The Public Safety Impact of Shortening Lengthy Prison Terms

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Introduction

In Spring 2022, the Council on Criminal Justice (CCJ) launched the Task Force on Long Sentences. The group of 16 experts represents a broad range of experience and perspectives, including crime victims and survivors, formerly incarcerated people, prosecutors, defense attorneys, law enforcement, courts, and corrections. Its mission is to examine how long prison sentences—defined as 10 years or more—affect public safety, crime victims and survivors, incarcerated individuals and their families, communities, and correctional staff, and to develop recommendations to strengthen public safety and advance justice.

The analysis presented here was commissioned by the Task Force to examine the relationship between long prison sentences and public safety in one state, Illinois. The project was made possible by a partnership between the Illinois Sentencing Policy Advisory Council, CCJ, and Maxarth LLC, a data analytics firm.

Long sentences are often imposed with an expectation that they will prevent some crime by incapacitating individuals and deterring them from engaging in future crime after release. While there are several other purposes of sentencing, including punishing offenders, restoring victims and survivors, and deterring others from committing crimes, the research question explored in this brief is whether people serving long sentences may be confined beyond their likelihood of engaging in criminal behavior. Incarcerating individuals beyond this point would increase the size of the total prison population—and associated costs—without producing additional benefits for public safety.

To examine this question, Maxarth LLC analyzed detailed arrest history data for people who were released from Illinois prisons between June 2016 and June 2019. For the 1,127 people in this release cohort who had served 10 years of more prior to release, microsimulations were created to estimate the number of arrests averted due to the individuals' long prison terms.[1] The number of arrests averted includes: (a) estimated arrests that did not happen because the person was incarcerated (incapacitation effect), (b) arrests that did not happen during a 30-month post-release tracking period because the person reduced their criminal activity (specific deterrence or rehabilitation effects), and (c) arrests that happened post-release because the person increased their criminal behavior following their incarceration (criminogenic effect). The incapacitation effect was calculated using the length of each person's prison stay (time served); the specific deterrence and criminogenic effects were calculated in the 30 months following each person's release date. The analysis accounted for the start of the COVID-19 pandemic in March 2020, which overlapped with the 30-month post-release tracking period for some members of the sample. See the supplemental methodology report for detailed procedures.

To estimate the impact of shortening lengthy prison terms, these microsimulations were then recalculated to estimate the number of arrests averted when each person's time served was reduced by one, two, and three years and by 10%, 20%, and 30%.[2] Any decline in the number of arrests averted in these simulations can be understood as the number of *additional arrests* resulting from the prison term reduction. For example, if an individual's 12-year prison sentence was estimated to avert three arrests, and the microsimulation indicates that only two of these three arrests would be averted if they were released a year earlier, then we can say that a one-year reduction in their prison term would create one additional arrest. To estimate how many additional arrests would take place as a result of releasing people serving long sentences from incarceration sooner every year, all results reflect estimates for the 376 people predicted to be released sooner every year (1,127 members of the sample divided by three years equals 376). See the supplemental methodology report for details about how the microsimulations were conducted and how results were annualized.

Key Takeaways

- **Modest reductions in the length of long prison stays would likely result in relatively few additional arrests.** Estimates show that reducing time served by one, two, or three years for the 376 individuals released annually in Illinois would result in 11 to 37 additional arrests. Reducing time served by 10%, 20%, or 30% would result in an estimated 17 to 63 additional arrests in Illinois.

- **The additional arrests likely to result from reductions in time served would constitute a virtually undetectable increase in the annual volume of arrests in the state.** The 11 additional arrests from a one-year reduction in time served comprise one one-hundredth of one percent (0.01%) of all 89,173 index crime and drug arrests in Illinois in 2020.[3] The estimated 63 arrests expected to occur should time served be reduced by 30% constitute less than one-tenth of one percent (0.07%) of all index crime and drug arrests in Illinois in 2020.

- **The additional arrests that may occur when prison stays are shortened are unlikely to be for violent crimes or weapons charges.** Estimates show that a one-year reduction in time served would result in two additional arrests for violent crimes, two arrests for property crimes, two arrests for drug crimes, and five arrests for "other" crimes. The analysis estimates that no additional arrests for weapons charges would occur. A 30% reduction in time served is estimated to result in 10 additional arrests for violent crimes, 9 arrests for property crimes, 10 arrests for drug crimes, 3 arrests for weapons charges, and 32 for "other" crimes. The increase in arrests with a 30% reduction in time served would comprise less than one-twentieth of one percent of property and drug crimes (0.02% and 0.03%, respectively) and less than one-tenth of one percent (0.08%) of all arrests for violent crimes.

- **No individual is estimated to have more than one additional arrest.** Reducing time served by one, two, or three years and by 10%, 20%, or 30% did not result in any of the 1,127 members of the analysis sample being estimated to have more than one additional arrest each. A 30% reduction in time served resulted in no individual predicted to have more than 0.68 additional arrests. Over 90% of the sample would likely have fewer than 0.3 additional arrests, while less than 2% would have more than 0.4 additional arrests.

- **Reducing long prison stays can significantly affect the size of the total prison population.** Reducing lengthy time served by one year could reduce the average daily prison population in Illinois by 1.3%; reducing lengthy prison stays by 30% would decrease the prison census by 7.2%.

- **The relatively small number of additional predicted arrests indicates that the vast majority of the people serving long prison terms have "aged out" of criminal behavior near the end of their stays, and that reducing long prison terms for them has little to no public safety impact.** Because these same individuals are serving the longest prison terms, they make up a disproportionate share of the incarcerated population. As such, shortening their prison terms can reduce the size of the prison population without significantly compromising public safety.

GLOSSARY OF TERMS

- **Age-crime curve:** The fact that as most people age, their likelihood of engaging in criminal offending first increases and then decreases (referred to as "aging out" of crime)

- **Criminogenic effect:** Producing or tending to produce crime

- **General deterrence:** The idea that punishing an individual offender will dissuade others from committing crimes

- **Incapacitation:** The prevention of crimes in the community that might otherwise be committed if an individual was not incarcerated

- **Long sentences:** The Task Force on Long Sentences defines long sentences as prison sentences of 10 years or more. Numerous state and federal statutes use 10 years as either the maximum or minimum allowable term of imprisonment

- **Rehabilitation:** The act of helping people desist from criminal behavior through therapeutic programs, activities, incentives, substance use treatment, and other services designed to change behavior

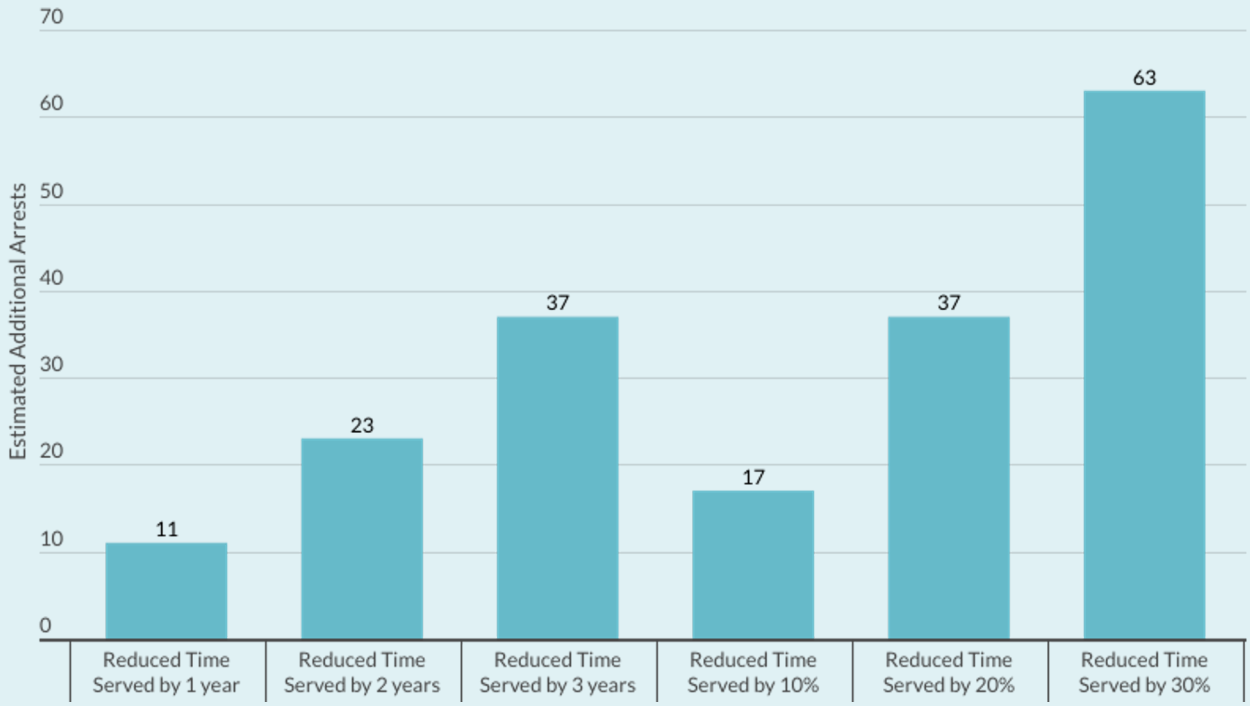
GLOSSARY OF TERMS CONT'D

- **Specific deterrence:** The idea that punishing an individual offender will dissuade that individual from committing future crimes
- **Time served:** The actual amount of time a person spends in prison as distinct from the judicial sentence

FINDING 1: A MODEST REDUCTION IN THE LENGTH OF LONG PRISON STAYS WOULD LIKELY RESULT IN RELATIVELY FEW ADDITIONAL ARRESTS

Figure 1 shows how many additional arrests are predicted to occur based on six different simulations for reducing time served (reducing time served by one, two, or three years and by 10%, 20%, or 30%). Note that these additional arrests are compared against the estimated arrests averted under the actual length of stay for each individual, not relative to a baseline of zero arrests.

