) of information necessary to complete the assessment (e.g., self-report, official records). Some tools were developed to assess specific populations, while others were developed for use in specific jurisdictions. Other tools were developed for widespread use across jurisdictions and others, still, were originally developed for a specific jurisdiction, but have since been adapted and/or validated for use in other jurisdictions. Some tools reside in the public domain, while others are proprietary. The proprietary nature of a tool, in turn, can have implications for transparency (or lack thereof) regarding the information and methods used to estimate risk.⁹

There have been dozens of studies conducted over the past 20 years that show risk assessment instruments can produce estimates of the likelihood of rearrest that are statistically and significantly more accurate than unstructured professional judgments of risk to public safety. However, the real-world performance of any given pretrial risk assessment tool for any given defendant will be affected by many things, including, among others, the training and experience of the individual completing the risk assessment and the amount and quality of information available to complete the risk assessment. **Even a well-validated risk assessment tool will not produce accurate estimates of risk for failure to appear and/or rearrest if it is not used correctly.**

Finally, pretrial risk assessment tools *estimate* the *likelihood* of failure to appear and/or rearrest. No matter how good the tool, there will always be cases in which an individual's level of risk is under (or over) estimated. However, research supports that the use of pretrial risk assessment tools — when implemented with fidelity — can help improve the calibration of pretrial decisions. Specifically, they can help reduce the frequency with which defendants are identified as high risk for failure to appear and threat to public safety when in reality they would have been successful on pretrial release, as well as the frequency with which defendants are identified as low risk, but fail to appear in court and/or are rearrested.

RESEARCH ON PRETRIAL RISK ASSESSMENT TOOLS

Research on pretrial risk assessment tools can largely be divided into two distinct tracks: (1) research on the tools' *predictive validity* and (2) research on the tools' *impact on decision-making*. For pretrial risk assessment tools to be considered “valid,” they must be able to estimate the probability of failure to appear and/or pretrial rearrest at statistically significant and politically acceptable rates. But, research demonstrating *predictive validity* does not equate with research demonstrating *implementation success*. Indeed, even a well-validated tool may not produce the intended results of more accurate, decarceral, and racially and ethnically equitable decisions relative to practice as usual for many reasons, including problems with implementation.

Most research to date has focused on predictive validity.¹⁰ These studies typically have produced promising results, showing that pretrial risk assessment tools can distinguish between defendants at low, moderate, and high risk of pretrial failure to appear and rearrest. That is, these studies find the lowest rates of failure to appear and rearrest

Even a well-validated risk assessment tool will not produce accurate estimates of risk for failure to appear and/or rearrest if it is not used correctly.

among defendants identified as low risk and the highest rates of failure to appear and rearrest among defendants identified as high risk. However, the research methods and statistics used in these studies often fail to meet the standards of practice in the field of risk assessment¹¹ and the standards for educational and psychological testing more generally.¹² Further, there has been no independent evaluation or synthesis of this research, limiting more definitive conclusions regarding the predictive validity of pretrial risk assessment tools overall and with respect to specific tools and pretrial outcomes.

There has been less research conducted on the implementation of pretrial risk assessment tools. As a result, their impact on pretrial decisions and outcomes is unclear. To demonstrate, one statewide evaluation found that rates of pretrial release, especially non-financial pretrial release, increased following implementation of pretrial risk assessment tools. However, these effects eroded over time and the impact on pretrial arrest rates was negligible. Moreover, several years after the implementation of the risk assessment tools in this jurisdiction, the rate of pretrial release was *lower* prior to implementation.¹³ An evaluation of a different pretrial risk assessment tool in another jurisdiction also showed mixed results, finding lower rates of failure to appear but higher rates of new arrests following implementation.¹⁴ Impact on release rates was minimal. Yet, evidence is emerging from evaluations of ongoing implementations that show increased rates of pretrial release attributable to the use of pretrial risk assessment tools.

