Document Title:	The Criminal Justice Base Rate Project: Final Report
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Document Number:	309431
Date:	August 2024

SEPTEMBER **2024**

THE CRIMINAL JUSTICE BASE RATE PROJECT: FINAL REPORT

By Zachary Hamilton, Ph.D.; Alex Kigerl, Ph.D.; Andrew Peterson, Ph.D.; Grant Duwe, Ph.D.; John Ursino, M.A.

EXECUTIVE SUMMARY

Widely used sources of crime data, such as the Uniform Crime Reports (UCR) and National Incident-Based Reporting System (NIBRS), provide invaluable information on patterns in reported crime and justice processing. Yet, due to their measurement of crime at the incident level, these data have not been used to determine an individual's likelihood of justice system involvement. By contrast, in the correctional field, individuals are used as the unit of analysis and common definitions to establish state-level *base rates*. Used for decades, base rates provide an estimate of justice system involvement, per individual, for a given jurisdiction's population.

Like the assessment of crime rates, base rates provide a summary statistic that describes an individual's likelihood of involvement with the criminal justice system. Both crime and base rates provide a simple ratio, consisting of a *numerator*, or number of events, and a *denominator*, number of people. For example, in a Bureau of Justic Statistics (BJS) review of prisoners released in 1983, Beck and Shipley examined prison releases of 11 states, outlining the base rate of those rearrested, reconvicted and reincarcerated within three years of release (Beck & Shipley, 1989). However, when using incident data, a crime rate's denominator is a standardized metric for the larger population or community (i.e., arrests per 100,000 residents). For these populations, base rates often reflect more formal justice system processes, which may include failure to report (to court), arrest, charge, conviction, or incarceration. Thus, the difference between these two metrics is that crime rates use *incidents* as the numerator and all typically use the same denominator annual metric (i.e. per 100,000 residents) and base rates use *individuals* with the denominator that can change based on the justice system population (i.e. Department of Corrections, state court, or county probation) and the jurisdictions definition (i.e., new felony conviction within three years). As a result, crime rates are a more general measure of criminal activity and base rates are a measure of criminal activity *and* justice system response, which allow for the tracking of a population, or sub-population's (e.g., gender, race, age) justice system involvement.

Base rates have several important applications. Given that base rates may vary by population, jurisdiction, recidivism definition, and follow-up duration, base rate calculations can be used to help set standardized risk level categories within risk assessment instruments. State-level base rate metrics also allow for the expected recidivism rate of justice-involved individuals to be compared to the actual observed rate of offending in the general population. Further, by identifying trends across key population demographics, base rates can be used to reveal regional variations and areas of disproportionality that may exist. In doing so, base rates provide important information for assessing the impact of supervision and programming resource allocation on an entire state's rate of justice involvement.

Knowledge of base rates can potentially save law enforcement, court, and correctional resources when used in discretionary court, parole, and probation decisions. Factors that are considered for an individual's potential release during pre-trial and parole hearings are largely subjective, and state and jurisdictional procedures vary dramatically (Renaud, 2019). Courts and parole boards commonly weigh items like criminal history and often rely on risk assessment instruments to assess the merits of pre-trial release, diversion, and reentry (Carroll & Burke, 1990). Base rates can help provide an 'average citizen' reference point on which to gauge these decisions and incorporate objective measurements of an individual's progression towards desistance. Using base rates in this context can also inform the extent to which individuals represent a risk to public safety, allowing for a comparison of their offending probability relative to the general population (Caplan, 2007).

Methods

To provide an understanding of justice involvement, usable for multiple agencies and populations, the current study sought to provide general population base rates. Using data gathered from state courts and two national data sets collected to track arrest and prison admission, we computed three definitions of system involvement – arrests, charges, and prison admission. To create state base rates, we assembled and analyzed several large data sets. The data assembled represented two metrics – numerators and denominators. The numerator represents justice system involvement by an individual in a given state, each year. The denominator provides a calculation of the number of people in the state, each year, that were eligible to commit a crime and had justice system involvement. Using justice system involvement as the numerator, we accessed census data to calculate state populations, representing the general population base rate denominator. These base rates were tracked over multiple years, spanning two decades.

Results

The results show that, at the start of the study period (2000), 6.15% of Americans were arrested. The arrest base rate decrease by more than 50% during the next two decades, where the lowest rate (3.21%) was observed in 2020, when the base rate decreased by 25% in a single year. This sharp drop was due, in no small part, to the policies, practices, and trends related to the COVID-19 pandemic.

The charge base rate was roughly one-third that of arrests. Unlike arrests, charges demonstrated an increase in base rates between 2000 (2.20%) and 2006 (2.65%), before witnessing the same precipitous decline through 2020 (0.72%). These trends are consistent with those of federal arrests and charges during this period (Motivans, 2022). To further describe the utility of base rates, we examine the state rates of arrests and charges for Washington and Ohio, where two prominent risk-needs tools are provided, and identify base rates of each tool's Low-Risk population, as compared to each state's base rate.

The prison admission base rate is much lower than either arrests or charges, with rates peaking at 0.34%. However, similar to charges, we see a steady increase in the U.S. prison admission base rate between 2000 (0.28%) and 2007 (0.34%), before declining for five consecutive years. Similarly, a steady drop was observed in 2019 (0.21%) and a steeper drop observed during the 2020 COVID-19 pandemic year (0.13%). These trends reflect prior research tracking the growth of the U.S. prison system, where roughly one-third of 1% of the population was admitted to prison prior to 2007. Since that time, the U.S. has witnessed a steady decrease in admissions (Cullen, 2018). Further we compared the prison admission rates of three states – California, New York, and Nebraska – identifying the impact of reform efforts deployed in those states.

The base rate arrest trend for men mirrors that of the national trend; however, compared to women, the male rate demonstrates a greater decline through the end of the study period. Yet, despite national declines, U.S. women's likelihood of arrest only declined by roughly 1% during the 20-year study period. By contrast, the average U.S. man has just over an 11% probability of arrest at the start of the study period; however, this rate was more than halved (4.9%) during the 20-year observation period. Even though the arrest base rate for men in 2020 was still twice that of women, men decreased their justice involvement more substantially during the last two decades. Again, this finding is consistent with documented trends that women are increasing as a proportion of the justice involved population (Carson, 2021).

The base rate results for arrest show that Black individuals decreased three-fold and White individuals reduced their base rates by half through the study period. However, Black individuals started at a higher rate (17.7%), consistently decreasing each year, with roughly 6% of the U.S. Black population arrested in 2020. By contrast, White individuals began with a base rate of 5.3%, where only 2.9% of the White population was arrested in 2020. The results indicate that the average Black individual in the U.S. possesses 3.3 times the likelihood of arrest as compared to the average White individual in 2000, reducing to a factor of 2.0 times by 2020.

Table E1. U.S Base Rate Reduction by Year by Race & Gender

Black	**2000**	**2020**	**Reduction**
Arrest	17.7%	6.0%	11.7%
Charges	4.0%	1.2%	2.8%
Prison Admission	1.0%	0.5%	0.5%
White			
Arrest	5.3%	2.9%	2.4%
Charges	0.9%	0.4%	0.5%
Prison Admission	0.1%	0.2%	-0.1%
Male			
Arrest	11.1%	4.9%	6.2%
Charges	2.6%	0.8%	1.8%
Prison Admission	0.5%	0.2%	0.3%
Female			
Arrest	2.2%	1.3%	0.9%
Charges	0.7%	0.3%	0.4%
Prison Admission	0.1%	0.1%	0.0%

While national trends indicate that the number of individuals admitted to prison in the United States has decreased in recent years, the prison admission base rate also varied by race. Specifically, the prison admission base rate only decreased for Black Americans, reducing from 0.9% to 0.5% over the study period. By contrast, the base rate for White individuals remained relatively stable, at roughly 0.2%. Yet, because the rate of change of Black versus White prison admissions varies greatly by state, we demonstrated the relative rate of change for two states – Pennsylvania and Wisconsin – indicating similar issues but at different magnitudes across states.

The results for the U.S. prison admission base rate trends by offense type show a similar pattern for drug offenses, where the base rate dropped by nearly 30% between 2008 and 2012. While the arrest base rate remained relatively stable, the prison admission base rate for property crime displayed a similar drop to that of drug offenses. Finally, like arrest trends, the prison admission base rate for violent offenses remained relatively stable throughout the study period. These findings are consistent with noted policy changes, where state reform efforts have reduced sanctioning for non-violent offenses and, in some cases, legalized possession and sale of marijuana (McNelis, 2017). To further illustrate the impact of policy changes, we provide comparisons of states that implemented marijuana reform, assessing the state drug base rate trends for Washington and Colorado contrasted with control and neighboring states.

When examining charges by age group, the results showed that over 5% of the U.S. population in the 18-24 age group were charged with an offense in 2007, decreasing to a base rate under 2% by the end of 2020. For those 35-44 years old, their base rate trend is similar to the U.S. charge base rate, beginning at roughly 2% and declining to under 1% by the end of the study period. This finding indicates that individuals between 35 and 44 possess a similar rate of justice involvement to the average U.S. citizen. Finally, those individuals 55 years or older possess a 0.3% base rate of incurring a charge each year. In relation to the 'age-crime curve,' we suggest that identification of key measures of risk may lead to a better understanding of desistance and reduced uses of supervision.

Regarding geographic variations, all regions decreased their arrest base rate during the study period, with the Western region decreasing from 8% to 4% and the Midwest region decreasing from 4% to 3%. Notably, by 2020, regional trends converge, where arrest base rates across all four regions range from 2% to 8%. When examining arrest base rates by race and region, the results showed the likelihood of a Black individual being arrested in a southern state fell from nearly 13% to roughly 6% by 2020. Black individuals in the West possessed a 22% likelihood of being arrested in 2000, with the probability decreasing to 10% by 2020. Similar trends were observed in the Midwest and the Northeastern regions throughout the study period.

Conclusion

Within the correctional field, base rates have been used to track the impact of interventions and the justice system generally. However, these rates are often computed using only samples of individuals under correctional supervision, lacking the important interpretation of the 'average' citizen's likelihood of justice involvement. In this study we sought to provide foundational knowledge, specifically describing the average rate of offending for each state. Moreover, we provide trends to examine the base rate changes across a 21-year time frame, variations by state, district definitions of recidivism, and contrasts by subpopulation. Our intent was to provide a new source of data, not provided through common metrics of criminal incident reporting. It is our hope that these findings will change the field's understanding of crime accounting metrics, providing what we hope is a more useful understanding of the average citizen's likelihood of offending.

In the risk assessment field, base rates have been used to establish risk level categories (RLCs). We identified a potential method to use the population base rate as an indicator for creating categories of Low-Risk individuals, representative of a state's average citizen risk of justice involvement. In our analyses, we provide examples of how base rates may be used to further create and assist in the fair development of assessment tools. Going forward, we envision risk assessment developers and practitioners could make use of state and national base rates, allowing correctional agencies to set and adjust risk level categories in reference to the average citizen's risk.

Using a well-known example of the age-crime curve, we found that individuals aged 35 - 44 have a recidivism probability like the U.S. arrest base rate. Expanding assessments to include multiple metrics, researchers may be able to predict when an individual no longer presents a 'greater than average' threat to public safety or possess a predictive probability at the population base rate. Moreover, we suggest that base rates can be used as a reference point to evaluate the effectiveness of programs and the impact of protective factors, such as employment and residential stability. Further, in the absence of a validated assessment or screening tools, judges and practitioners may consider using key indicators to estimate an individual's risk relative to the average citizen to better determine appropriate uses of diversion, pre-trial release, and alternatives to detention, incarceration, and supervision.

This report is meant to provide example uses of the base rates constructed. As the primary product of this project, we have provided an interactive database in which users may further explore the uses of the base rate calculations developed. (See https://nij.ojp.gov/base-rate-interactive-data). We propose that base rates can also serve as a source of information to forecast interventions' projected impacts. As new initiatives are developed, base rate trends can be established, and the impact of prior initiatives can be projected following an examination of prior and existing base rate trends. Similar to the U.S. Congress' use of Congressional Budget Office (CBO) prior to enacting key legislation, stakeholders may use base rates as a method of forecasting the future impacts of bills under consideration. Following the deployment of policies, programming, or developing trends, statistical models may be created to combine factors and forecast their projected impact. These forecasts have the potential to project the downstream effects driving resource needs from one justice system to another.

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ACKNOWLEDGMENTS

This project made use of multiple data sets and methodological adjustments in which we were provided support and assistance in crafting the data and methods used in this base rate project. Specifically, we would like to thank Sharon Belton and all those that assisted from Thomson-Reuters, Diana Sutton, Mike Mueller-Smith, Keith Finlay from the University of Michigan, and William Sabol and Thaddeus Johnson from Georgia State University.

INTRODUCTION

Over the last half century, research has advanced what is known about variations in crime patterns, justice processing, and the behaviors of individuals upon reentry and during supervision (King & Elderbroom, 2014). Crime incidents have been tracked locally and aggregated to create a national understanding of rates and how they change across both time and place. For example, the National Incident-Based Reporting System (NIBRS) collects data on reported crime, as well as detailed information about the individual(s) suspected of committing a crime. NIBRS established guidelines for clarifying which law enforcement department records the incident when jurisdictions overlap, which eliminates counting the same incident in more than one jurisdiction (National Academies of Sciences, 2016). The Uniform Crime Reporting (UCR) program also provides annual data from approximately 18,000 law enforcement agencies across the country (Biderman & Lynch, 2012). Due to improvements in tracking, it is now possible to understand whether the relative likelihood of crime has not only changed over time but also if certain crime types (e.g., violent, property, and drug) are more, or less, likely to be reported in a state. Advancements such as these have become important source material for strategic initiatives (Lapp et al., 2001) and research (Steiger et al., 1998), which help inform law enforcement and correctional resource needs for U.S. communities.

Tracking Justice Involvement

However, due to the decentralized nature of court records and the focus on crime incidents for common national systems, missing from these sources is the ability to assess an individual's likelihood of involvement with the justice system. Understanding the proportion of the general population with criminal justice involvement holds important implications for both policy and practice. While the aforementioned systems use 'crime incident' as the unit of analysis, incident tracking methods complicate the measurement of population-level assessments as multiple individuals can be involved in a single incident and one individual can be responsible for multiple incidents. Unfortunately, while these units are commonly produced as a rate within a population (e.g., arrests per 100,000 residents), they fall short regarding their ability to track justice system involvement at the person-level (Gendreau et al., 1979). Further, using incident as the unit of analysis has not been perceived as relevant from a corrections perspective, where the focus is the calculation of recidivism rates by identifying the proportion of individuals that reoffend each year or during an agency-defined follow-up period. Further, using one metric of justice involvement (i.e., arrests) is perceived as less stable and presents potential sources of bias based on localized supervision and law enforcement practices. Ranging from county probation to state prison systems, correctional agencies often rely on a synthesis of administrative office of the courts' systems of record to assess their population's rate of prior charges and reincarcerations (La Vigne et al., 2014). Thus, correctional systems use individuals, defendants, incarcerated persons, or people under community supervision as the unit of analysis.

Recidivism statistics are often tracked at the state level to assess the effectiveness of correctional agencies' interventions and their associated impact on public safety (King & Elderbroom, 2014). Unfortunately, state-wide recidivism rates are often imprecise or lack a regional comparison to assess the impact of policy and practice changes on substantive populations and preclude agencies' abilities to track justice interventions in contrast to trends observed nationally or in neighboring states (La Vigne et al., 2014). Using varying definitions and data sources, many agencies track recidivism over time and assess patterns from year-to-year. Since the 1980s, the Bureau of Justice Statistics (BJS) has reported recidivism rates for individuals released from state and federal prisons. While limited to individuals released from prison, the BJS recidivism reports have provided key findings routinely cited by the field, including the well-known statistic that *roughly two-thirds of individuals released from prison recidivate within three years* (Beck & Shipley, 1997; Durose et al., 2014; Langan & Levin, 2002; Wallerstedt, 1984).

However, data sets that access nationally representative courts' data have not been developed. Further, incident-centered reporting systems provide a unit of analysis that make it difficult to assess the relative risk of individual system involvement. To date, data sources such as court and prison records that document individual-level indicators, are scattered across multiple decentralized data systems, which limits the ability to monitor offending trends over time, geographical location, and across multiple outcomes (i.e., arrest, charge, & incarceration).

Base Rates

A common goal for correctional agencies is reducing recidivism, which is typically pursued through strategic uses of supervision and programming. As a global metric used to assess baseline changes in offending behavior, agencies compute their population's rate or *base rate*, which represents the number of individuals in a supervised population that offend, divided by the number of individuals being supervised (Beck & Shipley, 1989). Arrest, charge, and prison admission rates vary over time and can be impacted by legislative and law enforcement changes to statutes, sentencing, and charging strategies. For example, a 5% reduction in annual prison admissions may be attributed to effective program offerings and case management processes, but may also represent normal fluctuations, a reduced crime rate, decriminalization of certain offenses, and/or reductions in sentencing durations. As a result of these complicated interactions, administrators and researchers have difficulties tracking the impact of supervision and programming initiatives.

Many agencies also have the common goal of reducing racial and ethnic disproportionality. Establishing a base rate of recidivism and its pattern over time is, therefore, key to measuring the impact of an agency's supervision strategy, resource allocation, and the effectiveness of interventions and policy. Further, when policies or statutes change in a state, having a method to compare base rates to neighboring jurisdictions, states, or national trends may provide an understanding of progress and areas in need of improvement. Also, due to local variations in population density and demographic characteristics, the likelihood of recidivism may differ as well. Therefore, to compare across population types and states, a centralized definition and identification of states' recidivism base rates should be established.

The current study attempts to establish base rate metrics. We use individuals as the unit of analysis and common definitions of justice system involvement to establish state-level base rates, identifying the rate of involvement, per individual, for a state's population. With an understanding of an individual's likelihood of system involvement in each state, comparisons and trends over time were established to assess the population's risk, relative to the average state citizen.

Establishing base rates provides important information for assessing the impact of supervision and programming resource allocation based on an entire state's rate of justice system involvement. Base rates also allow for the identification of trends across key population demographics, revealing areas of disproportionality and regional variations. Additionally, state base rate metrics allow for the expected recidivism rate of justice-involved individuals to be compared to the actual observed rate in the general population. By accounting for the composition of both justice and non-justice system involved populations, accurate comparisons across groups can be tracked over time. In the next sections, we review agency and research constraints that would be improved through the gathering of state-level base rates.

LITERATURE REVIEW

Prior to describing the current study design and methods, it is necessary to explain the importance and potential use of base rates. While more obvious uses pertain to correctional research and assessments of offending patterns, there is additional value in addressing a variety of social and justice related needs. As part of a Bureau of Justice Statistics (BJS) special report, Beck and Shipley (1989) provided an assessment of recidivism for 11 states, tracking outcomes of rearrests, reconvictions, and reincarcerations in the three years following release in 1983. In subsequent years Langan and Levin extended the report to 15 states of 1994 releases, Durose and colleagues (2014) used 30 states of individuals released in 2005. In 2021, Antenangeli and Durose (2021) examined a 10-year period of prisoner releases (2002 through 2018). The BJS reports have provided well-known and often cited findings that, roughly two-thirds of individuals released from prison are rearrested within three years (Lagan & Levin, 2002), roughly 5% of individuals are charged with half the population's offenses (Beck & Shipley, 1989), and almost half return to prison within five years (Antenangeli & Durose, 2021). These landmark studies of prison release base rates source material for countless publications, using recidivism base rates to provide an understanding of the cycle nature of justice system involvement. In this section, we outline four primary uses of base rates – risk assessment, desistance and rehabilitation, relative risk, and informing legislative and policy impacts.