FIGURE 1: ESTIMATED ADDITIONAL ARRESTS FROM REDUCING LENGTHY PRISON TERMS

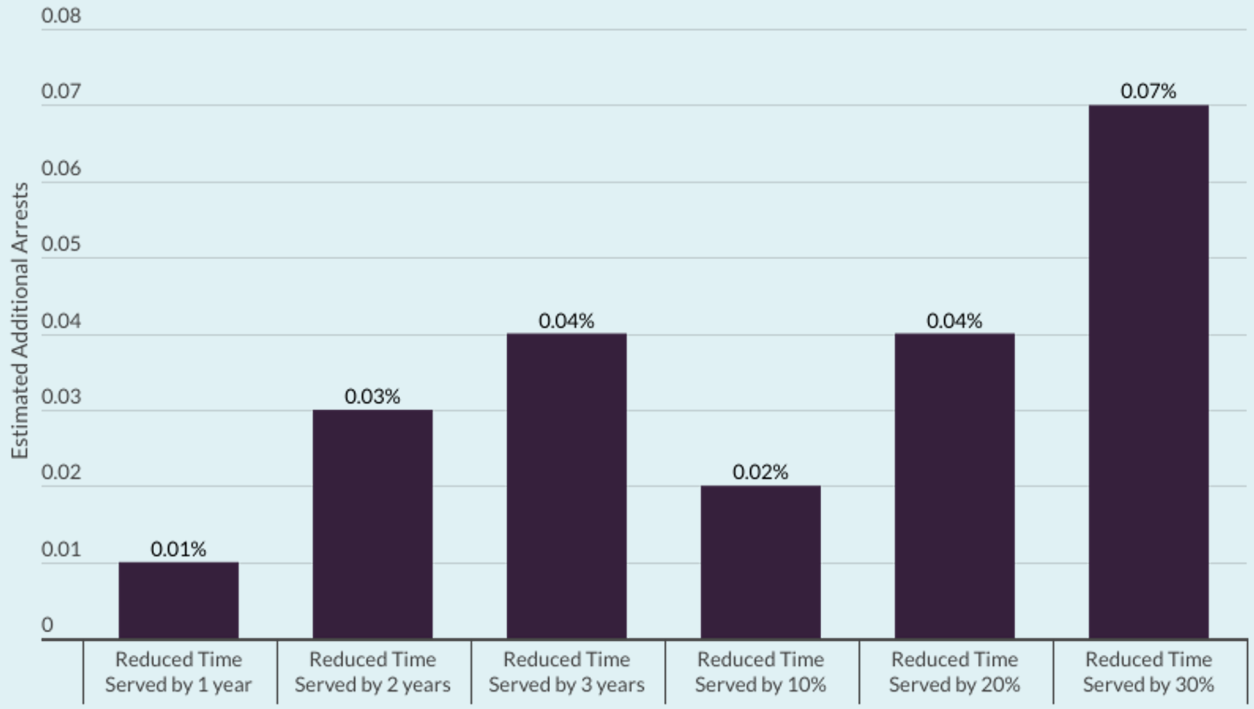


Calculations for this analysis show that the number of additional arrests expected to result from shortening lengthy prison terms is relatively small. For example, a policy that reduces lengthy prison terms by one year for the 376 persons released annually after serving 10 or more years would result in an estimated 11 additional arrests in Illinois. Reducing time served by two or three years results in an estimated 23 or 37 additional arrests, respectively. Reducing overall time served by 10%, 20%, or 30% also implies small increases in estimated arrests. A 10% reduction in time served would result in 17 additional arrests, a 20% reduction would lead to 37 additional arrests, and a 30% reduction would generate 63 additional arrests in Illinois.

FINDING 2: THE ADDITIONAL ARRESTS LIKELY TO RESULT FROM REDUCTIONS IN TIME SERVED WOULD CONSTITUTE A VIRTUALLY UNDETECTABLE INCREASE IN THE OVERALL VOLUME OF ANNUAL ARRESTS

Any additional arrests are cause for concern, but the number of additional arrests predicted by this analysis is small relative to the volume of overall arrests in Illinois. Figure 2 shows the estimated additional arrests as a percentage of the total arrests in Illinois in 2020. The 11

FIGURE 2: ESTIMATED ADDITIONAL ARRESTS AS A PERCENTAGE OF ALL INDEX CRIME AND DRUG ARRESTS IN ILLINOIS IN 2020

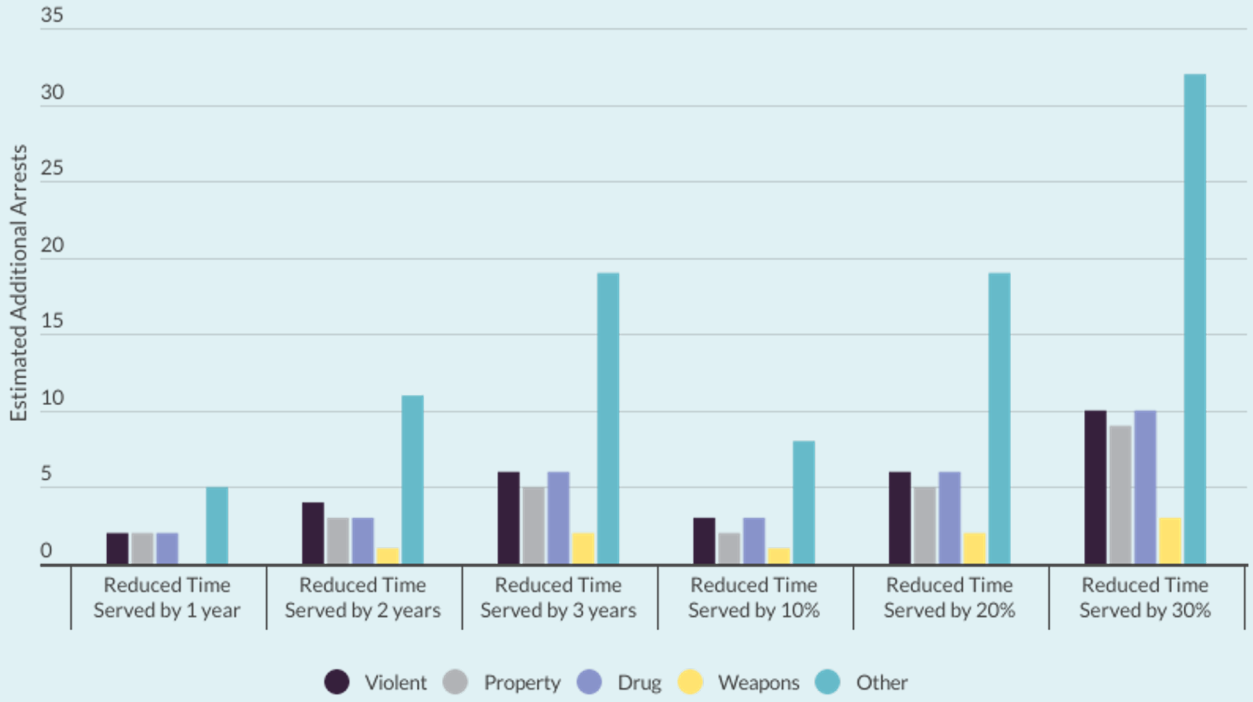


additional arrests from a one-year reduction in time served comprise one one-hundredth of one percent (0.01%) of the 89,173 index crime and drug arrests made in Illinois in 2020. The estimated 63 arrests likely to occur should time served be reduced by 30% constitute less than one-tenth of one percent (0.07%) of this total arrest number.

FINDING 3: ADDITIONAL ARRESTS THAT MAY OCCUR WHEN LONG PRISON STAYS ARE SHORTENED ARE UNLIKELY TO BE FOR WEAPONS CHARGES OR VIOLENT CRIMES

The analysis also produced information on the types of crimes for which people would likely be arrested based on their patterns of pre- and post-incarceration offending. As shown in Figure 3, few of the additional arrests would be for violent crimes (e.g., assault, homicide) or weapons charges.