Taken together, the current body of research on pretrial risk assessment tools supports their ability to identify defendants at different rates of failure to appear and pretrial arrest, and leaves open the possibility that they could have a positive impact on pretrial decisions and outcomes. However, there have been relatively few methodologically rigorous investigations of the use of pretrial risk assessment tools in practice. A survey conducted about 10 years ago, for example, showed that nearly half of all jurisdictions using pretrial risk assessment tools had not evaluated the validity of the risk estimates in that jurisdiction;¹⁵ fewer, still, had evaluated their impact. To the extent that jurisdictions adopt pretrial risk assessment tools, the implementation should be accompanied by an independent evaluation of the relationships between

the items, risk estimates, and pretrial outcomes in that jurisdiction, as well as the degree to which the implementation contributes to more equitable and less carceral decisions.

COMMON OBJECTIONS TO THE USE OF PRETRIAL RISK ASSESSMENT TOOLS

Some judges, prosecutors, defense attorneys, and others have objected to the use of pretrial risk assessment tools, challenging their utility, validity, comprehensiveness, and fairness. Below we discuss some of the common objections. Many of these issues are contentious — even among legal and social science scholars — and remain unresolved. A future critical issue brief will address these objections in greater depth.

Pretrial risk assessment tools will fail to achieve — and may frustrate — the aims of bail reform.

A national coalition of more than 120 civil rights organizations announced in 2018 that “[w]e believe that jurisdictions should not use risk assessment instruments in pretrial decision-making, and [should] instead move to end secured money bail and decarcerate most accused people pretrial.”¹⁶ The signatories to this statement argue that pretrial risk assessment tools do not consistently or meaningfully reduce rates of pretrial incarceration or ameliorate racial and ethnic inequities.¹⁷ These concerns are shared by others: more than 80% of public defender respondents to a recent survey, for example, believed that the pretrial risk assessment tool used in their jurisdiction “contributed to racial and ethnic disparities in the criminal justice system.”¹⁸ At the same time, advocates contend that pretrial risk assessment may distract from other reforms, such as increasing supportive services that help people succeed on release; narrowing the “net” of charges that make defendants eligible for pretrial detention; or requiring a meaningful adversarial hearing before preventive detention can be imposed.

The extant research evidence neither supports nor refutes these concerns. There have been few studies examining the impact of the use of risk assessment tools on pretrial decision-making. There has been even less methodologically rigorous study of whether the use of a pretrial risk assessment tool will contribute to reductions in racial and ethnic inequities. What research exists generally shows

Pretrial risk assessment tools are designed to provide evidence that informs pretrial decision-making; they are not intended to make the pretrial decision.

parity in risk assessment scores and comparable levels of accuracy in estimating the likelihood of *pretrial outcomes* across groups defined by race and ethnicity (although the outcome measures themselves, include rearrest, may reflect systemic inequities).¹⁹ Some research also shows that the use of risk assessment tools can contribute to increased rates of pretrial release among racial and ethnic minorities over decisions made in the absence of pretrial risk assessment tools.²⁰ However, only a few pretrial risk assessment tools implemented in a handful of jurisdictions have been evaluated in this way.

Pretrial risk assessment tools are too simplistic.

Pretrial risk assessment tools simply cannot adequately capture all aspects of a defendant's circumstances and case. They do not purport to do so. Instead, they are intended to capture and summarize the most statistically robust predictors of failure to appear and/or rearrest. They are designed for efficiency of administration, often without a defendant interview,²¹ and as a strategy to reduce consideration of factors empirically unrelated to pretrial outcomes. Consequently, they can be used to assess pretrial defendants in a relatively short period (i.e., between booking and arraignment). And, as described earlier, many pretrial risk assessment tools incorporate an explicit process through which the assessor can override the mathematically produced risk estimate through consideration of a defendant's individual circumstances and case.

Pretrial risk assessment tools are designed to provide evidence that informs pretrial decision-making; they are not intended to *make* the pretrial decision. They provide information regarding how a given defendant's score relates to scores of other defendants and to rates of failure to appear and/or rearrest among defendants who received the same score. Even so, pretrial decisions

must still include consideration the defendant's unique circumstances and characteristics — which is the job of the court actors, prosecutors, and defense attorneys. Pretrial risk assessment tools can change the starting point for those conversations by providing group-based information on the likelihood of success on pretrial release, rather than relying solely on subjective interpretations of a defendant's charge, record, and life circumstances.