Risk Assessment

One major advancement in the correctional field was the establishment of the Risk-Need-Responsivity (RNR) model (Andrews & Bonta, 2010). This model outlines the importance of assessing individuals' recidivism probability and prioritizing those with the greatest *risk* to receive interventions. Addressing dynamic, or changeable, personal characteristics that are related to the risk of recidivating represents an individual's *needs*, where reductions observed over time should provide an appreciable reduction in recidivism. Finally, *responsivity* outlines the need to deliver interventions that are appropriate for justice-involved populations and account for barriers that may prevent the effective delivery of programming.

A primary element of the RNR model is the establishment of an individual's *risk to recidivate*. Actuarial risk assessment instruments are now standard practice in corrections, and the information produced by these tools informs decision-making regarding program delivery and supervision (Andrews & Bonta, 2010). Risk assessment instruments contain items that are associated with recidivism, and the item response values are used to create a score that denotes an individual's probability of recidivism. The risk scores are distributed along a continuum, where larger scores reflect a higher risk to reoffend.

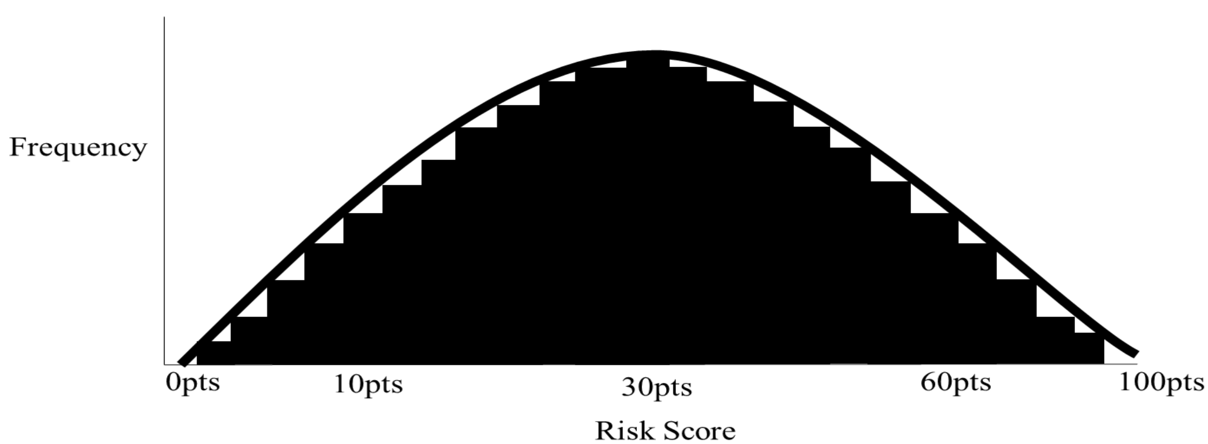
Typically, the continuum of assessment scores is then divided into risk categories for ease of use. When assessing the risk of a given category of individuals, an agency may estimate the relative risk of their correctional population. Agencies often utilize Risk Level Categories (RLCs) to prioritize interventions and supervision resources, reserving greater intensity of services for higher risk individuals (Kroner et al., 2020). However, assigning an individual to a risk category (e.g., Low, Moderate, & High) can sometimes be an arbitrary decision, where the difference between scoring someone classified as Low-Risk with a score of 10, versus a score of

11, will not provide a dramatic distinction in predicting a population's *risk to recidivate*. Also, due to variations in assessed risk and observed recidivism rates, the same risk score may result in a different risk distribution depending on the jurisdiction or population. Extending our example, a score of 10 may be considered Moderate-Risk for a group of people on probation, while that same score is considered Low-Risk for a group of people on parole from prison. Among risk assessment developers, the lack of standardized risk categories is a well-known issue that few have attempted to address (Hanson et al., 2017).

Setting RLCs

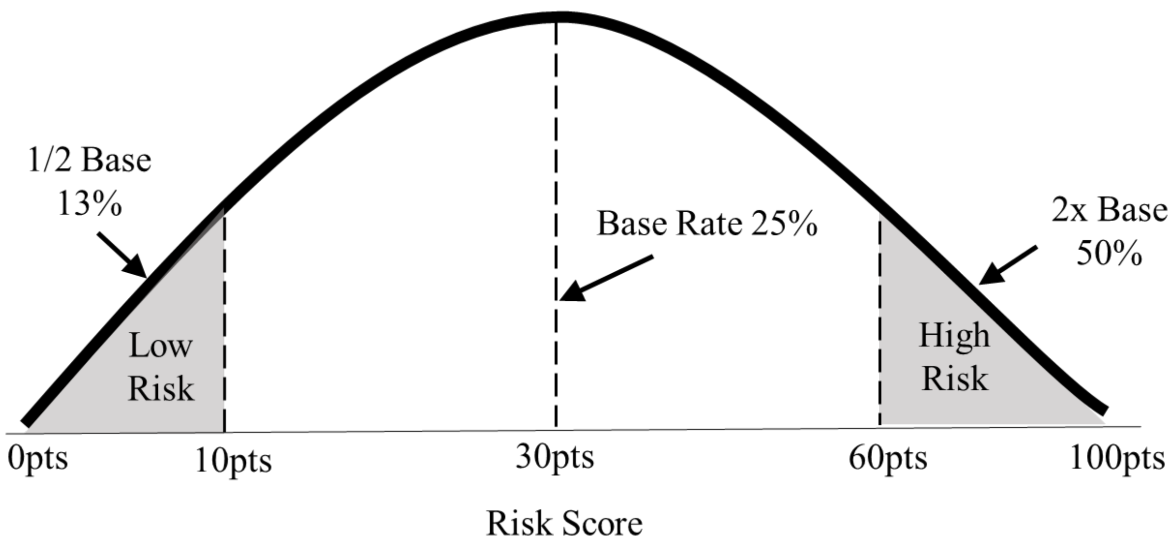
RLC's are commonly 'normed' to a population's base rate, assigning cut points/thresholds along the risk continuum of an agency's justice-involved sample, dividing individuals into categories based on their probability to recidivate (Smith, 1996). As an example, we provide a hypothetical assessment developed for adults on parole, with a scoring range from 0 to 100. When instruments are well-calibrated for a correctional population, a histogram of the scoring distribution is typically normal, or bell-shaped. In Figure 1 we provide a histogram of our hypothetical risk score distribution.

Figure 1. Example Risk Distribution



Further, if the frequency of recidivism (or base rate) for a given correctional population is 25%, the mean risk score for a well-calibrated tool will have a recidivism probability that is equal to the sample base rate. Continuing our example, a developer may identify a High-Risk group with a likelihood for recidivism that averages twice the population base rate (50%) and a Low-Risk group that possesses roughly half that rate (13%). We extend our visual example in Figure 2, where an individual with a predicted probability of 25% is associated with the average risk score (30pts). The Low and High-Risk cut points are then set respectively above and below the base rate, where the group scoring 10 points or lower has a recidivism rate of 13% and those scoring 60 points or higher have a recidivism rate of 50%.

Figure 2. Example Risk Level Placement



While base rate methods attempt to calibrate RLCs for a given population, those categories and cut points only reflect relative risk for the population on which they are developed (Clear & Braga, 1995). When risk assessments are applied to new populations, cut points may not be appropriately calibrated and substantial data collection and adjustment are required to meet agency needs (Smith, 2020). Further, the definition, duration, and recidivism type (e.g., violent, property, or drug) are also important metrics that impact the population base rate. Base rates also vary by the type of population (e.g., pre-trial, probation, or parole), legal definitions, supervision, and offense prioritization. Ultimately, risk assessment tool developers struggle to make one set of cut points applicable for all justice populations and recidivism definitions (Latessa et al., 2010).

Over the last four decades, risk assessment tools have been designed to be broadly used across multiple jurisdictions and correctional populations (e.g., the Level of Service Case Management Inventory [LS/CMI], Correctional Offender Management Profiling for Alternative Sanctions [COMPAS], the Ohio Risk Assessment System [ORAS]), whereas others have been customized to a specific jurisdiction or population (e.g., Minnesota. Screening Tool Assessing Recidivism Risk [MnSTARR], and the Static Risk Offender Needs Guide – Revised [SRONG-R]; the Prisoner Assessment Tool Targeting Estimated Risk and Needs [PATTERN]). While there are numerous differences among the risk assessment tools used for correctional populations, a common thread running through these tools is the reliance on the base rate for the development of risk categories. For example, the ORAS was created using a sample drawn from Ohio, which had a one-year rearrest base rate of 38%. Notably, the developers created four RLCs with average recidivism rates of 9% (Low), 34% (Low-Moderate), 59% (Moderate) and 69% (High-Risk), respectively (Latessa et al., 2010). Moreover, the PATTERN was developed and validated on the federal prison population, which had a 47% rearrest base rate over a three-year follow-up period. Four RLCs were created for the PATTERN, with average base rates of 10% (Minimum), 31% (Low), 55% (Moderate), and 75% (High-Risk), respectively. Finally, the STRONG-R assessment tool was created for a Washington State probation and parole population, where a 2-year charge base rate was 25% and RLCs were set at 50% for High, 25%

for Moderate, and 8% for Low-Risk. These examples demonstrate not only how sample base rates are used to set RLCs, but also how base rates may vary by population, jurisdiction, recidivism definition, and follow-up duration. These variations create inconsistent metrics that pose challenges for standardization.

A Prior Attempt at Unification

In an effort to make RLCs comparable across contemporary tools, Hanson and colleagues (2017) developed an algorithm to equate risk levels across five categories. The primary goal of their research was to answer the question: "How do we compare the results of assessments conducted with different instruments?" (p.3). Utilizing the base rate of offending for a given population over a two-year follow-up period, they created five RLCs in which individuals who reoffend at a rate of 5% or less are Category I while those with a rate of 85% or more are Category V. With rates that ranged between 30-49%, Category III (30-49%) represented the distribution surrounding the base rate, and Categories II (5-29%) and IV (50-84%) were created to account for the rest of the recidivism rate distribution. Notably, Hanson and colleagues utilized a non-U.S. development sample to establish the 'population' base rate when creating the specifications for Category III.

However, as noted above, an agency's definition of recidivism and population will impact the recidivism base rate, preventing the 'Five Category System' from providing a unifying method for RLC creation. Further, the authors estimated the RLC cut points using limited research evidence, with mostly Canadian samples and lower risk populations. The 'Five Category System' has not been adopted widely since its development. While the goal of creating a universal set of risk categories is admirable, foundational measurements of recidivism were absent. Furthermore, when developing a universal risk category system, it is imperative to understand not only the portion of the distribution with criminal justice involvement, but also the entirety of the population (Hall & Hullett, 2003).

It is worth noting that Hanson and colleagues (2017) advised that *ideally*, Category I "should have the same level of risk as the general population" (p.12). Expanding upon this concept, the offending rate of the *average citizen,* or the general population, provides a building block with which to create incrementally higher risk categories. Further, by establishing the general population base rate across multiple definitions (e.g., arrest, charge, and prison admission), RLCs can be more easily constructed by starting from 'the ground up.' Rather than using the middle of the distribution as the starting point, where correctional population base rates are known to differ widely, the 'ground' equates the lowest risk category to the average citizen. Specifically, if source information was developed to determine the offending risk of the average citizen in the population, risk categories could be more accurately developed and calibrated for any target demographic or criminal justice population.

Desistance & Rehabilitation

Another use for tracking base rates is the examination of desistance, which is when an individual no longer engages in criminal activity. Although it is difficult to ascertain the exact moment an individual's criminal career ends, numerous studies have that identified the predictors associated with desistance (Brame et al., 2017; Farrington, 2007; Wooditch et al., 2014). While risk and needs assessments attempt to categorize individuals into similar groups, a primary goal of any correctional system is to put people on the 'straight and narrow,' reducing their likelihood of recidivism though programming. Further, judges and courtroom work groups attempt to identify individuals that would benefit from reduced sentencing and supervision (Lowder and Foudray, 2021). Assessing a population's base rate is key to understanding the rate of the ‘average citizen’s risk’ to offend, or the point at which justice system intervention is no longer required. In this section, we discuss the relationship of base rates to redemption, programming effectiveness, and sentencing and supervision.

Redemption

Related to the concept of risk, the notion of redemption and desistance are theoretical constructs demonstrating the relative absence of risk (Blumstein & Nakamura, 2009; King & Elderbroom, 2014). Research on desistance and the age-crime curve has sought to identify the timing and conditions when individuals stop committing crime. In 2009, Blumstein and Nakamura attempted to examine redemption of New Yorkers that had been arrested for the first time as an adult, tracking the timing of recidivism events via survival analysis. Their analyses examined when an individual’s risk of recidivism was similar to that of an ‘average citizen’ in New York. To measure an ‘average citizen’s risk’ of offending, they created a rate using Uniform Crime Report (UCR) events as a numerator and population estimates from the census as a denominator. While a noteworthy first attempt to establish functional base rates, the authors noted limitations of utilizing arrest events, which may represent multiple events of a single citizen versus charge and conviction data that measure one event per individual (Blumstein & Nakamura, 2009). Further, they noted the need to provide comparative estimates across states, times, and sub-groups to provide a better understanding of risk and desistance.

Other researchers have attempted to establish base rates for similar purposes. Kurlycheck et al. (2006 & 2007) examined a three-state sample of men born in 1958. The researchers gathered juvenile and adult offending data to determine if the base rate of individuals with juvenile offenses decreased to be commensurate with individuals without juvenile offenses, where findings indicated risk to reoffend greatly decreases with time. Further, Soothill and

Francis (2009) completed a study in Britain and Whales, finding that the relative risk of individuals with and without juvenile offenses did not converge for nearly 30 years. Finally, Bushway et al. (2011) attempted to match justice involved individuals to those in the community with no prior criminal history, finding that individuals that engage in crime at a younger age have longer criminal careers. While each of these studies attempted to provide an understanding of the average citizen's risk to offend, analyses were restricted to a few states or a single data source, limiting the application of the findings.

Programming Effectiveness

Redemption is often tied to rehabilitative efforts and interventions, where effective interventions are thought to increase the odds of desistance for justice-involved individuals. Moving past the 'Nothing Works' era (Andrews & Bonta, 2010; Cullen, 2013), the 'What Works' movement within corrections has shown there are treatments, programs, and services that are effective in reducing recidivism (Duwe & Clark, 2015). Correctional programs are often evaluated by comparing recidivism rates of a treatment and control group. To achieve equivalence between the treatment and control groups, individuals may be randomly assigned or matched using a variety of statistical techniques (Bales & Piquero, 2012). Conceptually, the rate of recidivism observed for the control group represents the *base rate,* or the anticipated rate of reoffending for the population that are program eligible (Babst et al., 1968). A program can be considered 'evidence-based' when participants reduce their recidivism base rate compared to non-participants (Soydan et al., 2010).

While comparing treatment and control groups is an efficient model for determining whether a program is effective, routine evaluations can help identify reductions in program effectiveness (Mears & Kelly, 2002). After years of use, even established programs have been known to experience ‘drift,’ where effective elements such as consistent training, program duration, and methods of providing incentives and accountability reduce over time (Maguire et al., 2010). Moreover, occasionally programs are ‘brought to scale,’ which is when an agency expands the program to all those who are eligible. Routine Once a program is brought to scale, the pool of potential control groups subjects may be limited or non-existent. In these instances, comparing the participants’ recidivism rate to the state population base rate provides an alternative reference point in which to gauge a program’s impact.

As a related concept, the RNR model holds that to get the ‘biggest bang for the buck,’ higher-risk individuals should be prioritized for programming (Bonta & Andrews, 2010). Further, the RNR model maintains that programming should be delivered via cohorts, where individuals with similar risk levels are programmed together (Bonta & Andrews, 2007). Conceptually, higher risk individuals have the greatest probability of recidivism and, thus, have the most room for improvement. However, as noted previously, their risk level is relative to the population. Again, using our hypothetical example, a score of 11 may be considered ‘Low-Risk’ and an individual below that threshold may be considered ‘not eligible’ for an intervention in a prison population. However, that same score may be considered ‘Moderate-Risk’ in a county probation population and ‘eligible’ for program referral. While limiting programming resources to higher risk populations may seem like the most prudent use of agency resources, it is notable that programs are commonly developed and tailored to be effective for a variety of populations and levels of risk (Zajac et al., 2015). An alternative way to assess the impact of programming for lower risk individuals is to gauge their recidivism reduction, relative to the general population. In this way, one can see the positive effects of programming, or some ‘bang for the buck,’ even when delivered to populations that may not be considered High-Risk.

Further, while all citizens possess a non-zero probability of offending, as conceptualized by Blumstein and Nakamura (2009), desistance can be defined as a probability of offending that is similar to that observed in the general population. Although not the focus of contemporary correctional practice, reducing a Moderate-Risk individual or even retaining a Low-Risk person at the general population base rate is a noteworthy achievement. For example, Cognitive-Behavioral Therapy (CBT) is frequently used to reduce criminal thinking patterns and, in turn, reoffending (Andrews & Bonta, 2010). A meta-analysis of randomized experiments found recidivism rates for participants were 27% lower than comparison subjects (Lipsey & Landenberger, 2006). However, the common use of treatment and control groups to measure reductions in offending may be enhanced via the use of base rate information for the general population. Analyses on risk reduction using base rates have utility when examining the relationship between program effectiveness and public safety. By comparing an offending population to the general population base rate, we consider public safety and, instead, identify if the individuals are more/less likely to commit a crime than any one person randomly selected from the general population. Where public safety is a prominent concern, base rate metrics may have a unique ability to further inform policy decisions.

Sentencing and Supervision

Additionally, knowledge of base rates can potentially save court and correctional resources when used in discretionary court, parole, and probation decisions. Factors that are considered for potential release during pre-trial and parole hearings are largely subjective, and states' parole procedures vary dramatically (Renaud, 2019). Courts and parole boards commonly weigh items like criminal history and are known to utilize risk assessment instruments to assess the merits of pre-trial release, diversion, and reentry (Carroll & Burke, 1990). Using base rates can help provide an ‘average citizen’ reference point on which to gauge sentencing decisions and incorporate objective measurements of an individual’s progression. Using base rates in this context can greatly inform how an individual may, or may not, represent a risk to public safety (Caplan, 2007), allowing for a comparison of their offending probability relative to the general population risk or base rate.

This concept can be extended to supervision decisions. In 2021, approximately 4 million people were under community corrections supervision, roughly two times the incarcerated population (Carson & Kluckow, 2023). Yet, substantial correctional resources can be saved using base rates to measure individuals’ risks of recidivism. One of the core concepts of the RNR model is the dynamic nature of risk, where individuals may reduce their risk to offend over time by completing programing that targets their criminogenic needs. For example, if an individual is sentenced to five years of community supervision and, three years later, demonstrates an offending risk equal to the general population base rate after completing programming, early termination of supervision may be warranted and would also allow for reallocation of resources to higher risk cases.