FIGURE 3: ESTIMATED ADDITIONAL ARRESTS BY CRIME CATEGORY

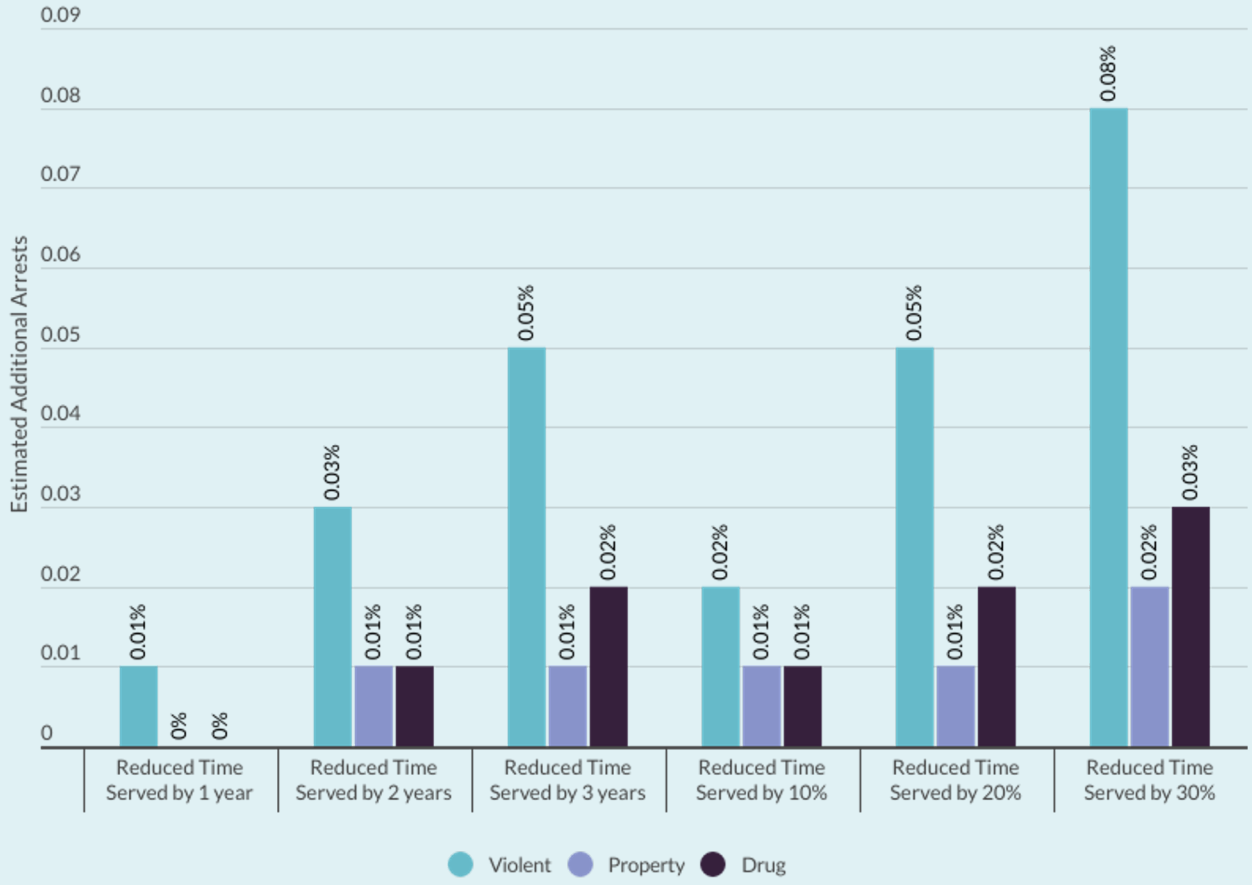


Notes: Violent crimes include battery, assault, homicide, and other violent crimes. Property crimes include burglary, trespassing, theft, and other crimes. The "other" category captures arrests for disorderly conduct, motor vehicle offenses, and other crimes. All crime categories include arrests for both misdemeanors and felonies. See Table 2 in the supplemental methodology report for a detailed breakdown of all charges included in each arrest category.

Calculations show that reducing time served by one year for the 376 people released annually likely would result in two additional arrests for violent crimes, two arrests for property crimes, two arrests for drug crimes, and five arrests for "other" crimes. The analysis estimates that no additional weapons arrests would occur. If time served was reduced by 30%, an estimated 10 additional arrests for violent crimes would occur, along with 9 arrests for property crimes, 10 arrests for drug crimes, 3 arrests for weapons charges, and 32 for "other" crimes.

As depicted in Figure 4, in the case of a one-year reduction in time served, additional arrests in each category comprise less than one one-hundredth of one percent of total arrests in that category. For a 30% reduction in time served, additional arrests for violent crimes make up less than one-tenth of one percent (0.08%) of all arrests in that category, while arrests for property and drug crimes each comprise less than one-twentieth of one percent of the total (0.02% and 0.03%, respectively).

FIGURE 4: ESTIMATED ADDITIONAL ARRESTS BY CRIME CATEGORY AS A PERCENTAGE OF ARRESTS IN THAT CATEGORY IN ILLINOIS IN 2020



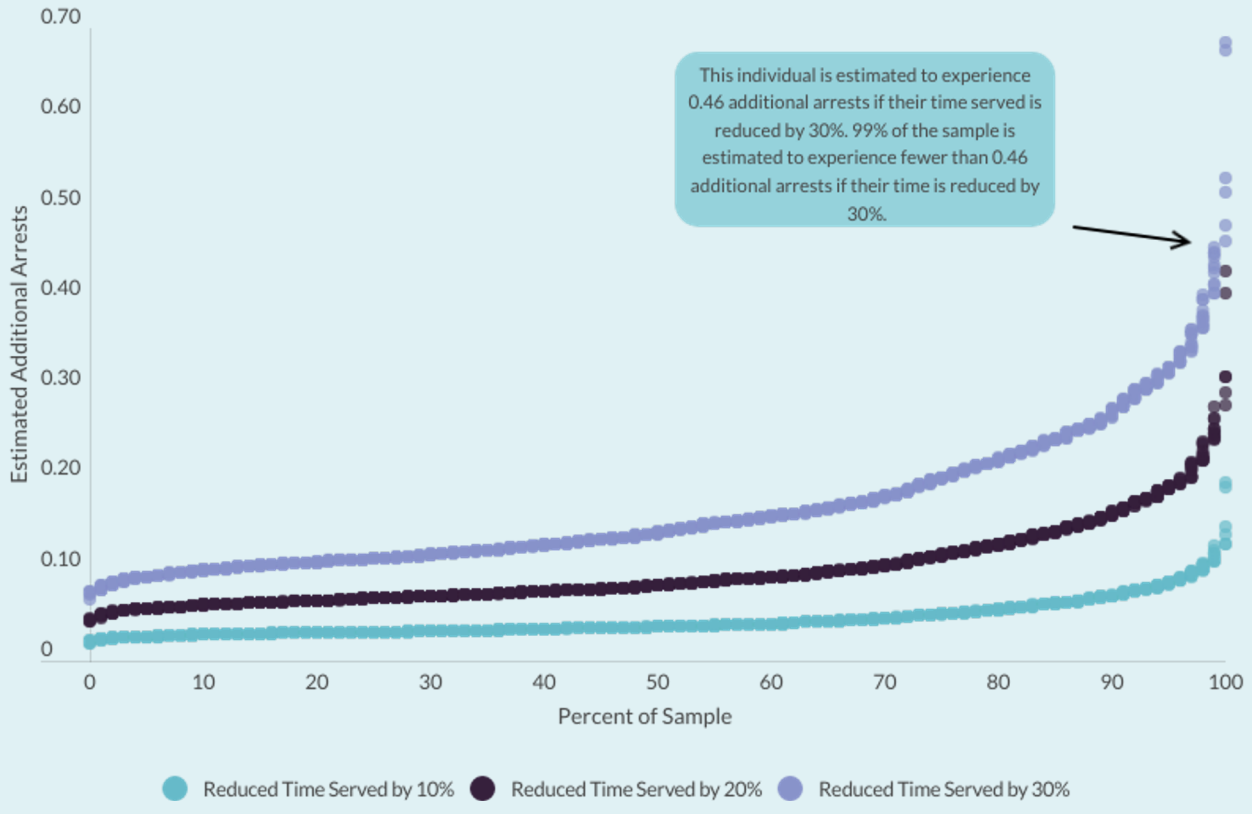
Note: The "weapons" and "other" charge categories are not included here due to data limitations.

FINDING 4: NO INDIVIDUAL IS ESTIMATED TO HAVE MORE THAN ONE ADDITIONAL ARREST

The analysis also generated estimates of how the additional arrests might be distributed across the sample and potentially concentrate among specific individuals. Because the microsimulation analysis produces an estimated arrest value individualized to each person, it is not possible to display results in whole numbers or estimate who would experience exactly zero additional arrests. Instead, values closer to zero indicate that an individual has an extremely low risk for any additional arrest; values around one indicate that an individual would likely have one additional arrest; values around two indicate that an individual would likely have two additional arrests, etc.