Pretrial risk assessments tools have limited utility in managing risk.

Some have argued that pretrial risk assessment tools offer limited value beyond estimating risk for failure to appear and/or rearrest because they do not explain *why* the individual received the score that they did nor *what can be done* to improve likelihood of success. This is true. Pretrial risk assessment tools are limited in the information they can provide regarding the reasons for possible failures to attend court or for being rearrested; it is a combination of factors rather than any given factor that contribute to an individual defendant's likelihood of success.

Pretrial risk assessment tools are not intended to inform case management and treatment per se, but rather to estimate the likelihood of failure to appear and/or rearrest if a defendant is released to the community without conditions. **Any conditions of pretrial release should only be imposed to increase the likelihood a defendant will appear in court with no new arrest.** For instance, research shows that court reminders and pretrial supervision, for some, can increase rates of court appearance for some categories of defendants.²² While some pretrial risk assessment tools may include treatment-relevant information, this information should not be used to impose conditions during the pretrial period for purposes other than risk management.

Any conditions of pretrial release should only be imposed to increase the likelihood a defendant will appear in court with no new arrest.

Pretrial risk assessment tools are not valid in my jurisdiction.

A common refrain is that pretrial risk assessment tools may work in some jurisdictions but will not work in others. A related concern is that the validity of pretrial risk assessment tools may change over time. These concerns speak to two overarching issues discussed elsewhere in this brief. First, the implementation of a pretrial risk assessment tool should be accompanied by an evaluation of predictive validity and impact of the tool on pretrial decision-making and outcomes in that jurisdiction. While research demonstrates that the factors that predict criminal behavior are typically fairly stable across time and jurisdiction,²³ there nonetheless may be factors that are jurisdiction-specific or whose relevance to failure to appear and/or rearrest change over time.²⁴ Second, the key to ensuring the utility of a given pretrial risk assessment tool in a given jurisdiction is to tailor risk estimates and pretrial decision-making policies to jurisdiction-specific failure rates over relatively recent timeframes.

COMMON PROBLEMS IN IMPLEMENTING PRETRIAL RISK ASSESSMENT TOOLS

The successful implementation of pretrial risk assessment tools into front-end decision-making processes is not without its challenges. Although individual jurisdictions may encounter unique challenges, below we summarize and discuss some of the common problems in implementing pretrial risk assessment tools.

Pretrial risk assessment tools are time-intensive and costly to implement.

The simple truth is that it can be time-intensive and costly to implement a pretrial risk assessment tool. Implementation requires staff time and training, not only for those who will be administering the tool, but also for those other stakeholders who will receive their results, including judges and magistrates, defense attorneys, and prosecutors. Efforts to adapt and validate a pretrial risk assessment tool for a specific jurisdiction also take time and resources. And, validation efforts and ongoing monitoring of pretrial outcomes require jail and court data systems to interface, often necessitating a minimum level of shared technological infrastructure. Implementation also may require dedicated staff to administer the tool, technology

to score and track results, and processes to ensure the communication of results to decision makers.

Post-implementation, in contrast, the ongoing use of a pretrial risk assessment tool is more about repurposing existing resources than creating new resources. Many pretrial risk assessment tools are free and very short, taking only minutes to complete. Further, if implementation of a pretrial risk assessment tool results in less carceral pretrial decision-making, then implementation costs could be offset by reductions in pretrial incarceration, contributing to cost savings over time.²⁵

Pretrial risk assessment tools require stakeholder buy-in.

Successful adoption of any new practice requires stakeholder buy-in; implementation of pretrial risk assessment tools is no exception. Collaboration between court administration, pretrial services, judges, and other stakeholders is essential to ensuring that risk assessment information is used to inform pretrial decision-making consistently. There is critical work that must be completed *before* implementing a pretrial risk assessment tool, including education and consultation. Best practice is that judges and other stakeholders are educated regarding the research on pretrial risk assessment tools, as well as the role of risk assessment tools in supporting (not replacing) judicial discretion. Judges and other stakeholders also should be engaged in the process of selecting a pretrial risk assessment tool, as well as the development of local policies and guidelines for its use, including the “risk tolerance” of the community and the response to different levels of risk presented by defendants (e.g., conditions of supervision).