Further, Bonta and Andrews (2016) posit that retaining lower risk individuals in correctional interventions has negative consequences. Built on the principles of social learning theory, the RNR model holds that lower risk individuals should be separated and removed from justice-involvement to avoid potential iatrogenic effects that result from ‘contamination’ and ‘labeling.’ From a rehabilitation perspective, once an individual progresses to a point where their assessed risk to reoffend is relative to that of the average citizen, greater system involvement is detrimental to desistance (Andrews, Bonta, & Wormith 2006; Lowenkamp & Latessa, 2004). Therefore, creating policy and release decisions around the state population base rate can provide a data informed rationale for early release, which may reduce costs, retain limited correctional resources, and increase an individual's likelihood of success.

Relative Risk of Sub-Populations

The justice system consists of a multitude of sub-populations, where gender, race/ethnicity, age, and state/region of the U.S. present variations in offending that provide notable and known patterns. Countless studies have observed a gender gap within nearly all justice involved samples, where men typically comprise 80% and women the remaining 20% of the population (Wagner & Sawyer, 2018). Further, despite representing 40% of the U.S. population, persons of color (POC) represent roughly 60% of the population with current justice system involvement. Regarding age, decades of research have described the age-crime curve, where the likelihood of offending peaks during individuals late teenage and early 20's, precipitously decreasing in likelihood thereafter. Moreover, justice system involvement varies by state/region, where states like Louisiana, Mississippi, Oklahoma, and Alabama have some of the highest incarceration rates in the country that is attributed to stricter sentencing laws, higher crime rates, and socioeconomic challenges contribute to these high rates (Wang, 2023). However, Northeastern and Western states, such as New York, Massachusetts, New Jersey, California, Washington, and Oregon tend to have lower incarceration rates compared to the national average, attributed to criminal justice reforms such as, decriminalization of certain offenses (e.g., drug-related crimes), and alternative sentencing programs are more common in these states (Sawyer & Wagner, 2023; World Population Review, 2024). Beyond these trends, variations in crime reporting trends vary by region, impacting current crime incident trends. In this section we examine variations of criminal justice system involvement and reporting trends by subpopulation.

Recently, research has focused on variations in the risk of offending for specific subpopulations. Van Voorhis and colleagues (2010) provided seminal work on gender responsivity and risk and needs assessment (RNA) development. Through the creation of an RNA designed specifically for women, Van Voorhis and colleagues (2010) observed common justice involvement pathways for women, presenting variations in risk factors and recidivism. Further, overclassification of female risk is a common issue for supervision agencies, where a better understanding of reoffending prevalence is needed (Hardyman & Van Voorhis, 2004). In response, Hamilton and colleagues (2023) examined risk score variations across a nationally representative sample of justice involved males and females, identifying substantial variations in criminal history indicators and their reduced ability to predict reoffending for females. Yet, women in the justice system continue to increase in proportion by comparison to men, indicating a slow decrease in the disproportional makeup of the justice system and a potential overclassification of women.

Similarly, disproportionate minority contact (DMC) with the justice system presents issues of variant recidivism likelihoods. Potential causes of disproportionality, such as differential enforcement, neighborhood disadvantage, and inherent biases, have recently drawn greater attention within justice research (Butler et al., 2022). In 2023, Sabol and Johnson examined racial disparity as it pertains to incarceration rates, finding that, despite the overall decrease in racial disparity over the last 20 years, Black adults are still imprisoned at a rate that is nearly 5 times that of White adults. Further, DMC propensity varies by region and is likely impacted by race/ethnicity proportions that are unique to each state (Hamilton et al., 2020).

Age also plays a prominent role in both the observed probability and perception of recidivism likelihood (Brame et al., 2017). Research has consistently demonstrated the range of

18-24 as prime years in an individual's criminal career (Brame et al., 2012). Likewise, recidivism research has long shown that as individuals age, their risk for recidivism decreases (Loeber, 2012). Yet, representative descriptive statistics of these populations' justice involvement rates are limited, which precludes our understanding of how recidivism probabilities change by location and across key sub-populations.

To understand regional differences, one must examine state reporting of recidivism incidents. The Uniform Crime Reporting (UCR) program, which is based on voluntary reporting from law enforcement agencies nationwide, has long presented data on crimes reported to police. Using prescribed definitions and creating incident rates per 100,000 residents, the descriptive statistics gathered from these incident reporting datasets have become resources for both researchers and practitioners. Yet, using aggregated incidents limits our ability to create population base rates.

Further, there are complications with using UCR data to develop base rates, where voluntary reporting of police jurisdictions creates issues of standardization (Loftin & McDowall, 2010; Lynch & Jarvis, 2008). The reporting procedures of local and state law enforcement agencies influence official crime rates calculated from UCR data (Maltz & Targonski, 2002; McCleary et al., 1982; Loftin & McDowall, 2010; Lynch & Jarvis, 2008; Nolan III, 2004; Pepper et al., 2010; Rand & Rennison, 2002). In their study that examined how the reporting habits of local agencies influenced the region's burglary crime rate produced by UCR data, McCleary et al. (1982) found that double counting of incidences artificially inflated incident rates. Double counting is when a crime incidence is represented more than once in official UCR data and is a major concern when creating base rates. Double reporting can arise when there is more than one call for service for the same crime event. Additionally, individuals who commit crimes in multiple states are counted more than once. For example, the BJS tracked offending patterns of 73,600 individuals released from state prisons in 2008 (Antenangeli & Durose, 2021) and found that individuals' propensities for being charged for multiple offenses varied by an array of personal and jurisdictional factors (Orsagh, 1992). Without the removal of duplicates per person, it is difficult to accurately track a population's base rate.

Additionally, local and state agencies have different definitions of a specific crime type (McCleary et al., 1982; Pepper et al., 2010). As alluded to earlier, while most serious offenses are considered crimes regardless of where they occur, definitional issues of both offense types and agency preferences make cross-state comparisons difficult. Further, there are a multitude of factors impacting the individual, law enforcement, court, and correctional agencies' tendencies to charge and use incarceration. Justice system actors' (e.g., police, parole, & court officers) discretion and agency goals may also impact crimes reported and charged (McCleary et al., 1982; Mosher & Rittberger, 2022 Pepper et al., 2010; Rand & Rennison, 2002).

Missing data is another formidable cause of measurement error in the UCR (Li, 2022; Loftin & McDowall, 2010; Lynch & Jarvis, 2008; Maltz & Targonski, 2002; Pepper et al., 2010). For example, in 2003, 30% of law enforcement agencies submitted less than six months of that year's data to the UCR (Lynch & Jarvis, 2008). More recently, the UCR transitioned to a new data collection system in 2021 (National Incident-Based Reporting System). As a result, nearly 40% of local law enforcement agencies did not successfully report to the UCR, marking a large gap in national crime statistics data that persist (Li, 2022). Non-reporting is systematic (Loftin & McDowall, 2010; Lynch & Jarvis, 2008), with findings that smaller jurisdictions are less likely to report their data to the UCR and suburban counties are less likely to report a full year of data when compared to urban counties (Lynch & Jarvis, 2008). Non-reporting raises concerns of data accuracy, where missing data imputation methods are needed to fill UCR records gaps (Loftin & McDowall, 2010; Lynch & Jarvis, 2008; Nolan III, 2004; Pepper et al., 2010).

Informing Legislative & Policy Impacts

Ensuring public safety is often a focal point in policy decision making. While research has shown that reduced sanctions can lead to increases in crime by weakening deterrent and incapacitation effects (Nagin, 2018), other studies suggest that sanctions themselves can lead to increases in crime by removing individuals from prosocial bonds and activities in the community (Cullen et al., 2011) and labeling/stigmatizing individuals as criminal, leading them to further engage in crime (Bernburg, 2019).

Base rates can be used as a standardized metric in forecasting and informing these legislative and policy decisions. Nevertheless, a population's base rate is not static (Hanson et al., 2017; Latessa et al., 2010; Smith, 1996). Like distinctions observed across state/jurisdictional lines, arrest rates change over time, resulting from a multitude of events, including but not limited to, sentencing and correctional policy changes, court system processing, in/out migration patterns of a state's population, law enforcement strategy and focus, and, more recently, the COVID-19 pandemic.

Policy Impacts

State and federal legislatures routinely create and modify statutes that are designed have an impact on the criminal justice system, often with the goal of reducing offending and protecting public safety. To illustrate, Agan and colleagues (2021) calculated base rates over a 3-year period by crime type, and across 35 U.S. jurisdictions that had elected prosecutors enacting criminal court reform policies. Notably, although base rates varied considerably across jurisdictions, policy impacts were compared via their impact on their jurisdiction's base rates relative to other jurisdictions. While researchers did not find substantial policy effects, their work provides a good example of how base rates can be used to track and measure the impact of legislation and policies across crime types, time, and jurisdictions.

While it has been frequently reported that incarceration rates quadrupled between 1980 and 2009 (Lynch et al., 2012), a modest decrease has been observed since that time (Schrantz, DeBor, & Mauer, 2018). Several factors may be responsible for this decline, including decreases in crime rates, reduced sanctioning, increased use of effective programming, and reduced correctional budgets. These reductions within the prison population signal a change in the arrest and charging of individuals within earlier stages of the system, a process. That is, legislative changes to statutes, sentencing, and budgets have demonstrated a notable impact on the nation's prison population, signaling that base rates of arrest and charges may be decreasing in tandem.

With this noteworthy trend in mind, not all states have witnessed similar reductions. As noted by Schrantz, DeBor, and Mauer (2018), while 42 states have observed declining prison populations, nearly half have observed decreases of less than 5%, and 8 states have seen prison growth during that same period. Further, some incarceration changes may be the result of policy changes, such as decriminalization of specific offenses. As an example, the State of Washington decriminalized marijuana in 2012 and has since retroactively vacated marijuana convictions as a result of the 'Blake Decision' (State of Washington v. Shannon B. Blake, 30-31).

In 2009, California provided incentives for counties to reduce the number of individuals on probation being sent to prison for technical violations and authorized non-revokable parole, removing many individuals from parole supervision (Lofstrom, Bird, & Martin, 2016). Further, in 2011 California expanded the use of community release via their Public Safety Realignment Act, using early release options such as electronic home monitoring (EHM), allowing those that present minimal risk to the community to serve the remainder of their time at home.

Finally, in 2018, the First Step Act was signed into law, allowing for the early release of thousands of individuals convicted of non-violent offenses (Hamilton et al., 2022). Following its passage, it has been estimated that the law helped 14,000 individuals either be released or have their prison sentences reduced. These and other sanctioning and policy shifts likely provided a substantial impact to the proportion of the population arrested, charged, and incarcerated, decreasing state and national base rates following implementation.

Population Shifts

Mass social events, such as the COVID-19 pandemic, very obviously played a role in the declining trends observed throughout the U.S. trends provided. In 2020, the pandemic caused policy changes both inside and outside the justice system. During 2020, when social distancing and quarantines were mandated, policy changes regarding arrests, detainment, and confinement were observed in nearly every state (Stephenson, 2020). Court proceedings were often held via video conference, geriatric prisoners were provided compassionate release, and law enforcement agencies and courts began to prioritize ‘who should’ versus ‘who could’ be detained or incarcerated in jail and prison (Surprenant, 2020). Further, social distancing guided people to work and stay at home, reducing citizen interactions and, in turn, criminal opportunities. As a result of the pandemic, arrests, charges, and incarcerations decreased dramatically in 2020, potentially impacting and interrupting a decade long trend of offending rates (The JFA Institute, 2021). However, these trends were not consistent for all crime types. Specifically, murder rates increased in 2020 by 29%, where 8 states saw rates rise by 40% or more (Gramlich, 2021), while violent crime generally rose by 5%. Some have described noted reductions resulting from law enforcement strategy changes, where Lum and colleagues' (2020) survey of more than 1,000 police departments identified a reduced use of proactive traffic and pedestrian stops and these strategies were suggested to have led to observed reductions in arrests nationally. Further, Cassell (2020) found a relationship between increases in homicides and a reduction in proactive policing strategies. With these explanations of violent crime trends in mind, certainly crime types, confinement, and criminal opportunities played a large role in changing rates of justice involvement.

Since the 2010 census, the U.S. population has also changed. While the U.S. population grew by 7.4%, rates of change varied by state and region (Jarosz et al., 2020). Since 2010, three states lost population – Illinois, Mississippi, West Virginia – and the Midwest grew at the slowest rate (3.1%), compared to the fast-growing Southern region (10.2%). Conceivably, a state's total population could increase over time while their number of arrests, charges, and incarcerations remain stable, resulting in a reduction in justice involvement base rates. By contrast, states that have decreased in population may see base rates grow over time.

These described changes, both legislatively derived and naturally occurring, will notably impact rates of arrests/charges, decrease prison populations, and potentially increase those on correctional supervision within a state. The COVID-19 pandemic represents a naturally occurring phenomenon, with effects that researchers are still attempting to describe today (Zvonkovich et al., 2023). Our findings demonstrate a consistent and sustainable reduction in justice system involvement. Yet, changes in justice system involvement were not consistent across the U.S., where a few key states/regions observed considerable reductions, while others observed limited changes and the potential for increases, or rebounds, observed following the removal of COVID-19 policies (Carson et al., 2022). Notably, justice system, and more specifically prison, crowding is not a novel phenomenon, and often requires substantial policy and legislative changes to sustainably decrease justice populations. Yet, legislative bodies are rarely provided with feedback or guidance as to the impact that proposed legislation will likely have on the justice involved population, thus demonstrating a need to assess trends before and after legislation is enacted and forecast how justice agencies will be affected in the future. With a consistent provision of base rate data, stakeholders will be better informed as to the ebbs and flows of justice involved populations and the impact legislation and policy changes create.

Current Study

Like the assessment of crime rates, base rates provide a summary statistic that describes an individual's likelihood of involvement with the criminal justice system. Both crime and base rates provide a simple ratio, consisting of a *numerator*, or number of events, and a *denominator*, number of people. When using incident data, a crime rate's denominator is a standardized metric (i.e., per 100,000 residents), while base rates measure a more specific target population and are used to track individuals' justice system involvement. For justice involved populations, base rates often reflect more formal justice system processes, which may include arrest, charge, conviction, or incarceration. Thus, the difference between these two metrics is that crime rates use incidents while base rates use individuals with justice system involvement as the numerator. As a result, crime rates are a more general measure of criminal activity and base rates are a measure of the population's involvement in the criminal justice system *and* the system responses to those activities, allowing for the tracking of a population or sub-population (e.g., gender, race, age) over time.

The importance of base rates is not confined to risk assessments, for they can also be used as source materials for intervention effectiveness and policy evaluations. As discussed, the highest risk individuals in a given population are relative. A new outcome can be established for programs to attain a rate of recidivism like that of the generalized base rate for the local population. Furthermore, policy makers can more strategically direct their efforts towards those populations that require further attention and/or have greater than anticipated contact with the justice system.

To provide an understanding of offending, usable for multiple agencies and populations, the current study sought to calculate general population base rates. Utilizing state court data sources and two national data sets collected to track arrest and prison admissions, we computed three definitions of justice involvement. Using individuals as a numerator, census data were used to calculate state populations, representing the general population base rate denominator. These base rates were tracked over multiple years, spanning two decades.

METHODS

To create state base rates, we assembled and analyzed several large data sets. The data assembled represented two metrics – numerators and denominators. The numerator represents an individual who becomes justice involved in a given state, each year. The denominator provides a calculation of the number of adults (18 years or older) in the state, each year. The current section outlines the project development, including the data gathered and base rate computation and analyses.

Base Rate Numerator

To calculate base rates, two sources were necessary to estimate the probability of offending for the general population: 1) numerator data consisting of justice-involved populations and 2) denominator data were derived from all residents within a given state. Ideally this project would collect state court records, for both felonies and misdemeanors, for all 50 states. This was not feasible for the current project because it would require access and cooperative agreements, data transfers necessitating several years to complete, and extensive resources to procure state records. Further, not all states are equipped to provide comprehensive court records dating back decades. Thus, the numerator, or justice-involved sample, was synthesized from five sources: Thomson-Reuters CLEAR, the Criminal Justice Administrative Records System (CJARS), the Washington Administrative Office of the Courts (WA AOC), the National Corrections Reporting Program (NCRP), and Uniform Crime Reports (UCR).

Thomson-Reuters CLEAR

Our first data source, Thompson-Reuters, is a private company that provides software and tracking resources for courts across the nation. For the last decade, they have amassed criminal court records from 34 states[4] while providing access to information spanning multiple decades. The Thomson-Reuters CLEAR is an online service provided to investigators and other stakeholders to perform background checks on individuals within the United States as part of their daily operations. The service relies on CLEAR's database comprising offense history records that are supplied by hundreds of criminal justice agencies throughout the United States on varying recurrent schedules, ensuring offense histories are complete and timely.

[4] Refer to Appendix I for a complete list of states which were available from the Thompson-Reuters data source.

Our research plan was to create a 21-year sampling frame (2000-2020), tracking annual charges for all states. However, after the project was approved and data access was granted by Thompson-Reuters, we discovered that data coverage from this source was not universal. That is, CLEAR data did not cover all 50 states and coverage was limited for sample years and charge types. However, the CLEAR data were substantial, including 31 states, with 17 possessing administrative court records needed to assess state charge rates. The remaining 14 states contained Department of Corrections coverage, where felony conviction base rates may be assessed. Notably, for 12 states, only partial coverage of the 20-year sample frame was available (see Appendix I). A copy of the data source was provided to researchers in September of 2020 and contains data from 34 states within the US, excluding states not contained in the data source or that possessed too many missing values to determine criminal outcomes and crime types.

Data available from CLEAR included gender, race, age, and crime type. Once received, data was cleaned and merged into a single offense history dataset. Because many measurements within the system were not uniform, cleaning and recoding was required to provide results that were consistent between each variable measured. Cleaning involved coding racial category strings as well as narrative descriptions of each offense type. Non-criminal offenses were coded separately for analysis purposes. Only adults were retained in the final dataset, setting the cut-off to 18 years of age or older. The resulting data file contained 511,065,638 unique offenses, across the 21-year study sample frame. The combined offense history table contained all charges reported by the source agencies of the CLEAR service. Each row in the table represented a single charge. The year to which the charge belonged was determined by the date the offense was committed.

The desired unit of analysis for the sample was unique individuals for each state and year combination. Many offense records contained a unique person identifier number, but some were lacking detail. To adjust for these discrepancies, identifying information (e.g., first, last, and middle names, birth date, and gender) was combined with a person's ID number to further reduce the dataset from incident level to individual level, resulting in 175,281,251 unique persons across 34 states and as many as 20 years (averaging 18.79 years of complete data per available state). For each crime category coded, if multiple offenses are indicated for an individual during a single year, duplicates were removed, and the individual was counted only once. If the same individual accrued additional charges during subsequent years, they were counted again and placed within the sample for each new year a numerator count was indicated. Therefore, subjects could be counted in a numerator only once per year but could appear in multiple years. This means that the recidivism probability estimates represent the chance of a criminal justice encounter amongst the general population each year, rather than a fixed follow-up duration over multiple years tracking each individual offender. It should be noted that if an individual was charged with multiple crime types in a year (i.e., violent & sex), they would be counted once in each category but would have only one charge indicated for the 'Total Offenses' category.