Figure 5 displays the number of additional arrests estimated to occur for each individual in the sample when prison stays are reduced by 10%, 20%, and 30%. The amount of time over which additional arrests might occur in the 10%, 20%, and 30% simulations varies for each member of the sample as a function of their overall time served and the amount by which time served is reduced.[4] Results for the one-, two-, and three-year sentence reduction scenarios are not visualized, as estimates of additional arrests were smaller and followed a

FIGURE 5: ESTIMATED ADDITIONAL ARRESTS PER PERSON

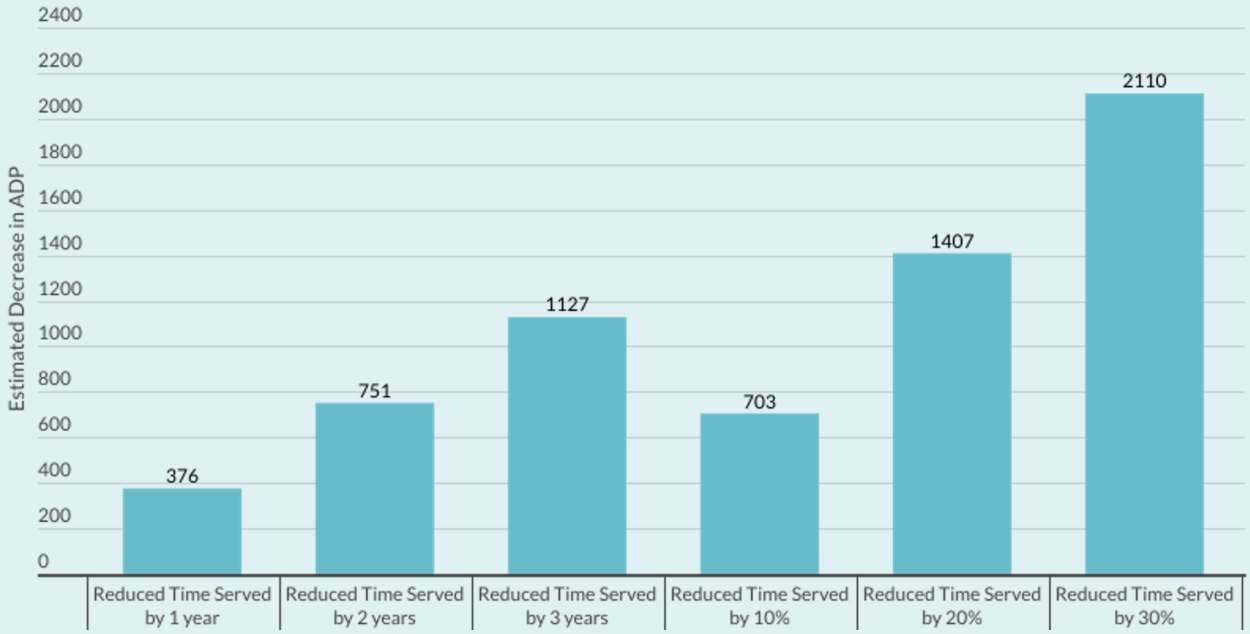


similar pattern. Moving from left to right across the figure indicates the number of additional arrests to be expected from increasingly higher contributors to the overall impact of the simulated policy. For example, in the 20% reduction scenario, the plot indicates that 80% of individuals in the sample are estimated to contribute 0.1 additional arrests or fewer each. Across all six simulated models, no individual estimates exceeded 1.0, indicating that none of the 1,127 members of the sample were estimated to increase arrests by more than one should time served be reduced, even by up to 30%. In fact, a 30% reduction in time served resulted in no individual predicted to have more than 0.68 additional arrests. Over 90% of the sample is estimated to have fewer than 0.3 additional arrests each; less than 2% of the sample is estimated to have more than 0.4 additional arrests each.

FINDING 5: REDUCING LONG PRISON STAYS CAN SIGNIFICANTLY AFFECT THE SIZE OF THE TOTAL PRISON POPULATION

Reducing time served for people serving long sentences will influence the total size of the prison population. Releasing some individuals sooner naturally means that prison populations will fall. Figures 6 and 7 show how much the Average Daily Population (ADP) in Illinois prisons would decrease if time served was reduced by one, two, or three years, and by 10%, 20%, or 30%. Figure 6 shows this change in raw numbers; Figure 7 presents this value as a percentage of the ADP.

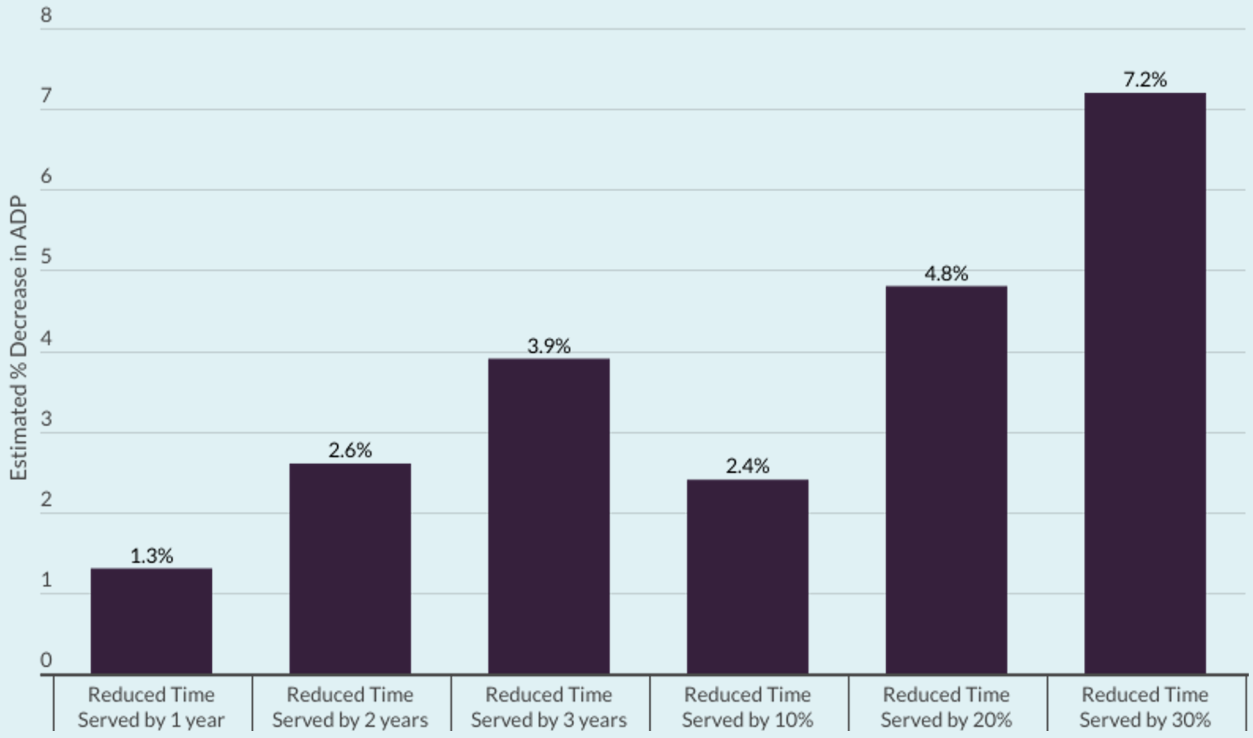
FIGURE 6: ESTIMATED DECREASE IN AVERAGE DAILY POPULATION



These results show that a one-year reduction in lengthy prison terms could reduce the ADP in Illinois by 376 individuals, constituting a 1.3% reduction in the total prison population.[5] Similarly, shortening time served by two or three years would yield ADP reductions of 751 (2.6%) and 1,127 (3.9%), respectively. At the highest end of the estimates performed, a 30% reduction in time served would decrease the daily prison census in the state by 2,110 individuals, or 7.2%.

Reducing time served—and, by extension, the total prison population—would have financial implications for Illinois. The Illinois Sentencing Policy Advisory Council conducted an analysis using dynamic marginal costs to estimate the fiscal implications of reducing the number of individuals held in state prisons.[6] This analysis shows that a 1,000-person reduction from its daily state prison population represents $12.5 million of the funds that the Illinois General Assembly annually appropriates to IDOC, and a 3,000-person reduction represents $147.9 million. As a point of reference, simulations of reducing time served by three years and 20% resulted in decreases of more than 1,000 individuals, while a 30% reduction resulted in a decrease of more than 2,000 individuals. While these reductions in and of themselves would not automatically produce cost savings for Illinois, they could lead legislators to make different choices about how to fund IDOC's general operations, including allocating the funds currently dedicated to supporting people serving long sentences into both prison- and community-based programs proven to reduce crime and victimization.

FIGURE 7: ESTIMATED DECREASE AS A PERCENTAGE OF AVERAGE DAILY POPULATION



CONCLUSION

Evaluating the utility and effectiveness of long sentences raises important questions, including how reducing such sentences might affect public safety. Findings from microsimulation analyses indicate a tradeoff: All reductions in time served are estimated to result in a small number of additional arrests, but they would likely be a small fraction of all arrests annually in Illinois, and would likely not be for violent crimes or weapons charges. These results suggest that most people serving long sentences have "aged out" of criminal activity—especially violent crime—near the end of their prison stay. Because any additional arrests would likely be for relatively minor crimes, reducing time served would reduce the size—and expenditures associated with—the prison population without jeopardizing public safety. Although results from similar analyses in other states may differ, the findings presented in this brief indicate that shortening lengthy prison terms can be done without significantly compromising public safety.

Endnotes

[1] Arrest data are used instead of conviction data in part because convictions involve many more decision-makers (e.g., prosecutors and judges) and factors than arrests, which tend to involve only law enforcement. In addition, given the emphasis placed on time and trajectories within this analysis, arrest data are preferable because arrests typically occur closer to the criminal behavior than convictions. It is important to note, however, that unlike convictions, arrests do not mean there was criminal behavior or guilt.

[2] The microsimulation calculated the 10%, 20%, and 30% reductions in time served based on the actual number of years each individual had been incarcerated prior to release. The average time served for all members of the sample was 18.8 years. Taking this average time as an example, a 10% reduction for an individual who spent 18.8 years in prison would be 1.88 years, a 20% reduction would be 3.76 years, and a 30% reduction would be 5.64 years.