There is a lack of resources in the community to address defendants’ needs.

Unfortunately, there is a lack of resources in communities across the United States to address the systemic inequities, as well as the individual risks and needs, that lead to — and result from — criminal justice contact. This reality will exist regardless of whether or not a pretrial risk assessment tool has been used. But, the implementation of a pretrial risk assessment tool may help clarify where there are unmet needs by providing individual- and population-level information; for example, the percentage of defendants

presenting with current substance use problems or experiencing homelessness. In this way, the results of pretrial risk assessment tools may provide empirical evidence to support requests for increased resources and funding to address unmet needs through enhanced community treatment services, housing programs, etc.

CONCLUSION

The role of risk assessment tools in pretrial decision-making is heavily debated within the context of bail reform. This critical issue brief does not take a position on the relative policy merits of pretrial risk assessment tools as a mode of bail reform. Instead, our objectives were more limited, but equally important: to provide legal stakeholders with an overview of pretrial risk assessment tools and how they operate; to describe the state of the research on their predictive validity and impact on pretrial decision-making; and to clearly communicate common objections and implementation problems. Future critical issue briefs will more thoroughly address civil rights concerns and critiques of pretrial risk assessment tools, as well as emergent methods and research surrounding machine learning techniques.

ENDNOTES

- 1 See, for example, the Public Safety Risk Assessment Clearinghouse: <https://psrac.bja.ojp.gov/>
- 2 National Conference of State Legislatures, *Trends in Pretrial Release: State Legislation Update*, April 2018.
- 3 M. Stevenson and S. Mayson, Pretrial Detention and Bail, Academy for Justice, *A Report on Scholarship and Criminal Justice Reform* (Erik Luna ed., 2018), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2939273
- 4 For meta-analytic reviews of research conducted over the past six decades, see W. M. Grove, et al. *Clinical versus mechanical prediction: a meta-analysis*, 12 Psychological Assessment 19-30 (2000) and S. Ægisdóttir, et al. *The meta-analysis of clinical judgment project: Fifty-six years of accumulated research on clinical versus statistical prediction*. The Counseling Psychologist 341-382 (2006). For one recent exception see J. Dressel & H. Farid, *The accuracy, fairness, and limits of predicting recidivism*, *Science Advances* (2018), <http://advances.sciencemag.org/content/4/1/eaao5580> (last visited Dec 3, 2018), but note critiques of their methodology and conclusions presented in A. M. Holsinger et al. *A rejoinder to Dressel and Farid: A new study finds computer algorithm is more accurate than humans at predicting arrest and as good as a group of 20 lay experts*, 82 Federal Probation 51-56 (2018).
- 5 J. Monahan & J. L. Skeem, *Risk assessment in criminal sentencing*, 12 Annual Review of Clinical Psychology 489-513 (2016).
- 6 See supra note 4.
- 7 D. Arnold et al., *Racial bias in bail decisions*, 133 The Quarterly Journal of Economics 1885-1932 (2018).
- 8 J. P. Singh, et al., *A comparative study of violence risk assessment tools: A systematic review and metaregression analysis of 68 studies involving 25,980 participants*, 31 Clinical Psychology Review 499-513 (2011); S. L. Desmarais, et al., *Performance of recidivism risk assessment instruments in U.S. correctional settings*, 13 Psychological Services 206-222 (2016); M. A. Campbell, et al., *The prediction of violence in adult offenders: A Meta-analytic comparison of instruments and methods of assessment*, 36 Criminal Justice and Behavior 567-590 (2009).
- 9 The vast majority of pretrial risk assessment tools have made their content and methods of estimation available to stakeholders and the public at large.