Within the CLEAR data, not all states provided the same level of coverage. Some only captured felony charges reported by their Department of Corrections (DOC) whereas others provided Administrative Office of the Courts (AOC) reporting that included both felony and misdemeanor information. The reporting by DOC and AOC sources also varied by year. Consequently, CLEAR sources with only DOC reporting do not include misdemeanor charge information.

Criminal Justice Administrative Records System (CJARS)

We then sought additional data resources to fill in numerator coverage gaps. We were successful in connecting with researchers for the US Census Bureau that had been involved in work on the Criminal Justice Administrative Records System (CJARS). Like Thompson-Reuters, project staff have been collecting state criminal history records, creating a nationally integrated repository of data following individuals through the justice system.

The CJARS system is maintained by the Institute for Social Research at the University of Michigan and is a project seeking to create a nationally integrated repository of data that tracks individuals as they pass through the criminal justice system. The repository contains comprehensive criminal justice history information on 16 US states, with details such as age, race, gender, and crime type, again, the charge and prison admission data sources only included those subjects 18 years or older. At the time the data were gathered and shared with researchers in January 2022, there were 41,890,973 unique persons across state and year. CJARS maintains their data source with privacy restrictions that prevent accessing identifiable records. While universal access is not yet available, CJARS agreed to supplement Thompson-Reuters data sources, providing charge data for an additional 7 states. Again, only partial coverage for the proposed sample frame is available for 3 of the 7 states. CJARS staff provided variables constructed from the data source operationalized to match those contained in the current dataset, consisting of demographics and offense type details aggregated by state and year.

The method used to reconcile similar offenses across states prior to merging relies on an offense classification system developed by Measures for Justice (MFJ). MFJ's classification framework is based on the codes originally created for the National Corrections Reporting Program (NCRP) in the early 1990s. These codes were designed to provide a detailed way of categorizing offenses as defined in state statutes. Since charge descriptions can significantly differ from one state to another due to variations in statutory organization and language, MFJ made several adjustments to enhance consistency and accuracy (Finalay & Mueller-Smith, 2021).

Washington State Administrative Office of the Courts (WAAOC)

In an initial proof of concept created for the study proposal, Washington State Administrative Office of the Court (WAAOC) charge data was used. However, neither CLEAR nor CJARS contained comprehensive data for the State of Washington, lacking misdemeanor and other records. While not practical for all states with the current project timelines, WAAOC established a single-state data resource that was feasibly obtained via researcher-agency data sharing agreements. This additional sample consisted of 1,644,908 unique persons by year. We note, both the TR and CJARS data sources lacked both charge records for this particular state, therefore, given the accessibility of WAAOC data, it was feasible to add this additional state to the current data collection.

National Corrections Reporting Program (NCRP)

Data pertaining to prison admissions were acquired from the National Corrections Reporting Program (NCRP). The NCRP is a database maintained by the Bureau of Justice Statistics (BJS), an agency within the U.S. Department of Justice. The NCRP is designed to collect, analyze, and disseminate detailed information on individuals under the supervision of the U.S. correctional system, including those incarcerated in state prison systems. It serves as a valuable resource for researchers, policymakers, and practitioners interested in understanding the characteristics, trends, and outcomes of individuals involved in the criminal justice system. The

NCRP provides comprehensive data on various aspects, such as demographic characteristics, offense types, sentence lengths, time served, release dates, and other relevant information. The program collects data from state and federal correctional agencies, facilitating a broad perspective on corrections-related issues at the national level. Data acquired consisted of age, gender, race, and crime type. The data acquired contained records for 49 states (excluding CT & DC), representing 19,087,492 incarceration events in total.[5]

The Uniform Crime Reports (UCR)

Finally, Uniform Crime Report (UCR) arrest records were also included. The UCR is a program administered by the US Federal Bureau of Investigation (FBI) that collects standardized crime data from law enforcement agencies nationwide. It gathers information on index crimes (such as murder, rape, and robbery) as well as non-index crimes, providing comprehensive statistics on crime patterns and trends. The UCR data is crucial for analyzing crime, informing law enforcement strategies, and evaluating crime prevention efforts. The resulting UCR dataset included in the analysis pertained to all 51 states (including DC) and contained a total of 229,321,584 arrests in the year range selected (2000 to 2020). Data acquired from UCR records included gender, race, and crime type, however specific age years were not available, although there were indicators for whether an offense was committed by either an adult or juvenile. Thus, only adult (18 year or older) instances were included.

[5] The data provided were in a deidentified format upon receipt, preventing the option of filtering by unique persons incarcerated per year. Thus, prison admissions were operationalized as admission events rather than individuals incarcerated during each year. While it is possible for an individual to be incarcerated, released, arrested, charged, convicted, and then incarcerated again over the course of a single year, when considering criminal justice processing times and the common duration of prison sanctions (e.g., 12 months or more), the probability of the described series of event occurring is relatively rare. Therefore, we interpret incarceration events as unique person events in the study findings. However, due to this slight variation in data collection for incarceration data, readers may choose to interpret findings differently.

However, it should be noted that arrest reporting coverage may not be complete for certain states during specific years, and not all law enforcement agencies provide reporting. To correct for potential biases, the UCR data source was constructed with arrest counts weighted to better represent regions with more missingness. Here we used citizen population sizes, per reporting agency (which include population estimates based on all ages), which were summed and divided into total census population estimates of all ages.[6] Thus, law enforcement jurisdiction population sizes that are less than the total census population estimates, are 'upweighted' allowing low reporting regions to be better represented. The resulting ratio was then multiplied for each arrest count measure type (e.g., violent, property, drug, etc.) to create finalized weighted estimates.

Data Coverage

Ultimately, we combined all the data sources to obtain charge records for all states, several of which provide only partial coverage of the 20-year sample frame. Appendix I provides a description of state coverage, broken down by agency type, data source, numerator outcome definition, and coverage year. While we do not detail the reasons for lack of coverage from some states, it is important to note where no numerator coverage is available. Further, while there were opportunities to collect county-level data to fill in missing areas of coverage, we only included findings from data sources that offered state-wide coverage to help ensure consistency of interpretation.

[6] In which case states lacking complete coverage would have population totals represented by reporting agencies only, with non-reporting agencies missing.

Base Rate Denominator

Including demographic and geographic population subgroups for the denominator is critical for base rate calculation. Due to the number of states and demographic groups included in this analysis, there is a need to compare state, racial,[7] gender, and age ranges to understand differential risks associated with each of these groups. We further recognize that geographic and demographic subgroups have differential exposure to the criminal justice system and require unique consideration.

To capture the general population in the denominator sample, we retrieved Census records pertaining to the demographics across state and year to match those reflected in the numerator data samples. Data was available for all 50 states and Washington DC, spanning the study years of 2000 to 2020. There were 3,741,198,342 unique persons across year and state in the final aggregated dataset.

To create the denominator for our risk calculations, we used Center for Disease Control (CDC) Bridged-race extracts to obtain population estimates for race, age (18-85+), gender, and year at the state level. Extracts were reformatted and cleaned to calculate a population number for each racial/ethnic subgroup for each age range. Separate records were created for each state, in addition to a combined file that provided totals for the entire United States (U.S.). The data collection procedures from the United States Department of Health and Human Services allowed for the retention of population counts for four racial/ethnic grouping – White, Black, Other, and a measure of Nonwhite, which is combined measure of Black and Other. These groups were then broken down by gender to create mutually exclusive racial/ethnic and gender groups for each

[7] We note that, due to inconsistent reporting across states, a variety of race and ethnicity subgroups were not able to be assessed for the current study.

calendar year. Next, we calculated population risk by matching criminal justice involvement counts with relevant populations, based upon similar geographic and demographic factors, ensuring counts are attributed to the same populations. We then computed base rates of criminal justice involvement for the study population, geographic, and demographic subgroups.

Analysis

In this section we provide a description of the key elements that are used to compute study base rates. We first describe dominator calculation, which is impacted by state and data source. Next, we describe numerator calculations, where base rates are created and vary by the type and subpopulation reported. Next, we describe imputation an interpolation procedure used to account for data loss within the study data sources. Finally, we provide a section that outlines the study dashboard, allowing for an interactive user resource of study computed base rates.

Following an aggregation of the study numerator data sources to create demographic and offense type measures by state and year, we then merged values into a single numerator data table. The denominator data pertaining to demographic information were also aggregated, resulting in a denominator table to correspond to that of the numerator. For the numerator data specifically, offense type information was also grouped into two different category types: 1) the count of felonies and misdemeanors and 2) more refined categories consisting of property, assault, weapons offenses, domestic violence, violent, homicides, violent property offenses, drug, alcohol, sex, escape, and other offenses. The UCR data source, however, contained a more granular set of offense types, such as embezzlement, arson, murder, and illegal gambling, among others. These additional categories were also included and are available only when the arrest data source is selected. It should be noted that each state relies on its own distinct definitions of each offense type, therefore the assessment of a given crime category may vary from state to state.

Thus, caution is warranted when considering any cross-state comparisons. The year range selected was 2000 through 2020 for both the numerator and denominator.

For the numerator data, certain states lacked completeness of reporting for certain years, leaving yearly gaps in the study sample frame. To account for missing information, time series interpolation and extrapolation were applied to impute estimates for missing years. *Interpolation* is the process of estimating a value between two temporally contiguous points in time, whereas *extrapolation* extends a data series forward in time based on forecasted values. The method of interpolation used for the data was the Kalman filter, which breaks a univariate time series into three components: trend, seasonal, and level/noise time series (Brookner, 1998; Pizzinga, 2012). Trends represent the slope, or basic direction of the time series, seasonal movements are the cycles that repeat at regular intervals in the data, and level/noise represent unaccounted variation, or the precise value of the time series (not including the trend or seasonal cycles). The Kalman filter smooths across time series to create missing value estimates. While a Kalman filter is adequate in estimating missing time series observations, some limitations may apply. A Kalman filter uses a linear model to fit the data, ignoring the possibility of any nonlinear components such as exponents or roots. Additionally, when multiple contiguous observations in time are missing, any present errors in imputation may compound over the series of consecutive estimates. Therefore, while interpolation and extrapolation are common methodological approaches in trend analyses, readers/users are still cautioned when describing trends for point estimates that have been imputed. Sixteen states were adjusted using this method, refer to Appendix I for the specific states and years imputed. Imputed years are represented with a 'Y,' other non-missing years with an 'X,' and entirely missing years left without imputation by a '0.'

We imputed missing data for two additional states using a different method, as the Kalman filter option did not forecast feasible results for certain years of state calculations (e.g., negative values). Instead, for two states (Louisiana & New Mexico), we extrapolated missing values using a weighted linear regression. The regression routine was trained on the non-missing years, weighted such that recent values were given higher priority, and used to make predictions of subsequent values which were previously missing. It should be noted that these imputations were computed at the state level for each state, where missing values were estimated. Estimated values are reflected in aggregate level reporting.

Interactive Dashboard

To allow for independent inquiries of the analyzed data, we built the 'Base Rate Project Interactive Dashboard.' Created in Tableau, users can select/deselect options to analyze collected base rate data.[8] A worksheet was added to the spreadsheet and populated by fillable form controls and programmed such that users interacting with the spreadsheet can select details of interest to present base rates specific to the user's selection. An interactive worksheet is provided and can be accessed at https://nij.ojp.gov/base-rate-interactive-data). The worksheet consists of a time series figure demonstrating the percentage of the population committing offenses each year from 2000 to 2020. As part of the interactive worksheet, a trend line automatically updates following a user's specification.

The options available from the fillable form controls include a radio button option to select different data sources from which the trends are derived. These sources include charges

[8] We encourage user to access the Base Rate Project data set and suggest the following citation: Kiger, A., Peterson, A., Hamilton, Z., & Duwe, G. (2024). *The Criminal Justice Base Rate Project*. National Institute of Justice. https://nij.ojp.gov/base-rate-interactive-data

(TR and CJARS sources), prison admissions (NCRP source), and arrests (UCR source). There are also separate checkboxes for each state if the user desires base rate reporting for one or more specific states exclusively. In addition, a choropleth map of the United States is depicted, with each state color coded via a gradient between dark red and white, with darker colors indicating higher offense rates. An individual state can be selected/deselected on the map to portray specific trends. A pulldown menu is also available to subset the data based on demographic details (age ranges, gender, race) or offense types (i.e., violent, property, or drug). Lastly, there is an additional grouping of checkboxes to only display trends based on higher-level regions within the United States. It contains four checkbox options for Midwest, Northeast, South, and West. Based on the resulting plot, users can determine trends present for the given selection, such as increased or decreased justice system involvement patterns over time.

RESULTS

The findings provided in this report present a few overall and interesting trends. While not exhaustive, we provide an interactive dashboard to allow users to mine the data further based on the example objectives outlined above, as well as those discoverable by users. We begin by examining national trends using the full sample. These findings are followed by breakdowns by gender, age, race, crime type, and region. additional examples are also presented, providing a comparison of state variations.

National Trends

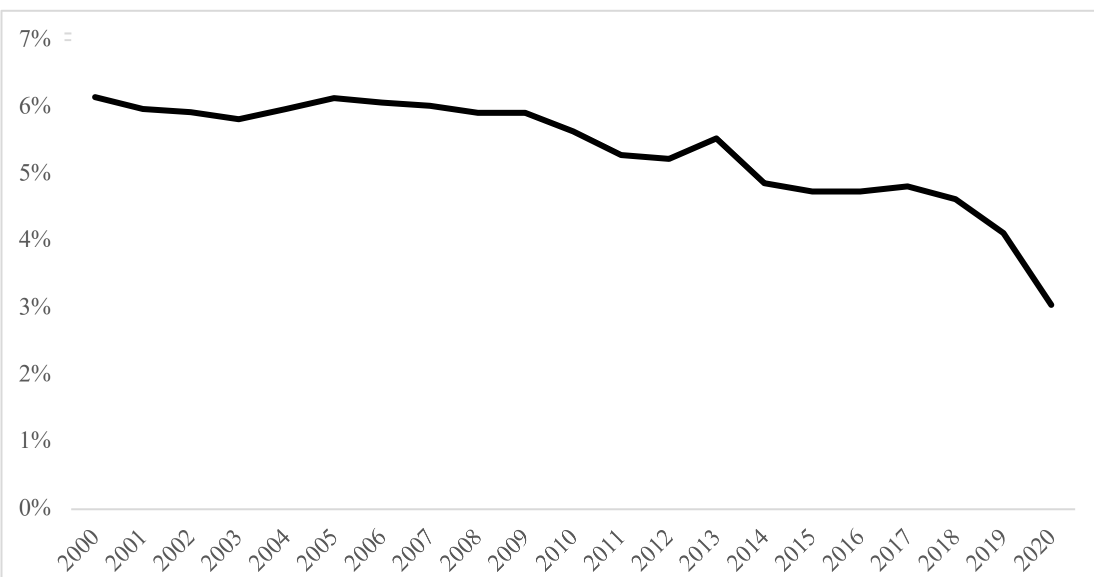
Examining the states that provided UCR records, we computed base rates for the total population for each year of the 21-year sample. As one observes in Table 1, the ‘general population’ (denominator) total increases from 2000 to 2013 before declining in the remaining years of the study period. These declines are a result of missing UCR reporting sites toward the end of the study range, yet missing data is not necessarily systematic and should not greatly influence the base rate reported.

A line chart of the study time series is provided in Figure 3. The arrest trend displays a distinct pattern, where the US base rate indicates that 6.15% of Americans were arrested in 2000. This trend steadily declines through the end of the study period, before declining sharply in 2020 (3.05%), indicating a more than 50% decrease during that span. Notably the lowest rate is observed in the last year, 2020, where the base rate decreased 25% in one year, which is due, in part, to reductions observed nationally that were a result of policies, practices, and trends related to the COVID-19 pandemic (Boham & Gallupe, 2020).

Table 1. U.S. Arrest Base Rates

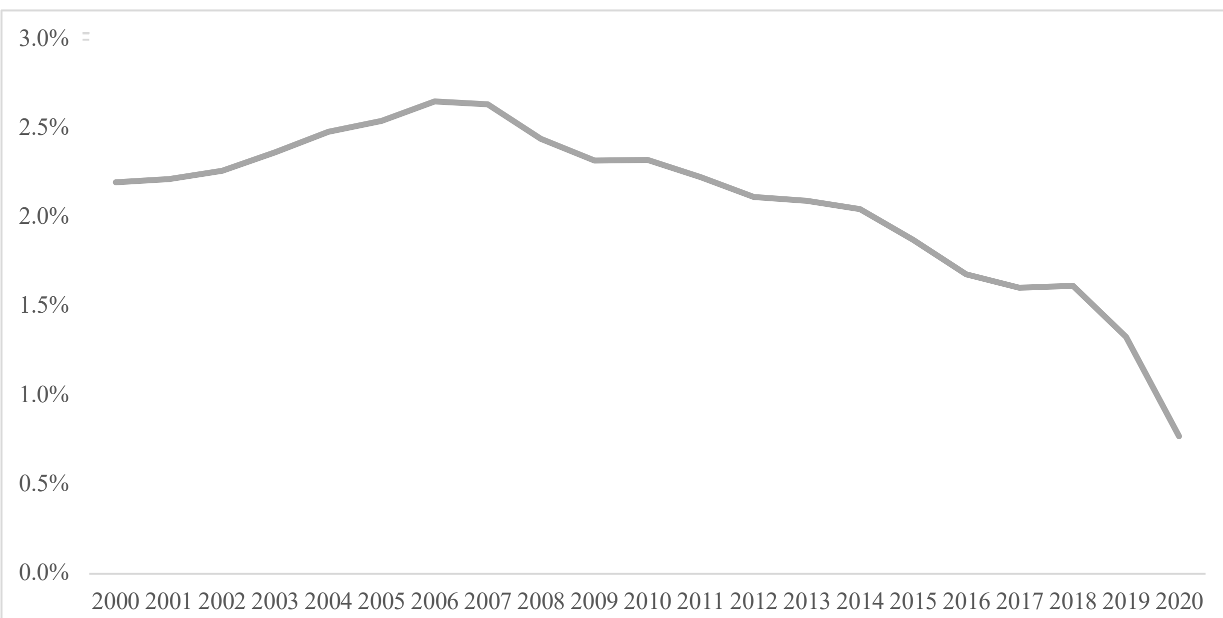
Year Of Offense	Base Rate	Population	Arrests
2000	6.15%	209,786,222	12,900,065
2001	5.97%	212,297,780	12,680,705
2002	5.93%	214,688,736	12,721,330
2003	5.81%	217,007,175	12,618,659
2004	5.97%	219,507,563	13,108,168
2005	6.14%	221,992,930	13,622,158
2006	6.07%	224,622,198	13,634,227
2007	6.02%	227,211,802	13,686,016
2008	5.92%	229,989,364	13,607,722
2009	5.91%	232,637,362	13,749,943
2010	5.64%	235,201,000	13,259,340
2011	5.29%	237,649,350	12,565,982
2012	5.23%	240,134,326	12,548,119
2013	5.54%	242,425,013	13,422,495
2014	4.87%	244,737,285	11,916,372
2015	4.74%	247,017,112	11,699,477
2016	4.74%	249,291,898	11,808,613
2017	4.81%	251,400,193	12,097,808
2018	4.63%	193,935,016	8,972,073
2019	4.12%	195,578,597	8,063,397
2020	3.05%	197,069,523	6,006,557