[3] Index and drug crime arrest data are drawn from the Illinois Uniform Crime Report (UCR). Index crimes include criminal homicide, rape, robbery, aggravated battery/aggravated assault, burglary, theft, motor vehicle theft, arson, human trafficking commercial sex acts, and human trafficking involuntary servitude. Drug crimes include all crimes involving controlled substances. The 89,173 arrests used in the analysis reflects all arrests in Illinois for index and drug crimes. See: Illinois State Police. (2022). Crime in Illinois, 2020. https://www.isp.illinois.gov/CrimeReporting/Cii2020

[4] For example, estimated arrests would occur over 1.88 years when time served is reduced by 10% for an individual who served the average of 18.8 years. These arrests would occur over 3 years for someone who served 30 years.

[5] Illinois Department of Corrections.(n.d.).Prison population on June 30, 2022. https://idoc.illinois.gov/reportsandstatistics/prison-population-data-sets.html

[6] Illinois Sentencing Policy Advisory Council. (2021). 2021 update: Dynamic marginal costs in fiscal impact analyses. https://spac.icjia-api.cloud/uploads/DMC%202021%20Update%20-%20IDOC%20and%20Jail%20costs-20210217T21163662.pdf

Methodology and Data Sources

DATA SOURCES

The analytic framework used to generate the results presented in The Public Safety Impact of Shortening Lengthy Prison Terms was created and applied by the author to develop individual micro-trajectories from past offending patterns to inform future offending behavior.[1] The emphasis of that work is less on predicting offending per se and more on using these micro-trajectories to develop counterfactuals against which to assess actual future offending or as a formal basis for estimating the number of crimes averted by incarceration.

Counterfactual analysis addresses the "what-if" question. What would happen if person *A* was released sooner? What if person *B* was not incarcerated? Counterfactual analysis is the only strategy available in non-experimental or laboratory settings because it is virtually impossible to randomly assigned people to prison or non–prison sentences, or too long or short prison terms. It is possible to compare people who are similarly situated but are experiencing different forms and durations of imprisonment and it is possible to compare an individual's actual offending patterns with a what-if pattern.

Using past criminal histories of a sample of people released from prison, for example, Bhati (2007) constructed a counterfactual offending trajectory for each individual in the sample to estimate the number of crimes averted by incarcerating them. The method can be used to estimate the number of crimes averted or created by changing time served. In Bhati and Piquero (2008), the authors used the same counterfactual offending trajectories as the context within which to assess future offending patterns. Released individuals were classified as having been deterred by incarceration if they offended at a lower rate than their criminal history-based micro-trajectory suggested. If they offended at about the same rate, then the incarceration merely incapacitated them. In some cases, individuals released from prison offended at rates higher than what was anticipated. These were classified as individuals for whom prison had a criminogenic effect. The study found that nearly 45% of releasees were deterred from future offending and that for about 5%, imprisonment had a criminogenic effect. The rest of them, nearly 50%, were merely incapacitated—meaning there was no deterrent or criminogenic effect. For this large incapacitation group, the question is whether the imposed time served was appropriate. If the individuals' criminal offending behavior was effectively terminated (low risk), then their time served was ineffective and costly. But if their criminal offending was still active (high risk) then incapacitation was very effective.

More recently, in a study in Florida, a related framework was used to study the specific deterrent effects of DNA databases (Bhati 2010; Bhati & Roman 2014).[1] The question that study attempted to address was: *does knowledge of the fact that individuals' DNA profiles are stored in a readily searchable database deter them from re-offending?* The analysis yielded mixed findings—small but

significant specific deterrent effects of DNA databases were found for some crime categories (burglary and robbery) but not for others (violent offenses).

A study conducted for The Pew Charitable Trusts in 2011 is the closest in scope to the Illinois analysis.[2] In that work, the authors used the micro-trajectory analysis to model the incapacitation and deterrent effects of incarceration. They then used these models to simulate the effects of shortening prison terms. That study used data from three states—Maryland, Michigan, and Florida—and concluded that large numbers of individuals could be released from prison sooner with minimal public safety implications. They also quantified the reductions in prison population that would likely accrue because of these shorter prison terms. The analysis presented in this report is almost identical in scope to that effort except the emphasis here is on lengthy prison terms.

ANALYTIC STRATEGY

There are two critical requirements for a research design that can provide answers to the kinds of questions posed above and the types of policy simulations we intend to conduct. First, the design should be at the micro or individual level. That is, the analytical strategy should be able to study heterogeneity among individuals—at least as far as readily available and demographic attributes are concerned. Macro-level studies, such as those entailing aggregate level crime and incarceration rates, do not allow analysis of individual heterogeneity and therefore cannot be used to identify low-risk individuals. Second, the analysis needs to be able to develop plausible counterfactuals as described earlier.

This report details a strategy that allows one to model, study, and project individual-level offending micro-trajectories. The strategy fulfills both the requirements listed above and is easily implemented using detailed dated criminal arrest history records. Such records have been difficult to access in the past but are becoming increasingly available to researchers.

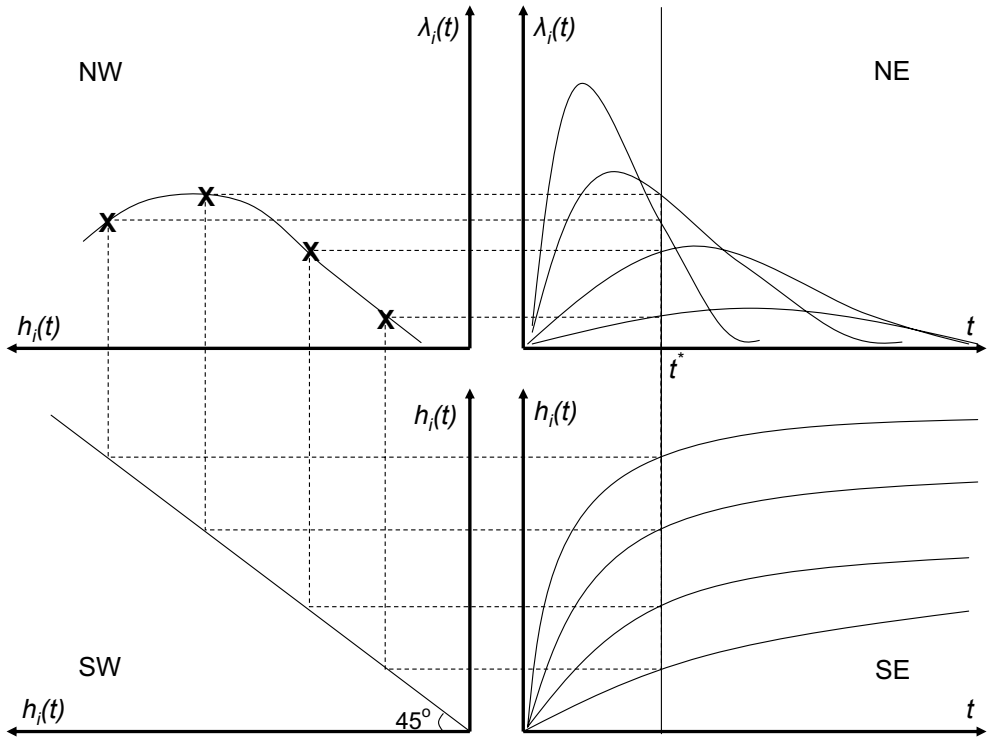
The Criminal History Accumulation Process (CHAP)

The Criminal History Accumulation Process (CHAP) is a convenient means of linking the current offending rate to age and criminal history—the key building blocks of the model needed for studying individual heterogeneity and generating counterfactuals. Consider Figure 1 as a graphical depiction of the CHAP.

The figure is divided into four quadrants (NE, SE, SW, and NW). The NE quadrant displays a familiar figure with four hypothetical offending patterns. The rate *y*-axis is the annual (or periodic) offending rate (commonly referred to as λ) and the *x*-axis represents age (denoted by t). Because the patterns reflect offending rates at particular ages, the λs are indexed by t ($\lambda(t)$). Because there are four different paths, they are indexed by i as well ($\lambda_i(t)$). At this point it is irrelevant whether these belong to four groups or four individuals. The discussion here is merely intended to derive a

functional form that will permit the analysis of heterogeneity in a succinct manner. The SE quadrant displays the accumulation of these offending patterns over the life course—what we know as the criminal history ($h_i(t) = \int_0^t \lambda_i(z)dz$). The SW quadrant is merely a graphical device to switch axes—a 45-degree line that maps the y-axis onto the x-axis. Finally, the NW quadrant allows us to link the current offending rate with criminal history.

Figure 1: The fundamental relationship between offending rates, criminal history, and age.



Consider any particular age (say t^*). At this age, what is it about the offending patterns that allow us to distinguish one trajectory from another? By tracing the offending rates of the four trajectories (at t^*) horizontally from the NE quadrant (to the left along the dotted lines) and by tracing the criminal history of these four trajectories (at t^*) starting in the SE quadrant, then proceeding horizontally (to the left) and then vertically (upwards), one finds by connecting the crosses that there is a non-linear relationship between the offending rates and the criminal history that explain the difference between the offending rates of the four paths at t^*. One can repeat the analysis at other ages and similar insights will emerge.