- 10 See, for example, J. Austin, et al., *Kentucky Pretrial Risk Assessment Instrument Validation*, JFA Institute and Pretrial Justice Institute (2010); J. Austin, et al., *Florida Pretrial Risk Assessment Instrument*, JFA Institute (2010); E. J. Latessa, et al., *The development and validation of a pretrial screening tool*, 72 Federal Probation 2-9 (2008); M. VanNostrand & K. J. Rose, *Pretrial Risk Assessment in Virginia*, Luminosity (2009); L. Winterfield, et al., *Development of an Empirically-based Risk Assessment Instrument*, Urban Institute (2003).
- 11 J. P. Singh et al. *Reporting guidance for violence risk assessment predictive validity studies: The RAGEE statement*. 39 Law and Human Behavior 15-22 (2015); K. S. Douglas et al. *Research methods in violence risk assessment*, *Research Methods in Forensic Psychology* (B. Rosenfeld & S. D. Penrod eds., 2011).
- 12 American Education Research Association, American Psychological Association, and National Council on Measurement in Education (2014). *The Standards for Educational and Psychological Testing*. Washington, DC.
- 13 M. T. Stevenson, *Assessing risk assessment in action*, 103 Minnesota Law Review (2018), <https://papers.ssrn.com/abstract=3016088> (last visited Nov 30, 2018).
- 14 J. Hedlund, et al. *Development and Validation of an Assessment For Pretrial Conditional Release*. (2005), <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.599.6812&rep=rep1&type=pdf> (last visited Dec 3, 2018)
- 15 Pretrial Justice Institute, *2009 Survey of Pretrial Services Programs* (2009).
- 16 Leadership Conference on Civil and Human Rights et al., *The Use of Pretrial "Risk Assessment" Instruments: A Shared Statement of Civil Rights Concerns* (2018), <http://civilrightsdocs.info/pdf/criminal-justice/Pretrial-Risk-Assessment-Full.pdf>.
- 17 See Shared Statement, supra ("implementation of these tools has not curtailed the continued over-incarceration of people of color pretrial
- 18 M. DeMichele et al., *What Do Criminal Justice Professionals Think about Risk Assessment at Pretrial?* (2018), <https://papers.ssrn.com/abstract=3168490> (last visited Sep 3, 2018).
- 19 An investigative report asserted bias against black defendants in algorithmic pretrial risk assessments; based on the analysis of one risk assessment tool using data from one jurisdiction. See J. Angwin et al., *Machine bias*, ProPublica (2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> (last visited Dec 3, 2018). For critique of their methods and conclusions, see A. W. Flores et al. *False positives, false negatives, and false analyses: A rejoinder to "Machine Bias: There's Software Used Across the Country to Predict Future Criminals. And It's Biased Against Blacks"*, 80 Federal Probation 38-46 (2016).
- 20 C. M. B. Brooker, *Yakima County, Washington Pretrial Justice System Improvements: Pre- and Post-Implementation Analysis* (2017), <https://justicesystempartners.org/wp-content/uploads/2015/04/2017-Yakima-Pretrial-Pre-Post-Implementation-Study-FINAL-111517.pdf>.
- 21 See M. VanNostrand & C. T. Lowenkamp, *Assessing Pretrial Risk Without a Defendant Interview* (2013), <https://jpo.wrlc.org/bitstream/handle/11204/1781/Assessing%20Pretrial%20Risk%20without%20a%20Defendant%20Interview.pdf?sequence=3> (last visited Apr 9, 2018).
- 22 C. T. Lowenkamp & M. VanNostrand, *Exploring the Impact of Supervision on Pretrial Outcomes* (2013), https://www.arnoldfoundation.org/wp-content/uploads/2014/02/LJAF_Report_Supervision_FNL.pdf.
- 23 P. Gendreau, et al., *A meta-analysis of the predictors of adult offender recidivism: What works*, 34 Criminology 575-608 (1996).
- 24 For instance, research conducted in New York City about 20 years ago showed that having a telephone in the residence was associated with lower rates of pretrial failure among defendants. Yet, the fact that households are increasingly abandoning their landline telephones for cell phones suggests that this would no longer be a reliable predictor of pretrial success.
- 25 S. Ferrere, *Estimating the Costs of Implementing Pretrial Assessment and Monitoring Services* (2018), Pretrial Justice Institute.



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