Figure 3. U.S. Arrest Base Rates



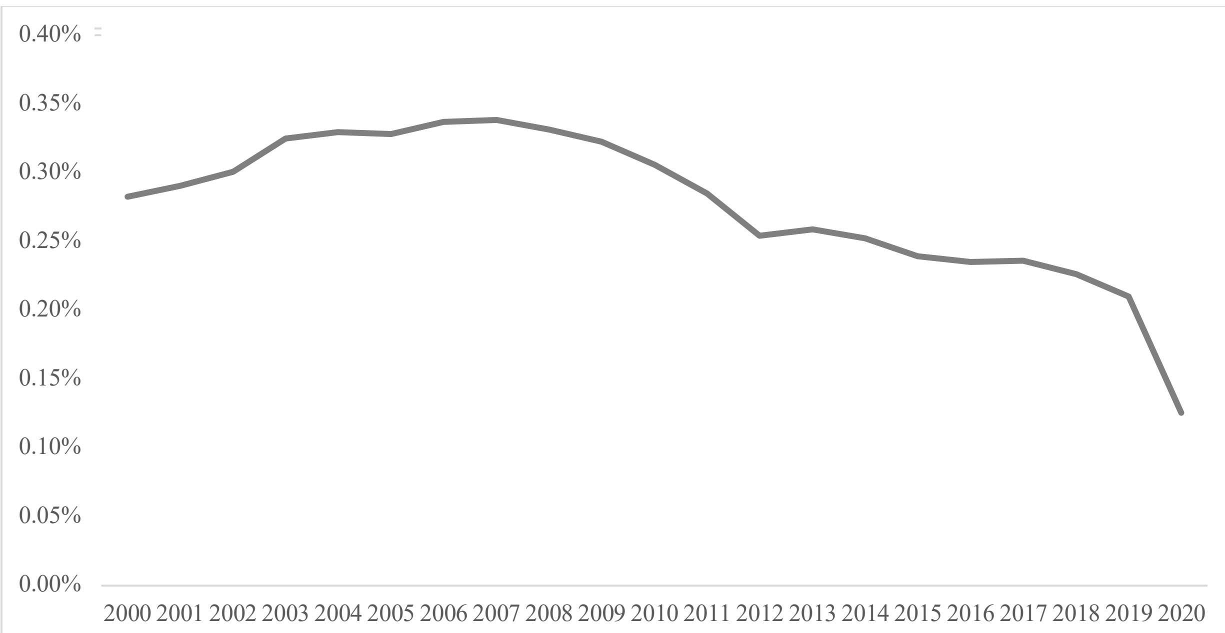
Next, we examine charges. Figure 4 provides a line trend of the U.S. charges for the selection of states providing charge indicators. Here we see a base rate that is roughly one-third that of arrests. While a similar trend is identified, unlike arrests, charges demonstrate an increase in base rates between 2000 and 2006, before then following the same precipitous decline through 2019 and a steep drop in 2020. These trends are consistent with those of federal arrests and charges during this period (Motivans, 2022). We note that the reduced number of states providing charge data may, in part, reflect the observed differences by comparison to the arrest trends. With that said, the similarities indicate a consistent decline for both trends after 2007 and are reflective of reported national trends, where roughly one-third of federal arrests resulted in charges starting in 2000, arrests declined by roughly 3% between 2010 and 2020, and there was a general increase in charges relative to arrests between 2000 and 2006 (Motivans, 2022).

Figure 4. U.S. Charge Base Rates



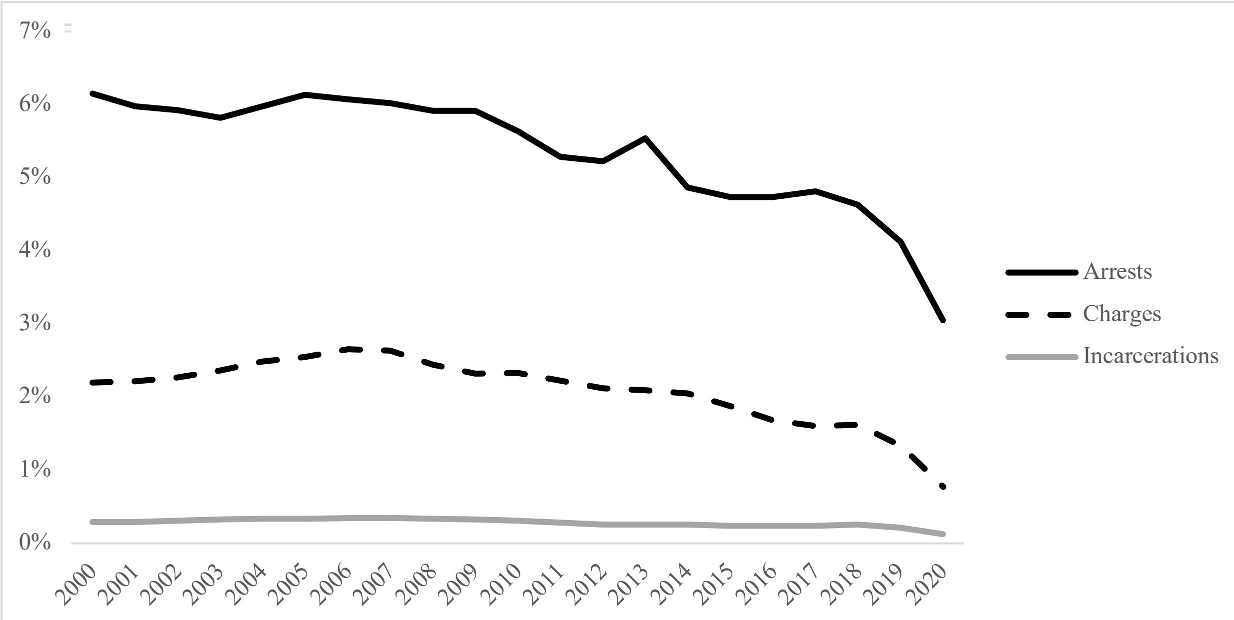
In Figure 5, we provide national prison admission base rate trends. The prison admission base rate is much lower, with rates peaking at 0.35%. However, like charges, we see a steady increase in the U.S. prison admission base rate between 2000 and 2007, before declining for five consecutive years. Like charges and arrests, the prison admission rates continue to decline through 2019, and we observe a 40% decrease in the 2020 COVID-19 pandemic year. These trends reflect other research tracking the growth of the U.S. prison system, where prison admissions increase until 2008 and then begin to decline (Cullen, 2018).

Figure 5. U.S. Prison Admission Base Rates



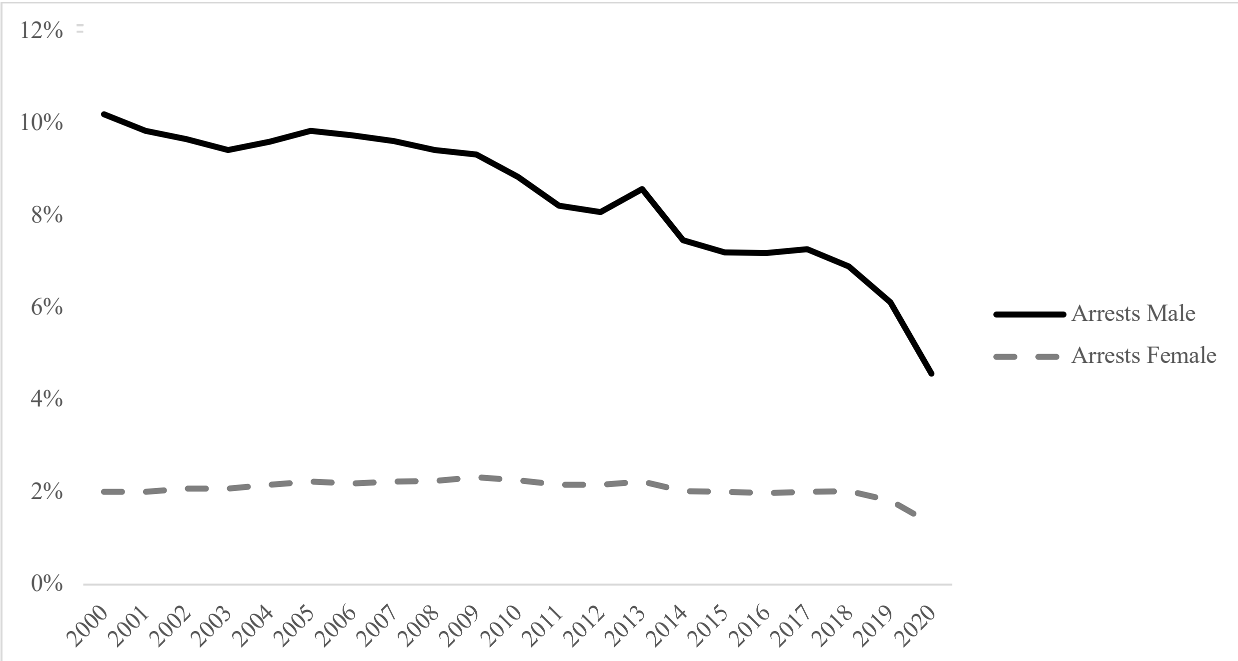
Finally, as an illustration of all the three base rates, Figure 6 presents the trends for arrests, charges, and prison admissions. While difficult to visualize trend changes of prison admissions due to the lower base rates compared to arrests and charges, a similar trend is observed across each. Thus, our findings indicate consistent U.S. trends across data sources collected by law enforcement, courts, and correctional agencies, with all three sources indicating substantial reductions in justice involvement beginning in 2008 and continuing through 2020.

Figure 6. Three U.S. Base Rates



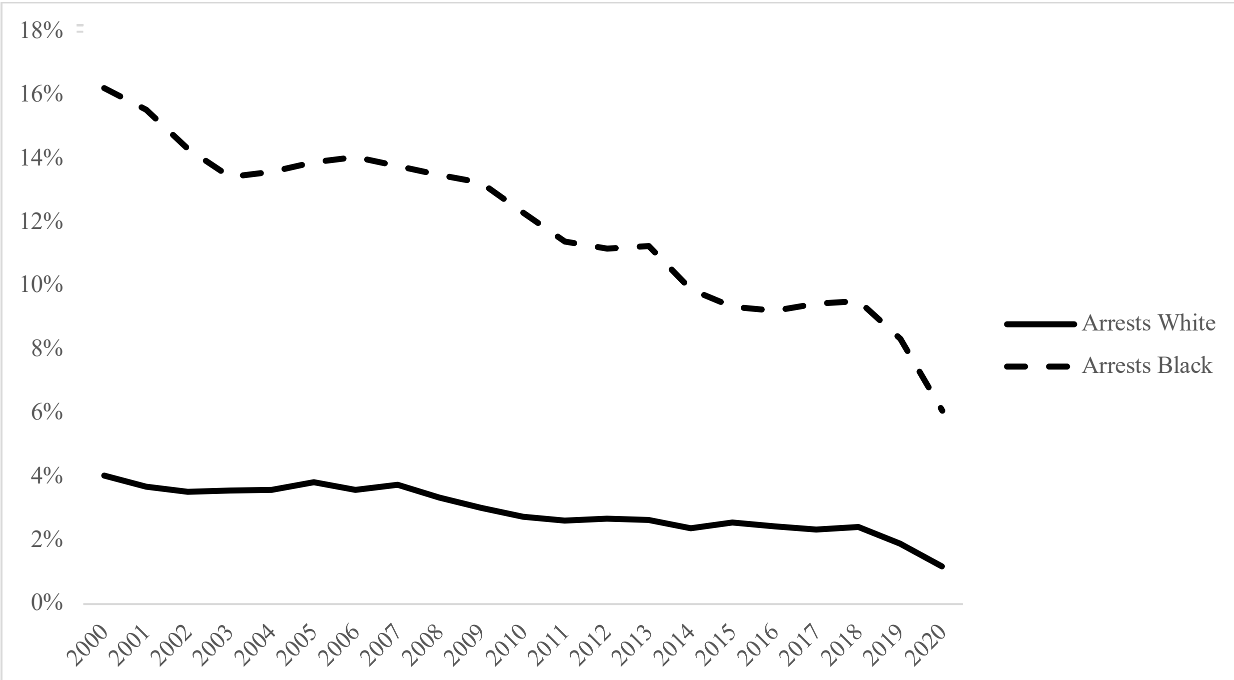
Next, we examine U.S. base rate arrest trends by gender (see Figure 7). The base rate arrest trend for men mirrors that of the national trend; however, the male base rate starts at 10% and decreases to roughly 4% by the end of the study period. Despite national declines, female base rates remained at roughly 2% until the COVID-19 pandemic year of 2020. Therefore, the average U.S. male possesses a 10% probability of arrest at the start of the study period, which was more than halved during the 20-year observation period, yet the female base rate remained relatively consistent at roughly 2%. While still representing a rate that is twice that of women, by the end of the study period men decreased their justice involvement substantially. This finding is consistent with cited trends that women are increasing as a proportion of the justice involved population (Carson, 2021). Similar base rate patterns are found for charges and prison admissions that users can track via the project dashboard.

Figure 7. U.S. Arrest Base Rate by Gender



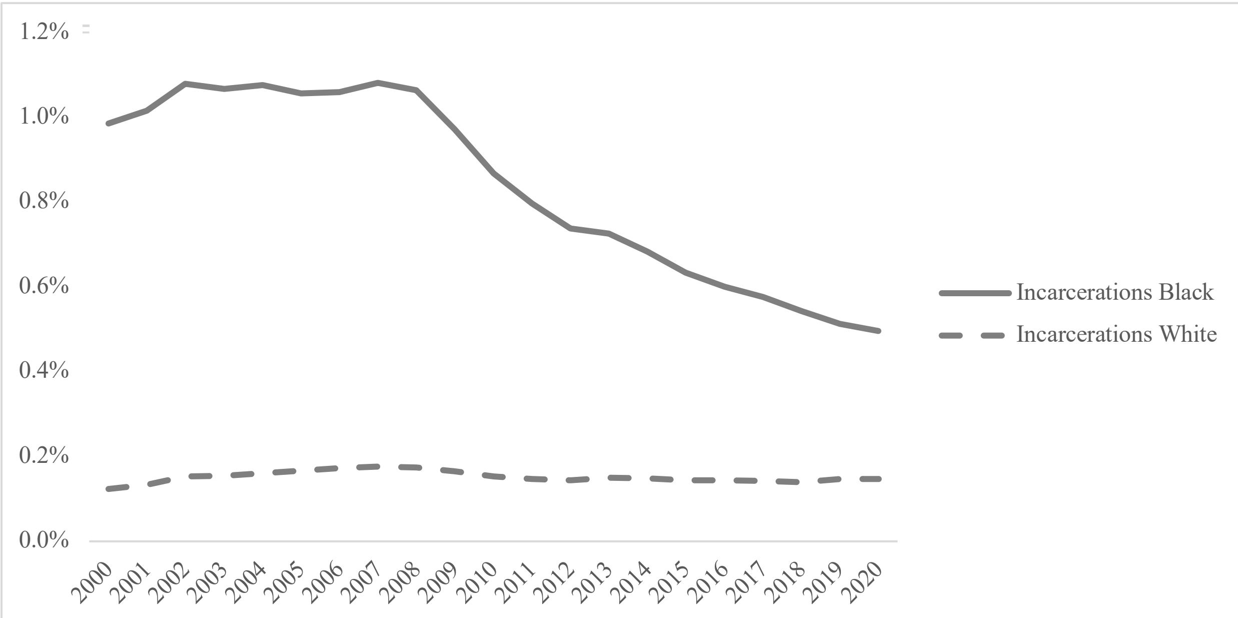
In Figure 8, we provide the base rate arrest trends comparing Black and White individuals. Trend lines indicate that both groups' base rates decreased by half through the study period. However, Black individuals start at a higher rate (16%), consistently decreasing each year, where less than 8% of the U.S. Black population was arrested in 2019. By contrast, White individuals start with a base rate of 4%, where only 2% of the White population was arrested in 2019. Removing the COVID-19 pandemic year of 2020, Black individuals in the U.S. have 4 times the base rate of the White population or possess 4 times the likelihood of being arrested during the 20-year study period. This finding is consistent with a recent study by Sabol and Johnson (2023), which reported that rates of offending have decreased for both Black and White individuals but at a greater rate for Black individuals.

Figure 8. U.S. Arrest Base Rates by Race



While national trends indicate that the number people incarcerated has decreased in recent years, the base rate of incarcerations has varied by race. As shown in Figure 9, the prison admission base rate only decreases for Black Americans, reducing from 1% to 0.5% over the study period. By contrast the base rate for White individuals increases slightly, but remains relatively stable, at roughly 0.15%. Similar to the comparison of gender base rates, we observe decreases in prison admission rates, which is due, to a great extent, by the observed reductions of the Black prison admission base rate. Yet, even as the gap decreases, Black individuals are still admitted to prison at a rate that is four to five times that of White individuals.

Figure 9. U.S. Prison Admission Base Rates by Race



Next, we examine base rate trends by offense type. To improve the time series visualization, we categorize offense into three major types – violent, property and drug. We present U.S. arrest base rate trends by offense type in Figure 10. Prior to 2008, the rate of individuals arrested for drug offenses (2.5%) was more than three times that of those arrested for property and violent offenses (0.6% & 0.7%, respectively). However, (excluding a small spike in 2013) following 2008, base rates for individuals arrested for drug offenses continued to decrease by more than a full percentage point by 2019 (1.5%). As will be described further, we anticipate that the decrease in drug base rates was due, in part, to many states' legalization of medical and recreational marijuana possession.