Upon reflection, this is not surprising. If two individual trajectories are ever to intersect, then at the point of intersection, the $\lambda(t^*)$ and the t^* are identical. The only thing that tells them apart at this point is how differently the two have evolved in the past—in other words, how much more or less criminal history the two paths have accumulated to date.

This suggests an extension of the commonly studied two-dimensional age-crime curve to the three-dimensional age-crime-history surface. If one considers this three-dimensional surface as more aptly representing life-course offending behavior, the need to account for unobserved heterogeneity when studying the age-crime relationship becomes obvious. The age-crime analysis is missing one crucial dimension. In fact, one can now visualize the familiar graphic in the NE quadrant of Figure 1 as reflecting slices from that more detailed three-dimensional surface.

What is more important is that visualizing life-course offending patterns in this three-dimensional space allows one to abandon the mindset of fixed, predictable, and immutable trajectories. The process is dynamic, complex, and rich. Importantly, individuals are no longer envisioned as traveling along a predefined trajectory. Rather, individuals may transverse across trajectories (paths). There are policy options that may speed up or slow down the criminal history accumulation process, thereby making the individual emerge on a new region of the surface. Looking at, and studying, life-course offending patterns in this way opens the possibility for asking richer theoretical and policy questions, devising more nuanced responses, and for constructing and employing micro-trajectories at the individual level that account for individual heterogeneity.

The fundamental link between offending rates, criminal history, and age depicted graphically in Figure 1 leads to a very succinct relationship, which lends itself to rigorous analytical consideration and manipulation. Note that Figure 1 suggests that λ is some non-linear (quadratic, cubic) function of age and a non-linear function of criminal history. This fundamental relationship may be written generically as:

$$\lambda_i(t) = f(h_i(t), t) \quad \forall\, i, t$$

which allows us to trace an individual offending hazard trajectory for each individual conditional on their current age and past history. In actual application, the exact functional form of the relationship is specified as a quadratic or a cubic link, and additional conditioning attributes may be included. However, this equation forms the key building blocks of the CHAP model that permit modeling heterogeneity and performing counterfactual analysis.

Data Needs and Estimation Strategy

In order to estimate the link between offending rates, age, and criminal history, we must have dated arrest sequences for a sample of individuals, along with their date of birth. This information allows us to construct a sequence of arrest ages for each individual in the sample. These sequences tell us exactly at what age a person was arrested for the first, second, or subsequent time. Harding and Maller (1997) refer to these sequences as individuals' arrest profiles.[3] It is also straightforward to convert these sequences into a variable measuring elapsed time between successive arrest events. And, in a similar manner, we can develop measures of all the relevant "clocks" that may be needed to accurately describe the evolution of the rate with time.

Next, we need some way to relate λ to the evidence we have in the sample. If we believe that λ increases or decreases with some variable x (e.g., age, spell-length, arrest number) then, at a minimum, λ should covary with x. But by how much? Provided that the sample is representative of all those incarcerated during a given time period, one may assume that the best estimate of this covariance is to be found in the sample itself. This principle—termed the analogy principle[4]—suggests that the expected covariance between x and λ should be equal to the actual covariance between x and the timing of arrest events observed in the sample. Such reasoning allows us to derive a set of constraints that the hazards should satisfy, irrespective of their functional form.

These constraints, however, are not sufficient to identify (yield a precise mathematical form for) the model. Typically, an infinite number of individual arrest trajectories will be consistent with the arrest patterns in the sample. We need a way to choose among them.

Information theory, an inter-disciplinary field that uses entropy and entropy-related measures to quantify uncertainty, provides the philosophical justification to make this choice. Edwin Jaynes, a physicist, argued in a series of influential papers that when faced with a problem that has an infinite number of solutions (the so-called ill-posed inversion problems) we should choose the solution that is least informative (or closest to our prior beliefs, if any) while satisfying what limited evidence we may have observed.[5] To operationalize such an approach, Jaynes needed some way to quantify the lack of information. Fortunately, within the context of a problem in communication theory, Claude Shannon had, just a few years earlier, developed a precise definition of uncertainty and termed it Information Entropy.[6] In what has come to be known as the Maximum Entropy formalism, Edwin Jaynes proposed to use Shannon's Entropy as the criterion to maximize, subject to all available constraints, in order to derive conservative inferences from the evidence.

In our analysis, since there are an infinite number of trajectories that could have generated the observed arrest histories, following Jaynes' reasoning, the optimal choice among them should be the set of individual trajectories that are the least informative. Therefore, if we can quantify the uncertainty implied by these trajectories then the conceptual solution suggested by Jaynes can be formulated as a constrained optimization problem. Solving this problem by variational methods yields a dynamic solution for the trajectory that is the most conservative among all of the models consistent with observed arrest patterns.

Full mathematical derivation of the solution can be found in Bhati (2007).[7] The resulting model that emerges from the approach takes the functional form:

$$\lambda_i(t) = \bar{\lambda}_i(t)\exp\left(\sum_j \phi_j(t) x_i' \beta_j\right) \quad \forall i, t$$

where $\bar{\lambda}_i(t)$ reflects a prior belief about λ, if any; x is a vector of attributes; β_j are a set of Lagrange multipliers that reflect the value of each of the constraints on reducing uncertainty about the

process; t captures the evolution of the hazard linearly with age; and $\phi_j(t)$ are the various non-linear transformations of age that define the shape of the trajectory.

Once the β_j parameters are recovered by solving the optimization problem, simulating the evolution of the hazard with age, conditional on a given set of attributes, is done by plugging the appropriate quantities into the main equation and computing the micro-arrest trajectories for that individual.

Estimating Incapacitation and Specific Deterrent Effects

The modeling strategy described above allows one to estimate the incapacitation and specific deterrent effects of incarceration. Incapacitation effects are computed by simulating each individual's micro-trajectory during their incarceration period (i.e., from the age of prison admission to age at prison release). In a similar manner, the offending trajectory can be projected for a specific follow-up period following release from prison. This trajectory is considered the counterfactual—which, as noted earlier, represents the arrest trajectory for the individual had they not been incarcerated. Next, using the counterfactual as a prior belief about λ, i.e., the $\bar{\lambda}_i(t)$ defined above, we can re-estimate the model using data from the post-release follow-up period. The updated trajectory reflects how the individual's micro-trajectory was deflected as a result of this incarceration. Comparing this counterfactual to post-release offending trajectory allows us to assess the extent to which the individual's behavior has been modified by the incarceration experience—i.e., the specific deterrent or criminogenic effects of prison.[8] For example, the incapacitation effects (INC) of being incarcerated between the ages of 35 and 37 may be computed as the accumulation of the estimated $\lambda(t)$ between those ages (i.e., INC= $\int_{35}^{37} \lambda(t)\, dt$).

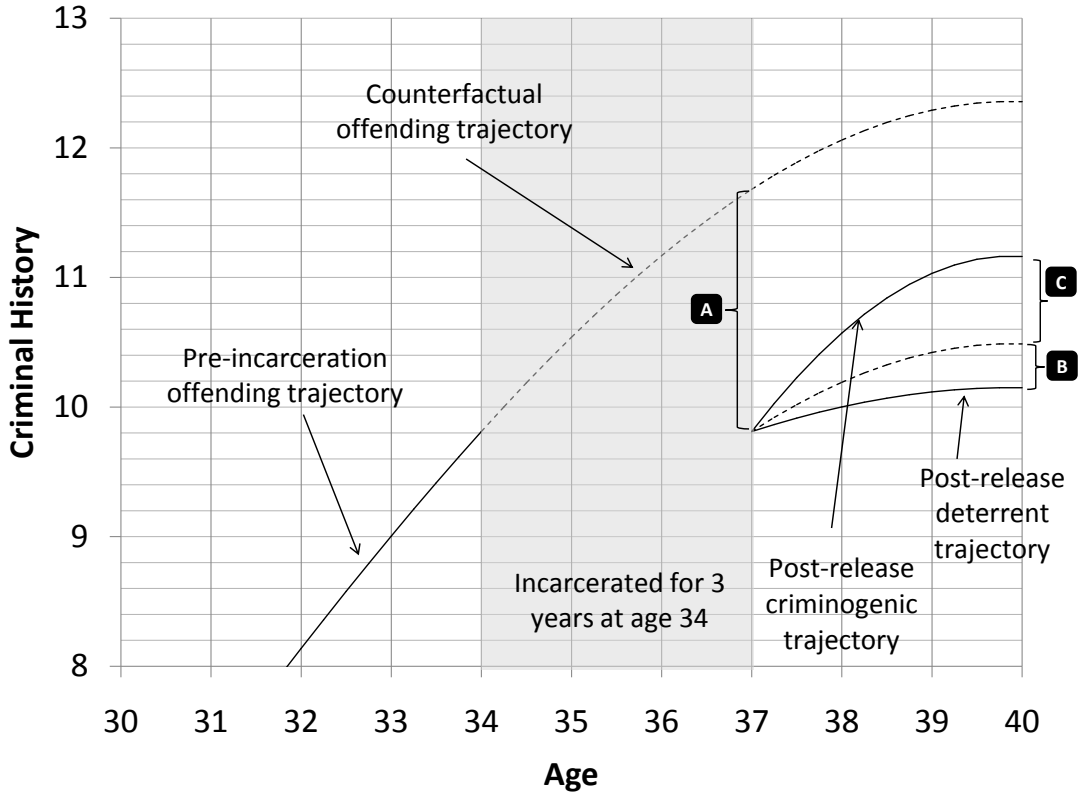
The specific deterrent effects (SDE) of the same incarceration episode may be computed as the difference between an accumulation of $\lambda(t)$ over a fixed follow-up period (post release) and the updated offending trajectory during the follow-up period. I.e., SDE= $\int_{37}^{40} \lambda(t)\, dt - \int_{37}^{40} \bar{\lambda}\ (t) dt$ where $\lambda(t)$ is a post-release data-based offending trajectory and $\bar{\lambda}(t)$ is the pre-incarceration data-based offending trajectory. The SDE therefore provides an estimate of the expected number of arrests an individual commits post-release over and above what was expected of him or her based on past arrest patterns.