Figure 10. U.S. Arrest Base Rates by Offense Type

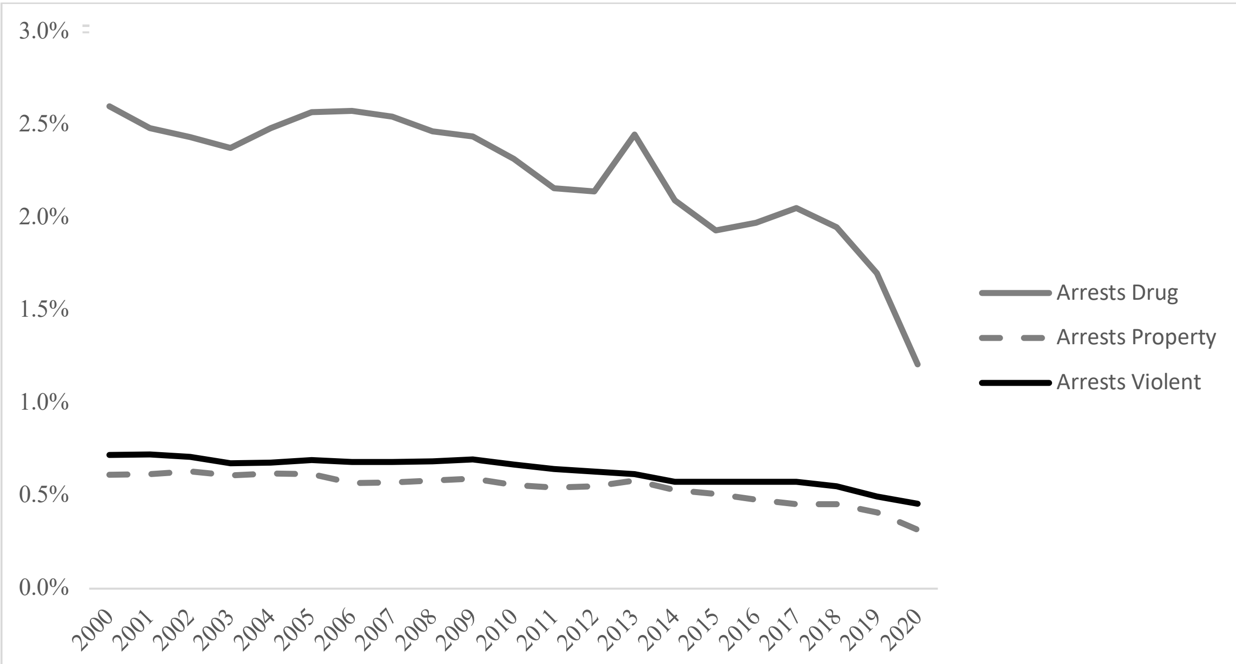
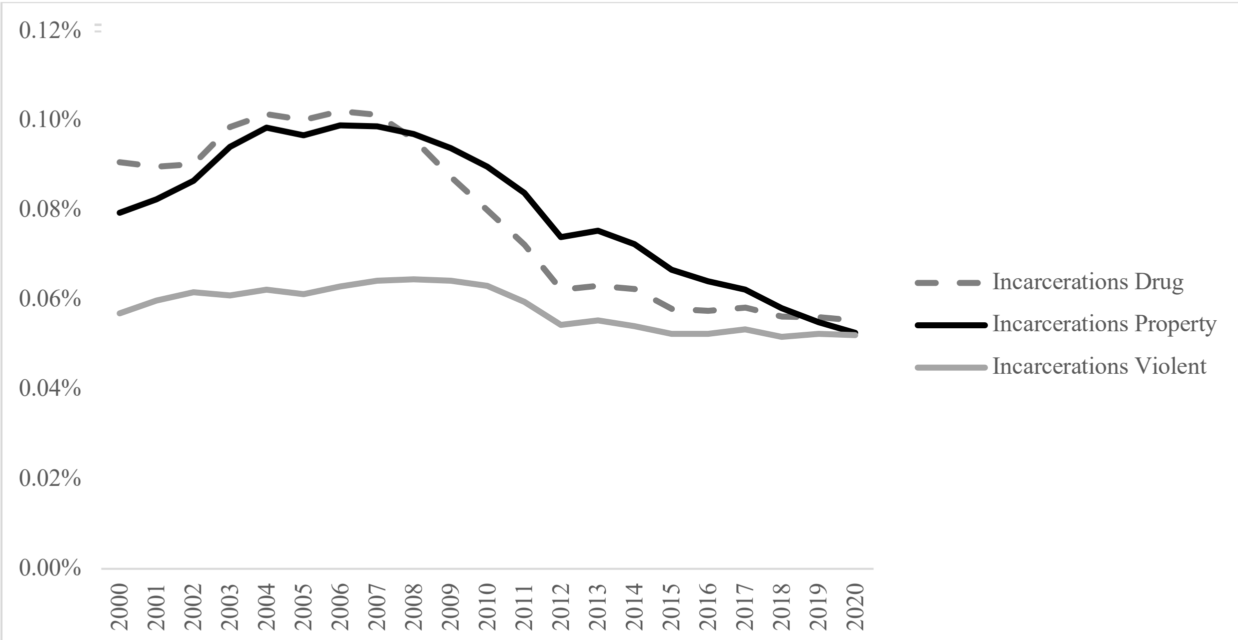


Figure 11 presents the U.S. prison admission base rate trends by offense type. Here we observe a similar trend for individuals committing drug offenses, where the base rate drops by nearly 30% between 2008 and 2012, and then continues to decrease thereafter. Interestingly, while individuals' arrest base rate remained relatively stable, prison admission base rates for individuals committing property offenses display a similar drop to that of drug offenses. Finally, like the arrest trends, an individual's likelihood of being admitted to prison for a violent offense remains relatively stable throughout the study period, declining only slightly between 2010 and 2012.

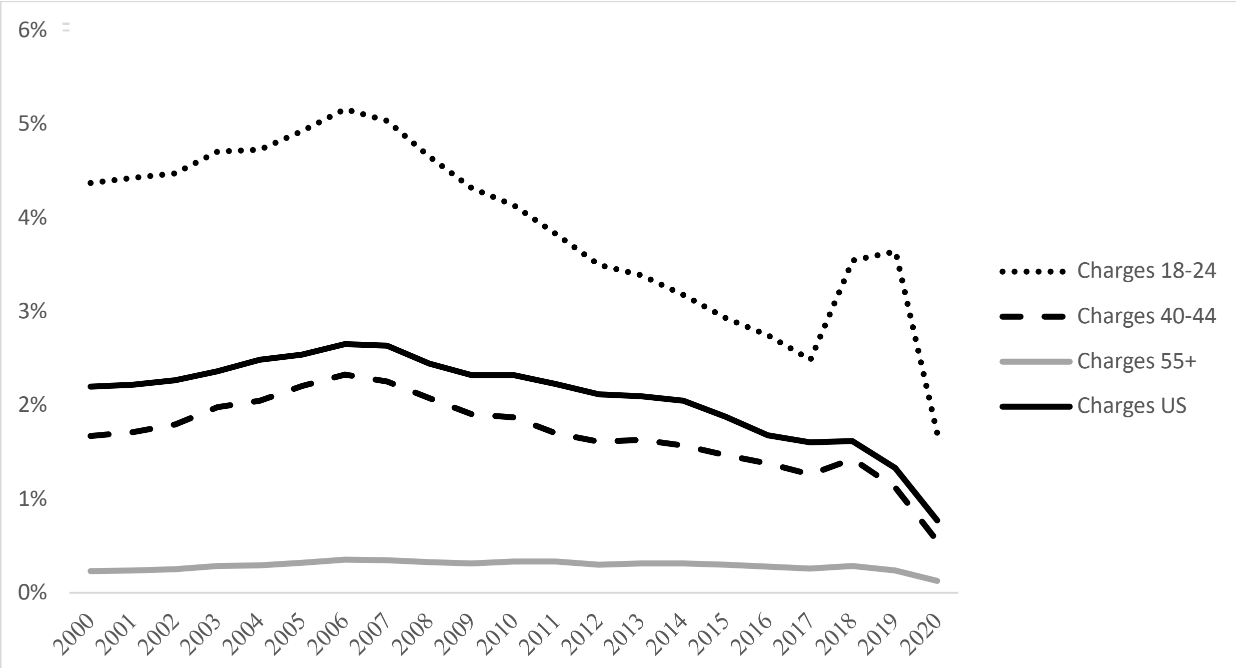
Figure 11. U.S. Prison Admission Base Rates by Offense Type



Age & Desistance

When examining charges by age group, we observe trends that are consistent with the age-crime curve. U.S. charge base rates are provided in Figure 12, broken down by three selected age rages. Regarding the youngest individuals – 18 to 24 – over 5% of the U.S. population in this age group were charged with an offense in 2007, decreasing to a base rate under 2% by 2020. For those 40-44 years old, their base rate trend is similar to the U.S. charge base rate, beginning at roughly 2% and declining to under 1% by the end of the study period. Finally, those individuals 55 years or older possess a 0.3% base rate of incurring a charge each year. Although everyone possesses a non-zero probability of offending, the typical individual age 55 and over represents a minimal risk and a close approximation to desistance, while those 34 and older may reflect a declining probability of recidivism. Thus, 34 years of age represents a watershed indicator, where individuals are likely to be rated as lower risk on most assessment tools and in need of less restrictions if supervised in the community.

Figure 12. U.S. Charge Base Rates by Age



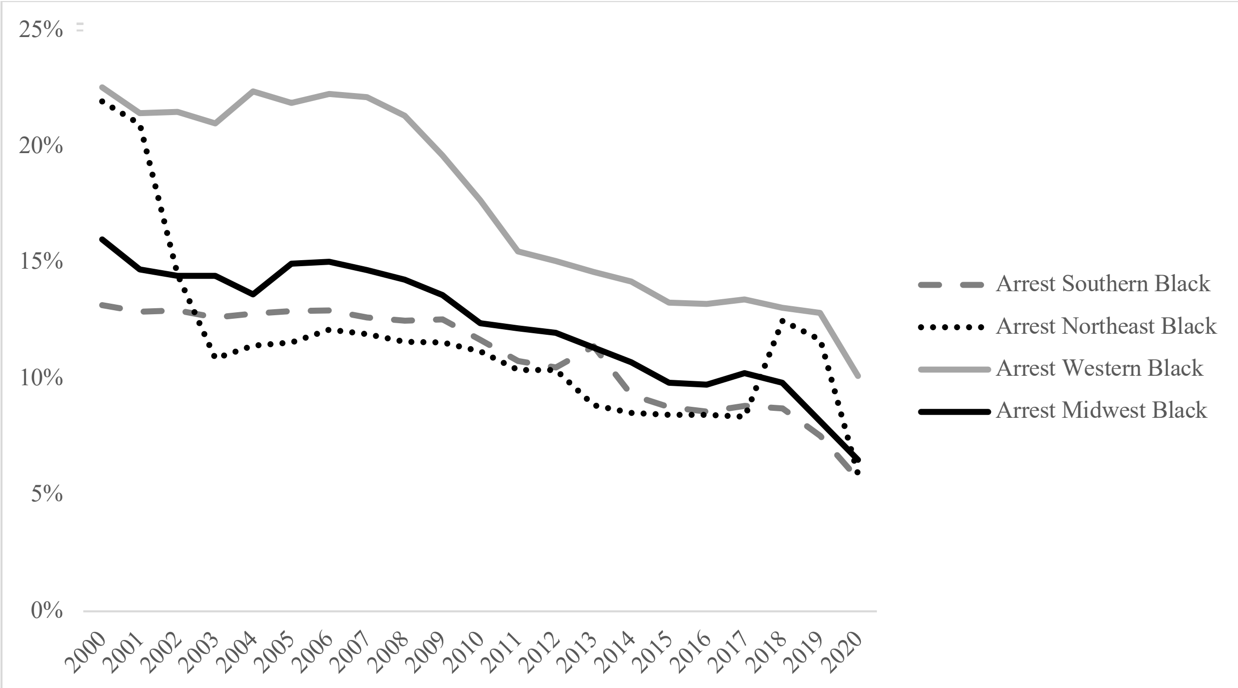
Regional Variations

While individuals reside in one state, cultural norms and expectations, as well as justice system activity, are anticipated to vary by region. In Figure 13, we examine the arrest base rate by region. We observe that all regions decreased their arrest base rate during the study period, with the Western region decreasing from 8% to 4% and the Midwest region decreasing from 4% to 3%. Notably, by 2020 regional trends converge, where arrest base rates across all four regions range from 2% to 4%.

Figure 13. U.S. Regional Arrest Base Rates

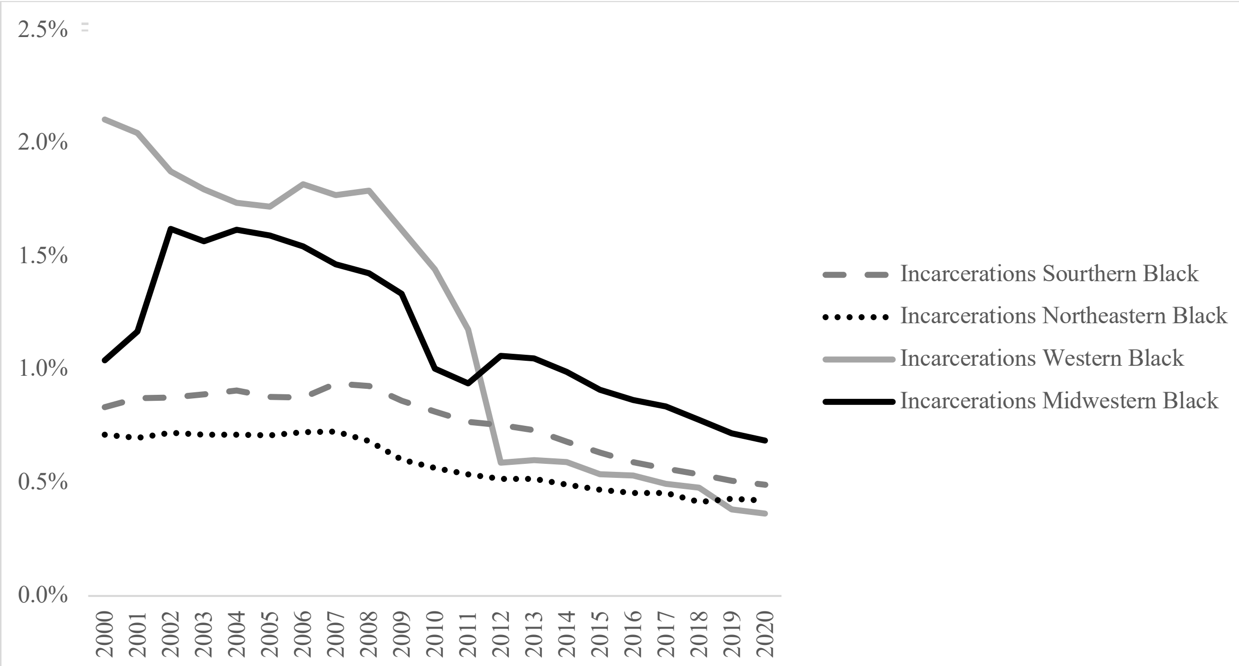
When examining race arrest base rates by region in Figure 14, the results indicate the likelihood of a Black individual being arrested in a Southern state fell from nearly 13% to roughly 6% by 2020. By contrast, Black individuals in the West possessed a 22% likelihood of being arrested in 2000, with the probability decreasing to 10% by 2020. The Midwest and the Northeastern regions had similar trends throughout the study period.

Figure 14. U.S. Regional Arrest Base Rates by Race



Next, we examined prison admission for Black individuals by region, where similar patterns to the previous analysis were observed in Figure 15. Specifically, Black individuals' base rates in the Southern and Northeastern region decrease from 0.7% to 0.5%. By contrast, the Western region's prison admission rate indicates that over 2% of the Black population was arrested in 2000 and again in 2001, before a substantial decline is observed though 2009 and a dramatic decrease though 2012, when the rate roughly mirrors that of the Southern and Northeastern region. Like the Western region, the Midwest region starts somewhat higher, but also decreases to a rate like the other three regions by 2020.

Figure 15. U.S. Regional Prison Admission Base Rates by Race

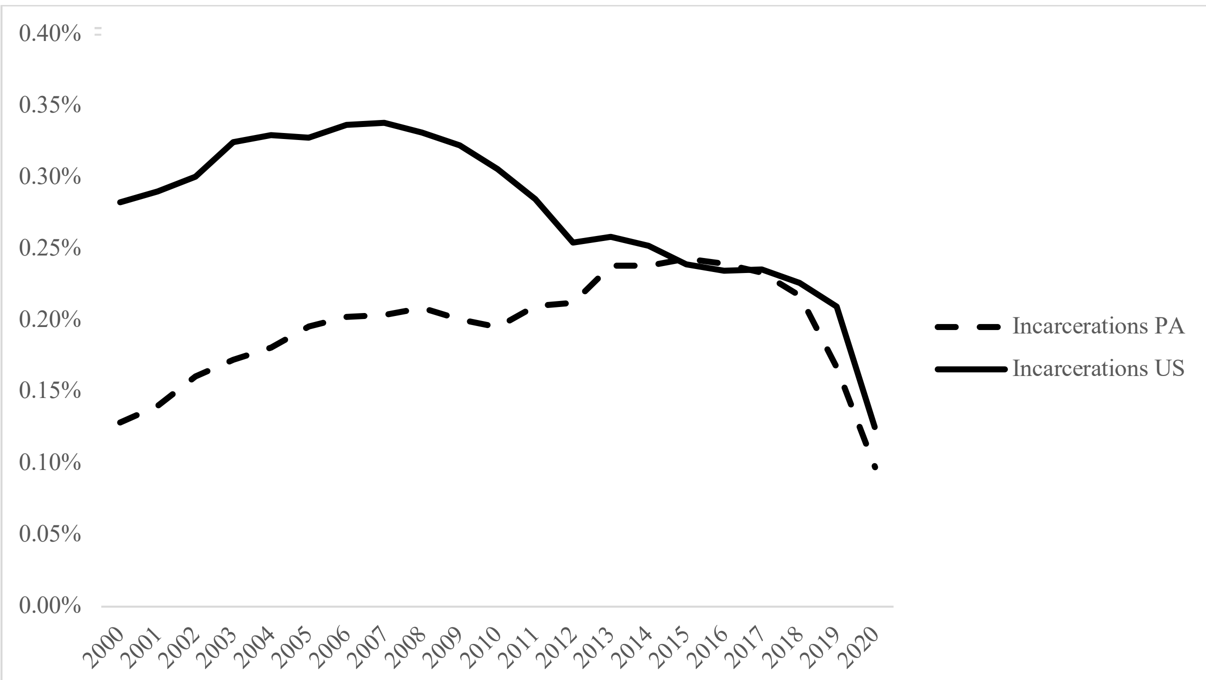


Comparing State & National Trends

Prison admission rates have been declining nationally, but the decrease has not been universally observed. As described, the U.S. prison admission base rate continued to increase from 2000 (0.28%) through 2007 (0.35%) before dropping to nearly one-quarter of a percent (0.25%) in 2012. In 2019, Vera reported that the incarceration rate in Pennsylvania had increased nearly 23% since 2000. Our base rate findings confirm these trends (see Figure 16), where the Pennsylvania citizens possessed a 0.13% probability of being admitted to prison in 2000 and a 0.24% probability of prison admission by 2015. Notably, while Pennsylvania did increase its base rate during this period, the peak for this trend roughly matches the U.S. base rate.