The net effect of the incarceration can be estimated as the sum of the incapacitation and the specific deterrent effect. Note that this number can be positive, negative, or null. Note also that since we are integrating the λ's for all the computations, in effect, we are assessing the amount by which the criminal arrest history would be more or less at the end of a three-year follow-up period had the individual not been incarcerated.

The sign and the magnitude of the effect depends on a number of things—particularly where the individual is in their history of criminal offending and how much time they spent in prison. Figure 2 shows how these computations are conducted.

The example shown in figure 2 involves a person who was incarcerated at age 34 for a period of 3 years. Using his past criminal history accumulation process, we first develop an arrest trajectory (termed here as the pre-incarceration arrest trajectory). According to this trajectory, the individual has approximately 10 prior arrest records. Next, the pre-incarceration arrest trajectory is plotted out over the course of his incarceration and though the follow-up period (3 years in this case). This constitutes the counterfactual arrest trajectory.

Figure 2: Calculating the incapacitation, specific deterrence, or criminogenic effects of incarceration.



The individual is then released from prison at age 37 and we have available re-arrest information for this individual until the age of 40. Using the follow-up data, we estimate a post-release arrest trajectory. Two scenarios are depicted in Figure 2. If the individual is deterred, they should accumulate fewer post-release rearrests relative to what they would have after netting out the incapacitation effect—i.e., if they picked up their criminal offending where they left off upon release. This is indicated by marker B. If the individual accumulated re-arrests at a quicker rate than anticipated, then we have a criminogenic post-release trajectory. This is indicated by the marker C. Finally, the difference between the number of re-arrests the individual would have

accumulated had they not been incarcerated—the incapacitation effect—is indicated by the marker A. The net effect of incarcerating this individual is computed using A, B, and C, depending on whether the person is deterred or not.

Application to Policy Simulations on Modifying Time Served

Although using the framework to compute incapacitation and specific deterrent effects is instructive, this research project is concerned with quantifying the implications of altering time served. In order to conduct those simulations, we are interested in quantifying *changes* in the incapacitation or specific deterrent effects that can be expected when people have their time served reduced. Once the basic set of CHAP models are developed, as described above, these simulations are computed merely by altering the points of integration or, in this case, the length of imprisonment. The public safety implication of reducing time served by 3 months, for example, can now be computed as the change in A, B and/or C.

Once the net effect of reducing time served by a certain amount is computed for every individual, these estimates can be summed over all individuals in the sample to obtain an estimate of the total number of arrests that would be increased or decreased because of the simulated changes in time served. Since this estimate is a total over all persons in the sample (and not a mean), it depends on the number of persons included in the calculation. Therefore, to ease interpretation of results, the estimates can also be annualized—i.e., converted to reflect the total number of additional arrests that can be expected by applying the policy to persons exiting every year (annual persons exiting prison sooner). If the analysis is conducted with a multi-year cohort—e.g., a 3-year cohort—then the total effect computed over all persons released sooner is divided by 3 to get the estimated annualized effect of the policy.

The simulated and current time served values can also be used to compute two different estimates of the average daily population (ADP). The difference in these (ADP under current and reduced average time served) provides an estimate of the reduction in ADP because of the simulated policy.

Finally, note that since the analysis is conducted at the individual level, we can also study the distribution of the effects of the time served-changing policy among the sample members to see whether the number of additional (or fewer) arrests are expected from a few persons or distributed more evenly across the sample. If the additional arrests are concentrated among a few persons, then there is the potential to target policies aimed at reducing time served.

SHORTENING LONG PRISON TERMS: A SIMULATION STUDY IN ILLINOIS

Data needed for developing the CHAP models and applying them to quantify the implications of shortening long prison terms were obtained from the state of Illinois. We obtained demographic

and related criminal justice system information about a cohort of persons released from the Illinois Department of Corrections (IDOC) between June 2016 and June 2019. These data include the critical information needed for our analysis—date of birth, prison admission date, and prison release date, along with detailed (dated) arrest histories. The data were pre-processed to exclude many cases that did not provide information on the question at hand. In particular, we excluded (i) persons labeled as sexually dangerous persons (these are civil cases but housed in the DOC), (ii) persons who were deceased (their release reason was noted as deceased or the arrest histories noted they were deceased), (iii) multiple prison exits on the same date (the prison exit related to the longest prison term was retained), (iv) prison terms of 0 days (admission and release date are the same), (v) persons admitted to prison without a new sentence (admitted purely for a technical violation or administrative reason), and (vi) persons returned to prison for purely technical reasons within a few days (0-6 days) of release (typically sex offenders who are technically violated because they fail to register for lack of a valid address). Individuals in the last category are excluded from the sample of prison exits because these persons cannot technically be considered having been released at all. Their technical violation is almost automatic—as if they were never released.

For everyone in this sample of prison exits, the prison length of stay was calculated by subtracting the prison admission date from the prison release date. This allowed us to identify persons who had served 10 or more years prior to release. There was a total of 1,136 such individuals; the remaining 44,248 individuals were released after serving less than 10 years in prison. This suggests that approximately 2.5% of the prison releases over this period was related to persons serving long prison terms. But this is a conservative estimate. Importantly, due to data limitations, we were unable to properly take into account jail credit. Individuals typically get credit for time served in jail prior to their sentencing. To the extent that this jail credit is not accounted for in the prison admission date, it is possible that our length of stay calculations are biased downwards. The data we received did include an indicator for jail time. However, from the data, it was not clear whether this measure is already incorporated in the prison admission date. If it is already incorporated, then simply adding jail credit and pushing back the prison admission date would amount to overestimating length of stay and thereby biasing the number of persons serving long terms upwards. On the other hand, by ignoring the jail credit measure altogether, we run the risk of having more conservative estimates of the number of persons serving lengthy prison terms.

To resolve these competing hypotheses about the jail time measure available in the data, we ran a simple test. We used the jail time measure to push back the prison admission date and conducted some validation checks. First, we note that with this revised measure of prison admission date we obtained a larger number of persons serving 10 years of more prior to release (N = 1,600 instead of N = 1,136). However, since we also have available detailed arrest histories for everyone in the sample, we are able to check if there were any arrests recorded within this additional period (prior to the recorded prison admission date). Unfortunately, we found that in nearly 75% of the 44,248 cases released after serving < 10 years and about 82% of the 1,136 long time served cases, people

had arrests recorded during this added period. In other words, we are unable to assume that these individuals were truly incarcerated during the jail time period (prior to their recorded prison admission date). While this does not resolve the issue, it does complicate the calculations of the incapacitation effects. Recall that for calculating the incapacitation effects, we are assuming that individuals are incarcerated (and cannot be arrested) between their prison admission and release dates. This is patently false in most of the cases if we take jail credit into account by extending back the prison admission date. As such, in the analysis reported here, we have chosen to use the recorded prison admission date in the time served calculations, noting that this assumption yields more conservative estimates.

As with any analysis involving post-incarceration arrest events, a follow-up period needs to be defined and used. The arrest data available in this analysis goes through December 2021, providing us a maximum 2.5-year follow-up period. However, oftentimes, because of additional (potentially competing) events, individuals may exit the at-risk pool prior to that duration without a rearrest event. In our analysis, that nuance exists for two possible reasons.

First, the data include information on technical violations. Individuals who are technically violated may or may not be returned to prison. We do not have information on their status after a technical violation. As a result, the follow-up period is truncated when a technical violation occurs prior to the 2.5-year follow-up period.

Second, the follow-up period for part of our cohort overlaps with the COVID-19 pandemic lockdown. Analysis of the arrest data showed a dramatic decline in arrest events in March 2020 that was not observed in prior years. This is consistent with the declaration of the pandemic in early March 2020. As such, we used March 1 (2020) as an additional competing event truncating the follow-up period if that date occurred within the 2.5-year follow-up period.

Therefore, when estimating the hazard trajectory model (the β_j Lagrange multipliers), the follow-up period was truncated at the first technical violation, or March 1, 2020, or 2.5 years after release, whichever date came first. Once estimated, though, the models were used to simulate the criminal history accumulation process for a standard 2.5-year follow-up period for everyone.

Table 1 shows the distribution of attributes available in the data for those serving less than or more than 10 years prior to prison exit. In addition, Table 1 also shows the recidivism rates among these persons. The reported recidivism rates are calculated for a period of 2.5 years following prison exit. This is because the prison release cohort ends in June 2019 while the arrest history data ends in December 2021, allowing for, at most, a 2.5 year follow-up period for the full 3 fiscal year release cohort.