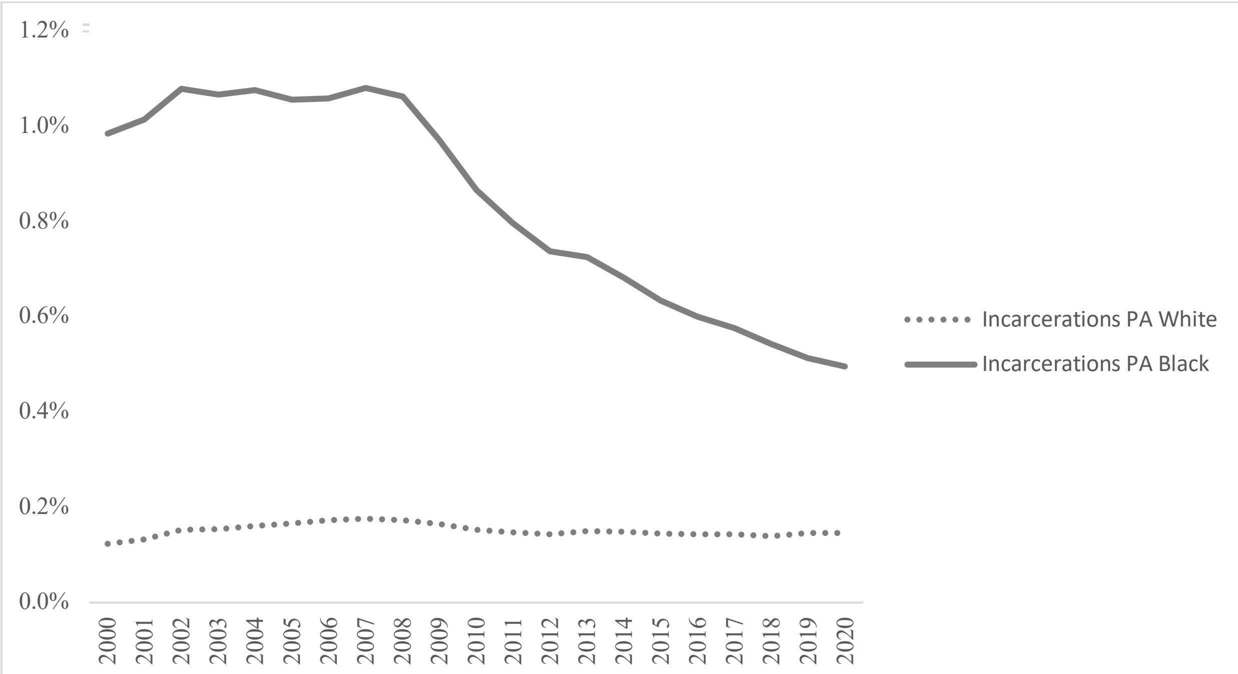
However, despite the observed increases in admissions, Pennsylvania decreased its prison population during this period, noting a greater rate of releases than admissions (Pennsylvania Department of Corrections, n.d.). Further, from 2016 through the end of the study period, the prison admission base rate began to decrease. This decrease has been attributed to a recent court decision (Hopkins v. the Commonwealth of Pennsylvania), which removed mandatory minimum sanctions and decreased prison admission base rates and additional reductions in 2020 were, at least in part, due to court processing restrictions resulting from the COVID- 19 pandemic (Frisch-Scott, Kimchi, & Bucklen, 2010).

Figure 16. U.S. vs. Pennsylvania Prison Admission Base Rates



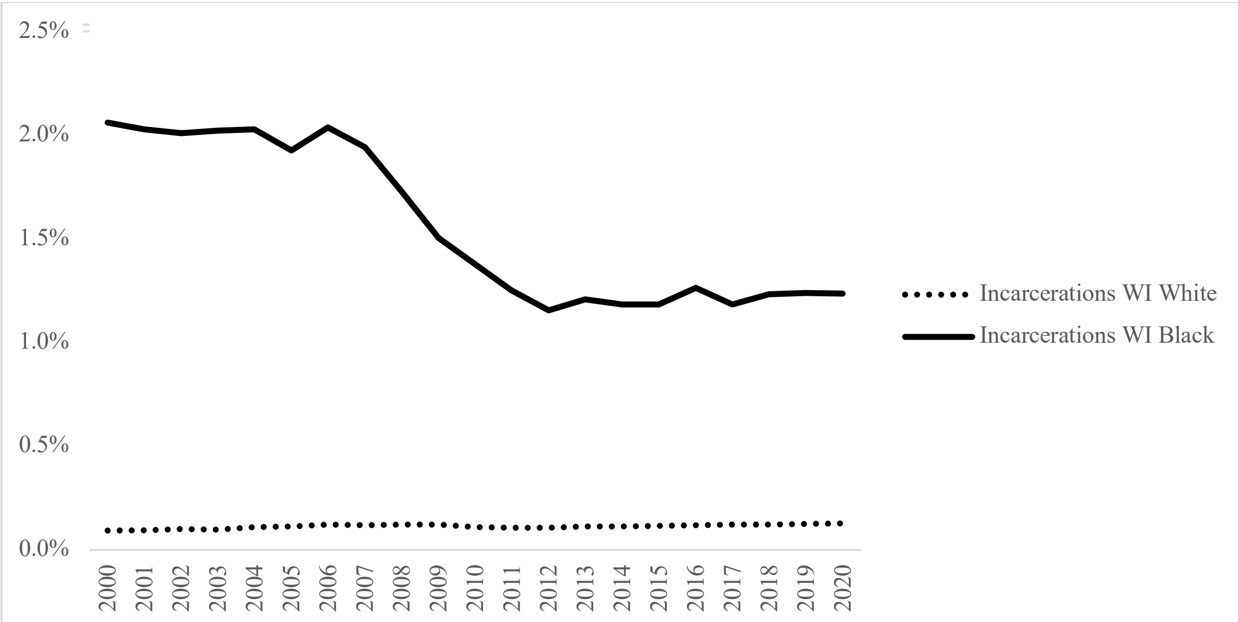
Like national prison admission base rates, the Pennsylvania prison admission base rate trend was not the same across racial lines (see Figure 17). Specifically, the White prison admission base rate ranges from 0.1% to 0.15% over the course of the study period. By contrast, the Black prison admission base rate is nearly 9 times that of the White rate between 2000 and 2008. By 2020 the base rate for Black individuals had decreased substantially, yet Black individuals in Pennsylvanians were still more than 3 times as likely to be admitted to prison than White Pennsylvanians (0.50% vs. 0.15%, respectively).

Figure 17. Pennsylvania Prison Admission Base Rates by Race



A similar trend is identified for the Wisconsin prison admission base rate (see Figure 18). Between 2000 and 2007, Black Wisconsinites possessed a 2% probability of being admitted to prison, compared to a White individual's probability of roughly 0.1%. In response to concerns of bias and disparity, Governor Doyle issued an executive order, and a taskforce was formed to create policies and an action plan to reduce correctional system bias (Wisconsin Office of Justice Assistance, 2008). Possibly because of these efforts, the Black prison admission base rate in Wisconsin decreased substantially. By 2012 the prison admission base rate decreased to 1.1% for Black and 0.1% for White Wisconsinites. Therefore, while the racial disparity decreased in Wisconsin, Black individuals still face 10 times the likelihood of admission to prison compared to White people. These findings are similar to those reported by Nellis (2021), who found that Wisconsin leads the nation in Black imprisonment disparity. Using the computed and most recent base rates, we find that roughly 1 out of every 100 Black people are admitted to prison each year in Wisconsin, compared to 1 out of every 1,000 White individuals.

Figure 18. Wisconsin Prison Admission Base Rates by Race



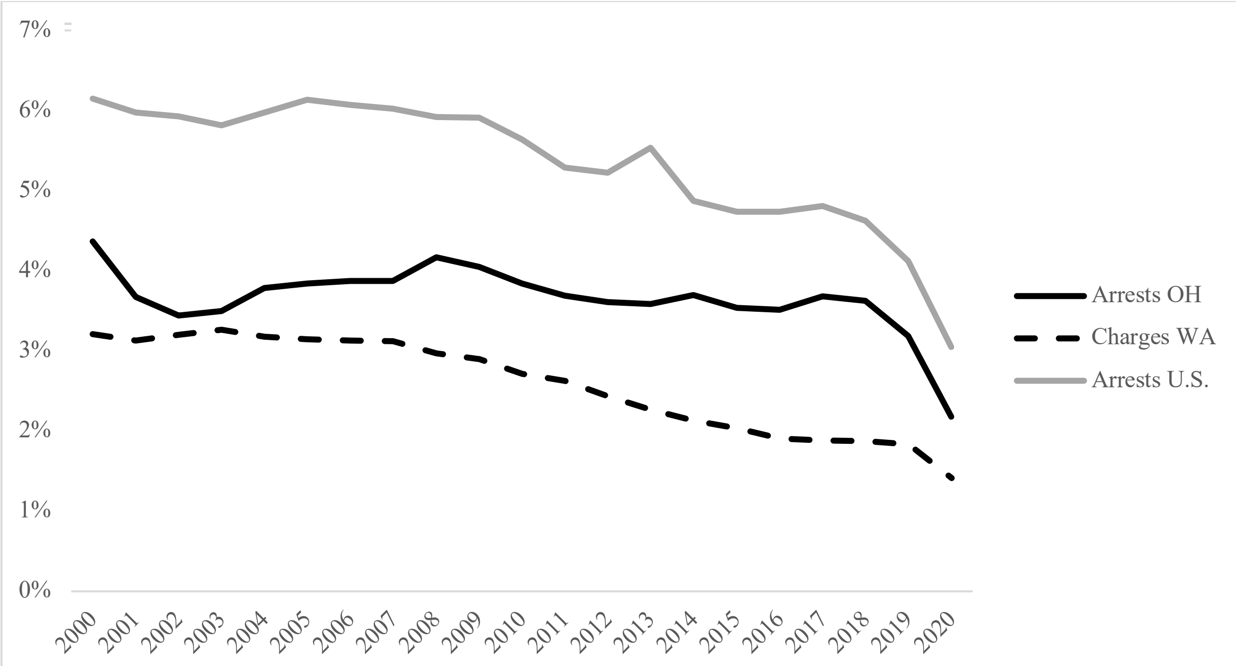
Base Rates & Risk Assessment

Many contemporary risk tools use development sample base rates to set risk level threshold in determining supervision strategies. In particular, the ORAS tool was developed in Ohio, defining recidivism as arrests within the first 12 months in the community. Yet, , the STRONG-R tool, developed in Washington, defines recidivism as new charges, while the BOP uses a 12-month rearrest definition for its PATTERN risk assessment tool. Understanding how tools differ in assigning risk levels (e.g., Low, Moderate, & High-Risk) requires an understanding of the base rate definition used in their development. In Figure 19, we provide the arrest rate for Ohio and the charge base rate for Washington State. As described previously, the ORAS Community Supervision tool set a Low-Risk category with a 9% arrest base rate. Excluding the COVID-19 pandemic year of 2020 the Ohio arrest base rate is roughly 3% to 4%, suggesting that the Low-Risk individuals on community supervision, possessing average rearrest rate of 9%, has more than twice probability of being arrested than average Ohioan.

By contrast, Washington State's STRONG-R assessment set a Low-Risk category at an 8% base rate, defined as a new charge within 24-months of reentry. Again, excluding 2020, here we see the 12-month charge base rate ranges from roughly 2% to 3% for the average citizen. Given our current inability to provide a 2-year charge rate, we would estimate that the base rate could potentially double to 6% of the Washington State population charged with an offense over a 24-month period. In which case the 8% Low-Risk base rate for the STRONG-R is slightly greater (2% to 4%) than that of the average Washingtonian.

Finally, the BOP's PATTERN risk tool identified four categories of risk centered around a base rate of a 3-year re-arrest rate of nearly 50%, where the lowest risk category was set at a recidivism probability that was roughly 20% of the base rate (or 10%). Examining the 1-year arrest trends for the U.S. population, we see a base rate range of 4% to 6%. In a recent BJS report, Durose and Antenangeli (2021) reported a 1-year base rate of 36%, where 20% of that base rate would translate to a 7% recidivism base rate for the lowest risk category. When examining Figure 19, the base rate ranges from 2% to 3% across the study period. Therefore, the PATTERN risk tool sets its lowest risk category at an average rearrest rate of 7%, which is two to three times the U.S. arrest base rate. Collectively, these findings indicate a new reference point for assessment developers to consider when setting risk levels, potentially building from the 'ground up' to accommodate the average individual's risk for a given outcome.

Figure 19. U.S., Ohio, & Washington State Base Rates

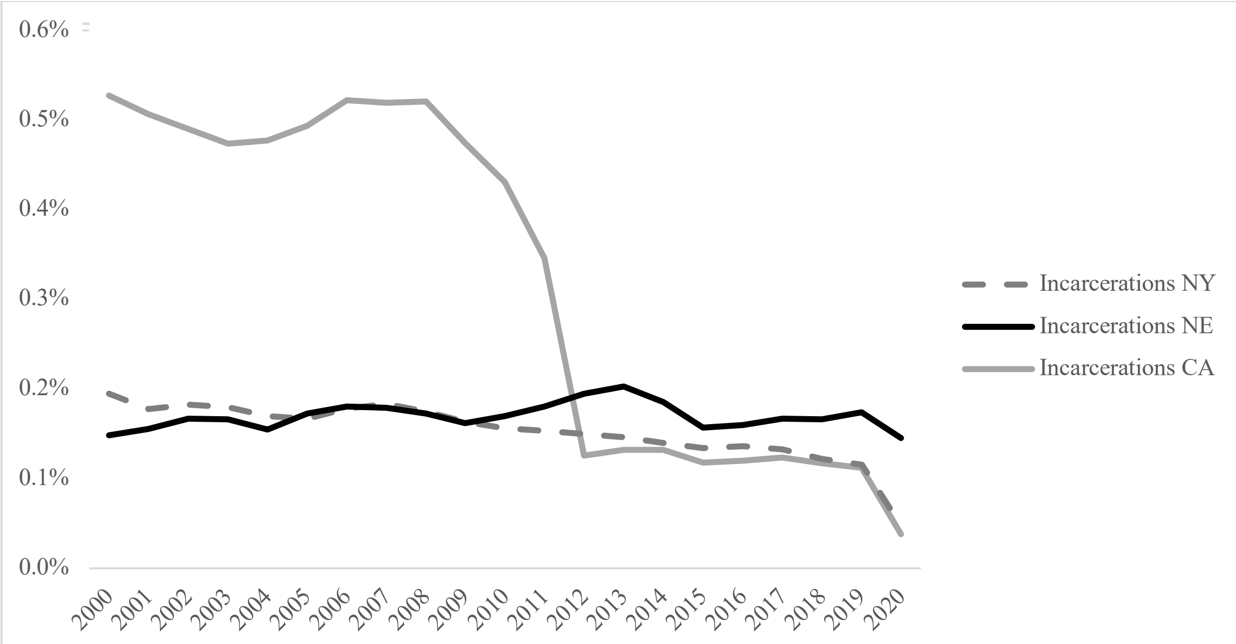


Tracking the Impact of State Interventions

We further show the potential use of base rates when tracking policy and statute changes for a given state or region. In Figure 20, we present the prison admission rates of three states – California (CA), Nebraska (NE), and New York (NY). Regarding California, we previously mentioned their efforts to decrease incarceration and correctional supervision beginning in 2009. We observe a direct result of these policy initiatives, where the prison admission base rate for California decreased by nearly 80% between 2008 and 2012. While not experiencing the same rate of decrease, New York also observed a reduction in their prison admission base rate. In 2013, Austin, Jacobson, and Chettiar identified the start of the trend in 2000 and attributed the decrease to a reduction of felony arrests in New York City because of the city's shifting focus on misdemeanors as part of the 'broken windows' policing model. Notably, the 'broken windows' model was no longer the focal strategy in New York beyond 2013, however the lasting and possible downstream effects of shifting law enforcement strategies may have resulted in the continued decreases in New York's incarceration rates. Finally, in 2015 the Council of State Governments released their Justice Reinvestment Report, observing a growing incarceration total in Nebraska. Yet, the report did not identify a substantial increase in the annual number of prison admissions, instead attributing the increase to longer sentences, more parole revocations, and greater admissions via reincarceration.

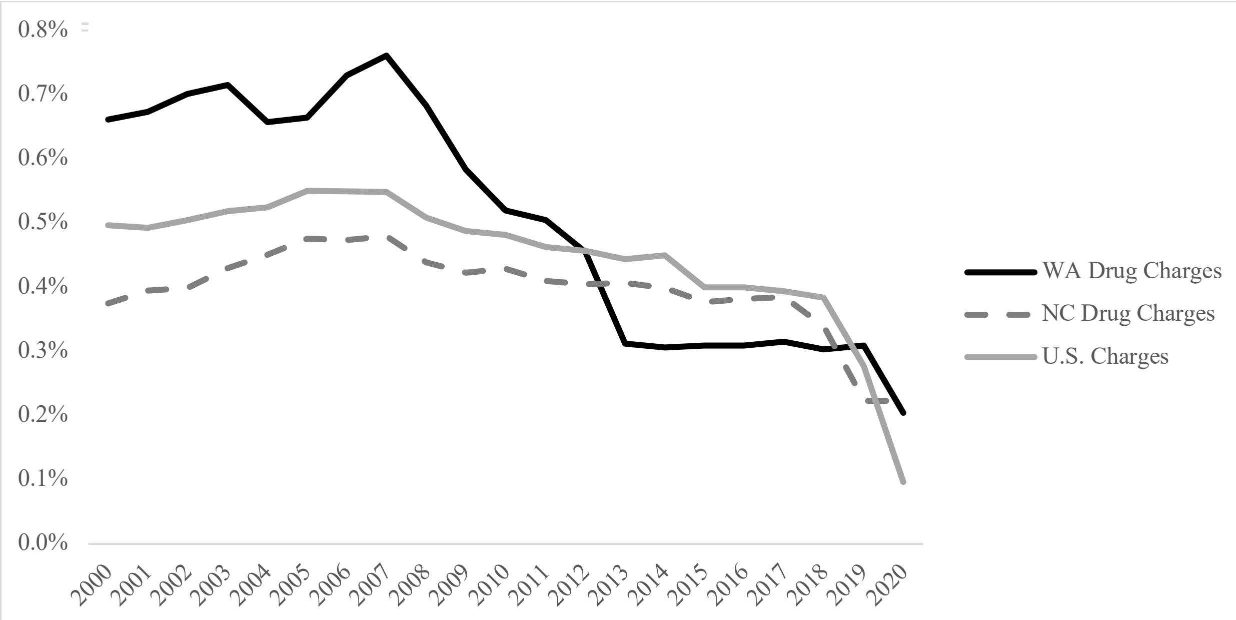
These contrasts in state policy and legislative changes to both law enforcement and corrections agencies demonstrated three distinct state trends resulting in Nebraska's prison admission base rate increasing, exceeding that of both New York and California by the end of the study period. These findings also demonstrate the differential impact of justice involvement strategies, where changes to law enforcement priorities provide a lagged effect on incarceration rates, while those aimed directly at reducing the correctional population can have a more dramatic impact. Finally, all states observed a relatively similar decrease in 2020 due to COVID-19 pandemic effects.

Figure 20. Prison Admission Base Rates by State



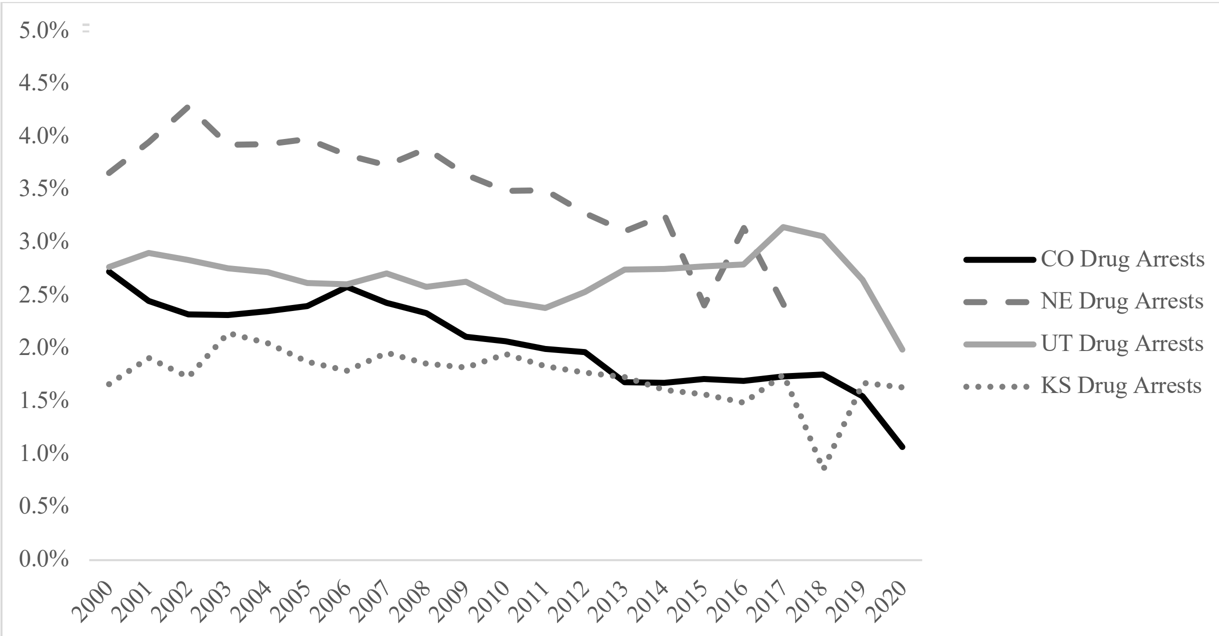
To further explore state variations, we compared drug charge base rates for Washington State and North Carolina. As indicated, Washington State legalized recreational marijuana in 2013 but prior to their voter initiative, major cities began to reduce sanctions and law enforcement priorities began to change as early as 2003. As shown in Figure 21, drug charges in Washington State decreased precipitously between 2008 and 2012, and base rates remained relatively flat from 2013 through 2019. By contrast, in North Carolina, marijuana possession and sale has remained illegal, and the slow decrease in drug charge base rates mirrors that of the national charge base rate trend.

Figure 21. Washington State & North Carolina Drug Charge Base Rates



Colorado enacted a voter initiative to legalize marijuana in 2012. States bordering Colorado were concerned that drug possession crimes would 'leak' into their jurisdictions, causing increased rates of justice involvement (Ellison & Spohn, 2016). In Figure 22 we show that two of the surrounding states – Nebraska and Kansas – demonstrated decreasing drug arrest base rates, while Utah saw a slight increase after 2012. Thus, while not isolated from the issues of marijuana legalization, surrounding states display a complex set of findings in need of further exploration.

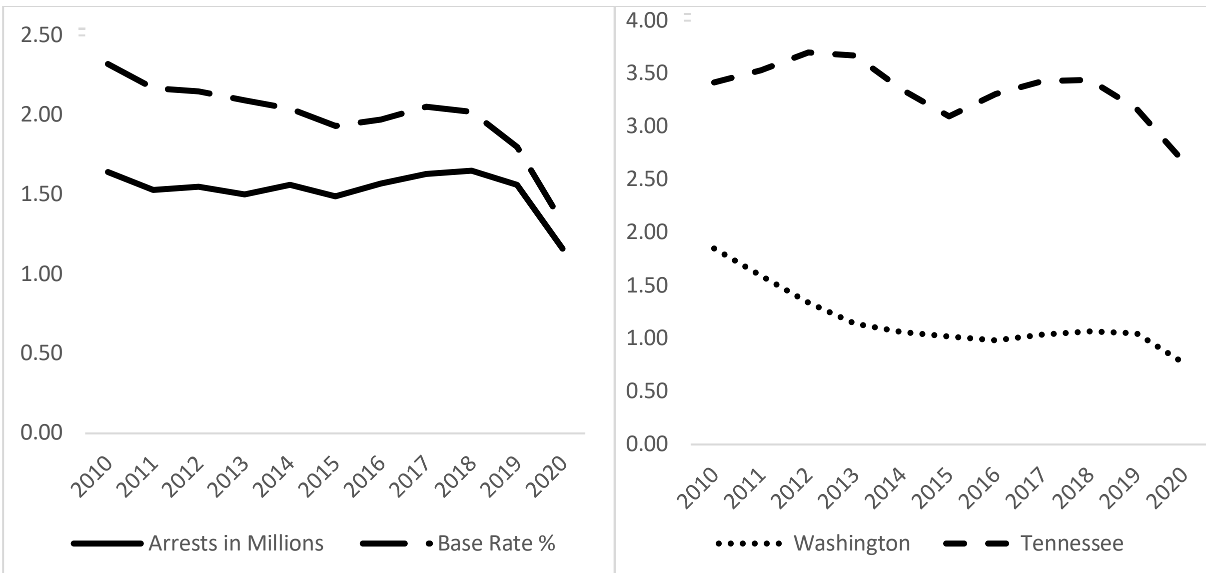
Figure 22. Comparison of Drug Arrest Base Rates by State



Finally, to provide an understanding of the type of information that base rates provide. In Figure 23 we provide a side-by-side comparison of UCR drug arrests between 2010 and 2020. Notably, UCR arrests (in millions) are provided in the left pane, which was provided by the National Center for Drug Abuse Statistics (NCDAS) 2024 report. In this figure one can observe arrests remaining relatively stable, at roughly 1.5 million, from 2010 through 2019, before decreasing precipitously in 2020. In this same chart we provide base rate calculations, which indicate that the likelihood of arrest decreased from 2.3% to 1.8% during this same period, before declining sharply in 2020.

While national count and base rate trends are similar, state drug arrest base rate demonstrate distinct trends. Specifically, while Washington State drug base rate have consistently declined since 2010, Tennessee's rates have ebbed and flowed, over this same period. Notably, Washington State legalized recreational marijuana use in 2008, with this change in statute potentially contributing to the smoother and consistent decrease in a resident's likelihood of being arrested for a drug offense, over time. Demonstrating these comparisons of arrests, base rates, and breakdowns by state, using of UCR data, provides users with a greater understanding of the utility of base rates compared to traditional crime incident reporting.

Figure 23. Drug arrests and base rates comparison by Washington and Tennessee



As our examples have demonstrated, base rate trends possess important utility. Unlike incident reporting, base rates provide a reference point for policy passage to track trends over time. While legislative and policy reforms may intend to alter the average citizen's justice involvement, sometimes these effects are assumed but not tracked. Further, a state trend, viewed in isolation of the regional or national trends, may be misunderstood and perceived as a change in population or policy effect. Our goal with the presented findings was to provide examples of base rate usages, while supplying users with an interactive dashboard to explore inquiries further.

DISCUSSION

Base rates have an important impact in describing the average person's risk of offense. While base rates are a simple ratio to compute, quality, consistency, and the unit of analysis of prior national and decentralized data compilations have been limited. Our project goal was to provide source material, combining data collection efforts to provide base rates of three justice system outcomes – arrests, charges, and prison admissions. In this report, we provided background knowledge of justice involvement base rates and potential uses of the created data. Further we developed an interactive Tableau dashboard to be explored and mined by researchers, practitioners, and advocates.

This report began with a discussion of common uses of base rates. In the risk assessment field, base rates are commonly used to establish risk level categories (RLCs). With examples of how base rates are used in practice, we proposed a potential method in which the population base rate is the reference point for creating categories of Low-Risk individuals. In our analyses, we compared charge rates of the development samples of three contemporary risk assessment tools in Washington State, Ohio, and the U.S. population. Going forward, we envision that risk assessment developers and practitioners making use of state and national base rates, allowing correctional agencies to set and adjust risk level cut points in reference to the average person's risk of offending.

Further, we discussed how base rates can be used as a reference point to identify desistance. Defining desistance as a recidivism probability similar to that of the average citizen, base rates can be used to identify the relative rate of recidivism for a group of respondents. Providing a well-known example of the age-crime curve, we determined that individuals aged 35 to 44 present a recidivism probability similar to the U.S. arrest base rate. Expanding assessments to include multiple metrics, researchers may be able to predict when an individual no longer presents a ‘greater than average’ threat to public safety or has a predictive probability at the population base rate. Extending beyond the example of age, we suggest that base rates may be used not only as a reference point to evaluate the impact of protective factors, such as employment and residential stability, but also as a method to gauge the effectiveness of programs that have been brought to scale and may be hard pressed to establish a feasible control group. Further, absent an exhaustive assessment or screening tool, judges and practitioners may use key indicators to identify individuals that present characteristics of the average individual’s risk to offend. This may help stakeholders determine effective uses of diversion, pre-trial release, and alternatives to detention, incarceration, and supervision.

As several of our example analyses indicated, base rates facilitate the tracking of trends across multiple outcomes. Our examination of regional consistencies described varying levels of disproportionality of Black versus White individuals, indicating greater base rate disparity in the Western region. We also demonstrated how base rate trends can be used to capture changes within a state and, more broadly, to the U.S. in general. Specifically, we highlight increases in the prison admission base rate in Pennsylvania during a time when the U.S. rate was similarly situated. While cited reports indicate a net reduction of incarcerated individuals in Pennsylvania, these base rate findings demonstrate the complexity in observing the effects of changes created in policies, legislative initiatives, and court decisions.

We also examined prison admission base rate distinctions of three states – California, Nebraska, and New York – each with unique policy and statute changes across law enforcement, legislative, and correctional changes with varying degrees of impact on a state’s base rate. Further, we considered how major state initiatives can impact the base rates of its citizens.

Specifically, we compared the Washington State voter initiative, legalizing the possession and sale of marijuana and the impact on arrest base rates for drug offenses, in reference to a potential control site – North Carolina. Moreover, we analyzed the regional impact of Colorado's voter initiative to legalize marijuana on neighboring states. These changes, following policy, statute, or governmental initiatives may be best examined and triangulated via base rates across all three systems. Users are encouraged to access the interactive dashboard to evaluate the impact of similar policies and initiatives.

Due to the ongoing concern with overclassification and disproportionate minority contact, we examined base rates by gender and race/ethnicity. The results showed the decrease of justice involvement in all three base rates – arrests, charges, and prison admissions– differed by key sub-groups. Specifically, men decreased at a greater rate than women, and Black citizens' base rates decreased at a greater proportion as compared to White individuals. While we offered Pennsylvania's and Wisconsin's base rate disparity as an example of reductions suggesting progress and parity, areas of remaining disparity are noteworthy. The continued evaluation of disparity via state and justice system specific base rates will help identify, target, and assist stakeholders in developing innovations to decrease existing areas of need.

While trends explore the past and the impact of interventions, base rates serve as a source of information to forecast projected impacts of interventions. As new initiatives are developed, base rate trends can be established, and the impact of initiatives can be projected following an examination of prior and existing base rate trends. For example, Dollar, Campbell and Labrecque (2022) examined the impact of justice reinvestment initiatives (JRIs) in Oregon via interrupted time series analysis (ITSA), identifying how newly adopted legislation impacted prison usage. Further, Rosenfeld and Berg (2023) used time series trends to forecast New York City's crime rates though 2024 and argue that renewed attention to forecasting is needed to guide legislative and policy directives. Similar to the U.S. Congress' use of Congressional Budget Office (CBO) prior to enacting legislation, stakeholders may use base rates as a method of forecasting future impacts of bills under consideration. Following the deployment of policies, programming, or developing trends, statistical models may be created to combine factors and forecast their projected impact. These forecasts have the potential to project downstream effects driving resource needs from one justice system to another.

Limitations

While no study is without limitations, the apparent gaps described represent an issue with systems of record. Although it is not uncommon to mention issues of non-reporting for UCR and other national data sources, we provided methodological solutions to reduce potential errors, such as interpolation and extrapolation. Further, data base and dashboard collections used weighting procedures to improve the accuracy of prediction. While not without potential caveats, we believe these adjustments improve the use of the provided base rates, allowing for better visualization of national and state-by-state comparisons.

Further, many reporting systems used here describe and identify crimes committed within a state. However, it is notable that, while not nearly the majority, many offenses were committed by individuals in one state that are residents of another. The National Crime Information Center (NCIC) database is often used by justice system agencies to identify the totality of offenses committed by an individual, regardless of location of the offense. NCIC is a nationally representative database with considerable restrictions for researcher access. Therefore, while the current research established a robust and representative sample of U.S. justice involved subjects that has likely not be collected previously, we are not able to examine the proportion of offenses that cross stateliness. Ideally, our work will be replicated, expanding the data repository to provide an even-greater national representation of base rates across time and stateliness.

With that said, one system of record – court charges – incurred the highest rate of missing and incomplete data across the study period. Unlike the UCR and the NCRP, courts systems of record are challenging to access and many states do not provide a centralized compilation of records. We were fortunate to gain access to Thompson-Reuters CLEAR database as well as CJARS, and Washington State provisions of charge data. However, there were many states and years of the study period that were left missing. Unlike arrest incidents and prison admission records, there is no existing database available to track national trends of administrative office of the courts records. While we succeeded in establishing one of the best compilations of charge data, substantial caveats remain, and future efforts should attempt to fill noted gaps (see Appendix I).

Although the NIJ resources used to complete the Base Rate Project provided a substantial step in understanding and the utility of base rates, the work presented in this report expands the initial proof of concept. With current and potentially improved resources going forward, we advocate for a national archive with routine updates via the BJS or a similar Office of Justice Programs (OJP) to extend our efforts forward. Similar to the reports that make use of UCR and NCRP data, we hope our findings will inspire future work to provide available and interactive databases that make these information systems transparent and available for researchers and practitioners.

Conclusion

In an effort to expand the understanding and use of base rates, we have provided a more unifying metric that facilitates understanding the decentralized and variant nature of the U.S. justice system's outcomes. Risk assessment development is often overlooked as a critical component to justice reform efforts. As many agencies ramp up efforts to decrease the lasting effects of mass incarceration and the prison boom era, risk and needs assessments will be used to help guide agencies and policy maker's ability to discern the most effective strategies while maintaining public safety. To further remove public safety concerns and increase reentry success, these assessments provide an understanding of who is most in need of programming and supervision. Although risk-needs assessments are already in use in many jurisdictions, we hope that the critical value of base rates for developing risk and supervision levels is better understood. Further, with a compilation of base rates at the state level, this project provides a source of information that can be used to adjust assessment risk levels locally, including a given state's base rate, to provide a better and more accurate assessment of an agency's population. While it is assumed that a justice involved population will have a greater base rate than a general population, each population will differ, and assessments may be 'normed' locally to identify the level of risk tolerance their agency is willing to accept. That is, a jail, probation, or parole agency can reset the Low-Risk cut points of their risk assessment tool in accordance with the population base rate. In this way, risk and needs assessment tools can be uniquely calibrated to the availability of resources and the local rating of danger to public safety.

Over the last decade, the prison reform movement has focused on reducing the number of people confined in state and federal correctional facilities. As a result of this effort, along with other factors such as budget limitations and the COVID-19 pandemic, states and local jurisdictions have decreased the penalties for drug and non-violent crimes and charged fewer people for these offenses. Further, reform efforts can also have unforeseen consequences, as greater releases to community supervision may result in gaps and misalignment of supervision and treatment resources. By tracking base rate trends over time, stakeholders can gain an understanding of their population's risk, obtain feedback of the impact of their decisions, and create more efficient uses of existing and/or shifting resource needs.

With justice reform efforts underway in nearly every state (Porter, 2020), researchers and policymakers seek to appropriately frame the issues their states endure and seek to address. Describing the average citizen's likelihood of justice system involvement can provide readers context using individuals as the unit of analysis. Through our work here, we have provided underlying information that knits together once siloed and decentralized data sources. By converting units of analyses to the person-level, base rates across systems can be compared and used to assess the impact of programming, policies, practices, and forecast the impact of proposed legislation on a state's citizens and the populations under supervision.

We hope that the interactive database, created as the main project deliverable, provides foundational evidence needed to track justice involvement across multiple metrics and allows for a more consequential understanding of what is, and what is not, evidence-based impacts of justice system reform efforts. Further, we believe the compiled project efforts have implications for agencies and advocates seeking to improve conditions of marginalized groups by providing information regarding disproportionality of system involvement that continues to impact disadvantaged groups. While many prior researchers have outlined the systematic biases within the criminal justice system, our findings shed additional light on the relative likelihood of becoming justice involved, in any given state, over the past two decades.

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Appendix I. Data Source Yearly Coverage by State

0: Missing data; X: Non-missing data; Y: Interpolated/extrapolated data

State	Data Source	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20
AL	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AL	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AL	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AL	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AL	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AK	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AK	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AK	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AK	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AK	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AZ	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AZ	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AZ	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AZ	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AZ	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AR	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y	Y
AR	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
AR	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CA	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CO	TR	X	X	X	X	X	X	X	X	X	0	0	0	0	0	0	0	0	0	0	X	0
CO	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

CO	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CO	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CO	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CT	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y
CT	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CT	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CT	NCRP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	X	X
CT	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
DE	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DE	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DE	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DE	NCRP	0	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X	X
DE	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
DC	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	0	0
DC	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DC	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DC	NCRP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DC	UCR	0	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
FL	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	CJARS	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	0
FL	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
FL	UCR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	X	X	X	X
GA	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
GA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
GA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
HI	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y	Y
HI	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HI	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

HI	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
HI	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ID	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ID	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ID	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ID	NCRP	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X	X	X
ID	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IL	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IL	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IL	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IL	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IL	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IN	TR	X	X	X	X	X	X	X	X	X	X	X	0	0	0	0	0	0	0	0	0	0
IN	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	NCRP	0	0	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IN	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IA	TR	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y	Y	X	X	X	Y	Y	Y	Y
IA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
IA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
KS	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
KS	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KS	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KS	NCRP	0	0	0	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X
KS	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
KY	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
KY	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KY	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KY	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

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KY	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
LA	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y
LA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
LA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ME	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ME	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MD	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MD	CJARS	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y
MD	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MD	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MD	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MA	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MI	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MI	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MI	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MN	TR	0	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X	X
MN	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MN	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MN	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MN	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

MS	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	0
MS	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MS	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MS	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MS	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MO	TR	X	X	X	X	Y	Y	X	X	X	Y	Y	Y	Y	Y	Y	Y	Y	Y	X	Y	Y
MO	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MO	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MO	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MO	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MT	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
MT	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT	NCRP	0	0	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X
MT	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NE	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NE	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NE	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NE	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NE	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NV	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NV	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NV	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NV	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NV	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NH	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NH	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NH	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NH	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NH	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NJ	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

NJ	CJARS	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y
NJ	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NJ	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NJ	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NM	TR	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y	Y	Y
NM	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	NCRP	0	0	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X
NM	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NY	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NY	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NY	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NY	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NY	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NC	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NC	CJARS	X	X	X	X	X	X	X	X	X	X	X	X	X	X	s	Y	Y	Y	X	Y	Y
NC	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NC	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NC	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ND	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	CJARS	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y
ND	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ND	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OH	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OH	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OH	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OH	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OH	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OK	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OK	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

OK	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OK	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OK	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OR	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	CJARS	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y
OR	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
OR	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
PA	TR	0	0	0	0	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X
PA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
PA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RI	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y	Y	Y	Y	Y	Y
RI	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RI	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RI	NCRP	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RI	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SC	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y	Y
SC	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SC	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SC	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SC	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SD	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SD	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
TN	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
TN	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TN	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

TN	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
TN	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
TX	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
TX	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TX	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TX	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
TX	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
UT	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
UT	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UT	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UT	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
UT	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
VT	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
VT	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VT	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VT	NCRP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	X	X	X	X
VT	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
VA	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
VA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VA	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
VA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WA	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WA	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WA	WA AOC	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WA	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WA	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WV	TR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WV	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WV	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WV	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

WV	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WI	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WI	CJARS	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Y	Y
WI	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WI	NCRP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WI	UCR	0	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WY	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WY	CJARS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WY	WA AOC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WY	NCRP	0	0	0	0	0	0	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WY	UCR	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X