With few exceptions, the characteristics of individuals released after serving long sentences are different from those released after shorter prison terms. For example, the long time served cohort was comprised of a higher percentage of males and racial/ethnic minorities (Blacks and Hispanics)

than those serving shorter prison terms. The types of charges these cohorts were serving time for are very different between these two cohorts. While 85.7% of the long time served cohort was serving time for person-related charges, that was true for only 32.8% of the short time served cohort. Less than 3% of the long time served cohort was serving time for property related charges, compared to nearly a third (29%) of the short time served cohort. Similarly, only 5% of the long time served cohort was serving time for drug charges, while nearly 34.8% of the short time served cohort was serving time on drug charges. On the other hand, 6.4% of the long time served cohort was serving time on sex offenses, compared to only 1.4% of the short time served cohort. In general, a much higher proportion of the long time served cohort was serving time on person and sex charges. while a higher proportion of the short time served cohort was serving time on property and drug-related charges.

By design, most of the cohorts were either admitted directly from court or were recorded as discharged and recommitted. Note that the IDOC records new prison admissions (with new sentences) as Discharged and Recommitted if the individual has completed a prior incarceration period with the department. This is to identify persons who are ineligible for participation in some prison programs because they have returned to prison. As such, both categories (Direct from Court and Discharged and Recommitted) are in fact the same for the purposes of our analysis.

Interestingly, the long time-served cohort has about half the number of prior arrests as the short time-served cohort. About a third of them (36%) have between 2 and 5 prior arrests and about a quarter (24.9%) have between 6 and 10 prior arrests. A little under a third of the short time-served cohort, on the other hand, have between 11and 20 prior arrests (29.9%) and a little under a quarter of them (23.9%) have between 6 and 10 prior arrests. The long time served cohort has an average of 7.3 prior arrests while the short time served cohort has an average of 14.7 prior arrests.

Table 1: Descriptive statistics for data used in study.

Totals	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*
	44,248	100.0%	56.3%		1,136	100.0%	43.0%
Gender	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*

Male	39,698	89.7%	57.4%		1,100	96.8%	43.6%
Female	4,550	10.3%	46.9%		36	3.2%	25.0%
Race	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*
White	14,926	33.7%	49.0%		225	19.8%	28.4%
Black	24,094	54.5%	63.3%		746	65.7%	47.9%
Hispanic	4,916	11.1%	45.2%		160	14.1%	40.6%
Other	312	0.7%	37.2%		5	0.4%	60.0%
Most Serious Charge	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*
Person	14,497	32.8%	60.4%		974	85.7%	45.5%
Property	12,818	29.0%	58.4%		31	2.7%	48.4%
Drug	15,398	34.8%	51.4%		57	5.0%	31.6%
Sex	629	1.4%	30.4%		73	6.4%	16.4%
Other	906	2.0%	62.8%		1	0.1%	100.0%
Admit Type	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*
Direct from court	19,149	43.3%	50.3%		700	61.6%	40.7%
Discharged & recommitted	21,054	47.6%	59.7%		307	27.0%	45.9%

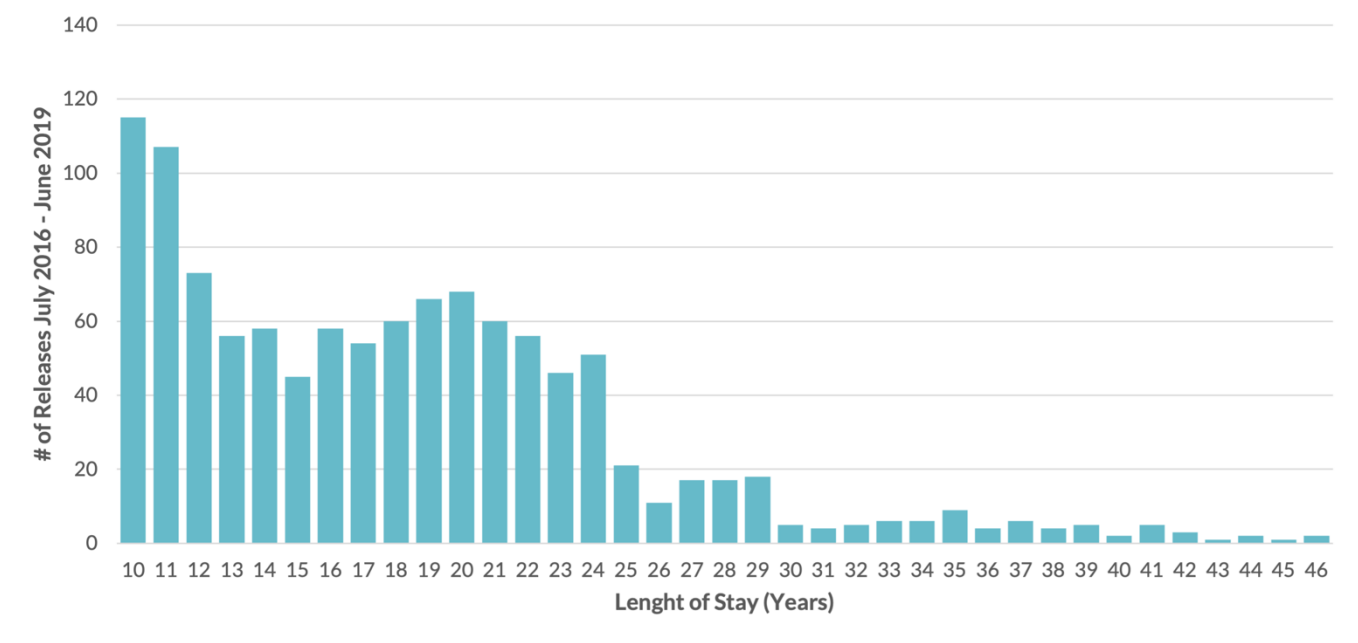
MSR violator, New sentence	3,730	8.4%	66.7%		97	8.5%	47.4%
Parole violator, New sentence	2	0.0%	50.0%		7	0.6%	57.1%
Return additional mittimus	223	0.5%	67.3%		6	0.5%	66.7%
Transferred from juvenile	90	0.2%	75.6%		19	1.7%	47.4%
Exit Type	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*
Discharged from Institution	244	0.6%	45.1%		46	4.0%	19.6%
Release to Supervision	44,004	99.4%	56.4%		1,090	96.0%	44.0%
Number of Prior Arrests	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N	*%*	*Recid*		*N*	*%*	*Recid*
0-1	1,761	4.0%	26.5%		184	16.2%	37.0%
2-5	8,390	19.0%	45.6%		409	36.0%	41.3%
6-10	10,572	23.9%	54.2%		283	24.9%	46.3%
11-20	13,230	29.9%	60.8%		205	18.0%	46.8%
21-30	5,962	13.5%	64.2%		40	3.5%	42.5%
31+	4,333	9.8%	69.7%		15	1.3%	53.3%
Averages	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	N				*N*		
Priors (number of arrests)	14.74				7.32		

Age at Admission (years)	34.21				27.61		
Age at Release (years)	35.80				46.36		
Age at 1st Arrest (years)	19.53				19.49		
Length of Stay (years)	1.59				18.75		

Both cohorts have similar average age of first adult arrests (approximately 19 years). The long time served cohort was, on average, younger than the short time served cohort when they started their current incarceration period (27.6 years compared to 34.2 years). However, upon release from prison, the long time served cohort was older than the short time served cohort (46.3 years versus 35.8 years). This is not surprising given the big difference in the average time served in prison prior to release between these cohorts. The long time served cohort had served an average of 18.8 years prior to release while the short time served cohort had served, on average, only 1.59 years.

This suggests a large skew in the distribution of the time served prior to release—both the short and long time served cohorts. Figure 3 shows this skew among those serving 10 years or more prior to release. There are a little over 100 individuals who served 10 or 11 years prior to release.

Figure 3: Distribution of length of stay in prison (10+ years).



Then the numbers drop and stabilize at around 50 in each 1-year time served increments until about 24 years. Only a handful of individuals served 25 or more years prior to release. Each additional 1-year increment after 30 years only includes less than 10 persons in the cohort. Therefore, while the average length of stay for this cohort is 18.75 years, many more people were serving less time than that average than were serving more.

Table 2: Charges by arrest category.

Category	Charges
Violent	Assault, Battery, Criminal Abortion, Deadly Weapons*, Homicide, Interference with Public Officers*, Intimidation, Kidnapping, Motor Vehicle Offenses*, Offense Involving Children*, Other Weapons, Ritualism, Robbery, Sex Offenses*, Terrorism
Property	Arson, Burglary, Criminal Damage and Trespassing, Deception*, Disorderly Conduct*, Motor Vehicle Theft, Theft
Drug	Cannabis Control Act, Controlled Substances Act, Drug Paraphernalia Act, Hypodermic Syringes & Needles Act, Liquor Control Act Violations*, Meth
Weapons	Deadly Weapons*
Other	Attempt, Cruelty to Animals, Deception*, Disorderly Conduct*, Gambling, Illegal Sales, Interference with Public Officers*, Liquor Control Act Violations*, Motor Vehicle Offenses*, Offense Involving Children*, Probation/Parole Violations, Sex Offenses*, Sex Offender Registration Violations, Sex Offender Violations, Status Offense, Traffic (minor)
*Some charges appear in multiple categories because the categorization depends on the specific nature of the crime involved (e.g., if a disorderly conduct crime included property damage).	

ENDNOTES

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[8] These computations were conducted and presented in Bhati (2007) and Bhati and Piquero (2008).