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.

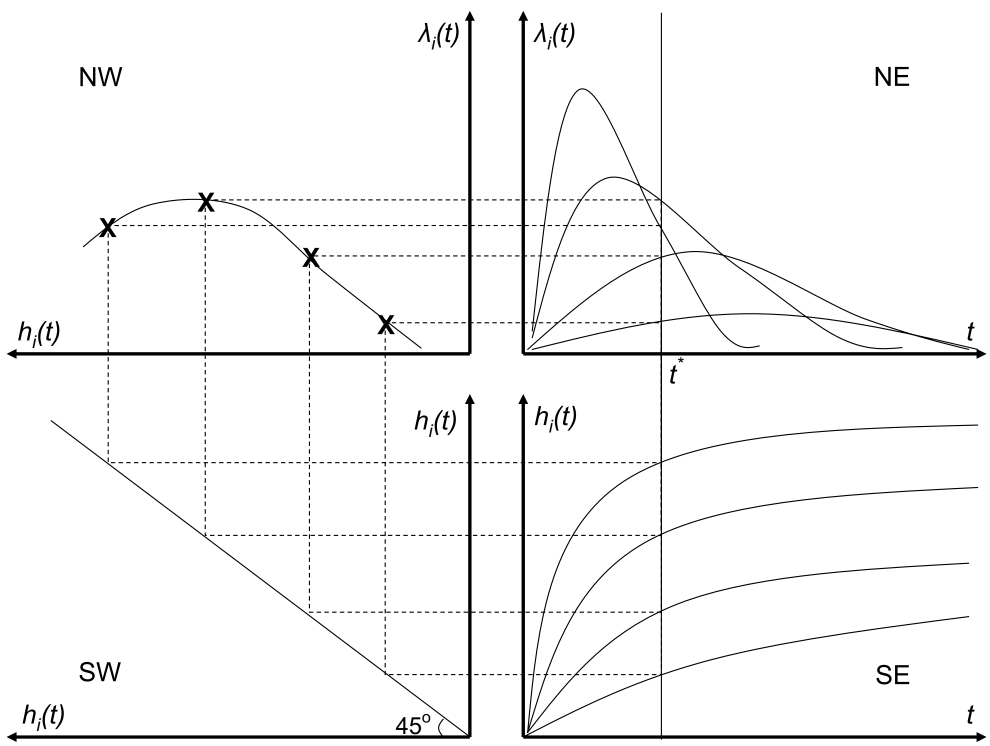
This report details a strategy that allows one to model, study, and project individual-level offending micro-trajectories. The strategy fulfills both the requirements listed above and is easily implemented using detailed dated criminal arrest history records. Such records have been difficult to access 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= $\int_{35}^{37} \lambda(t)\, dt$).

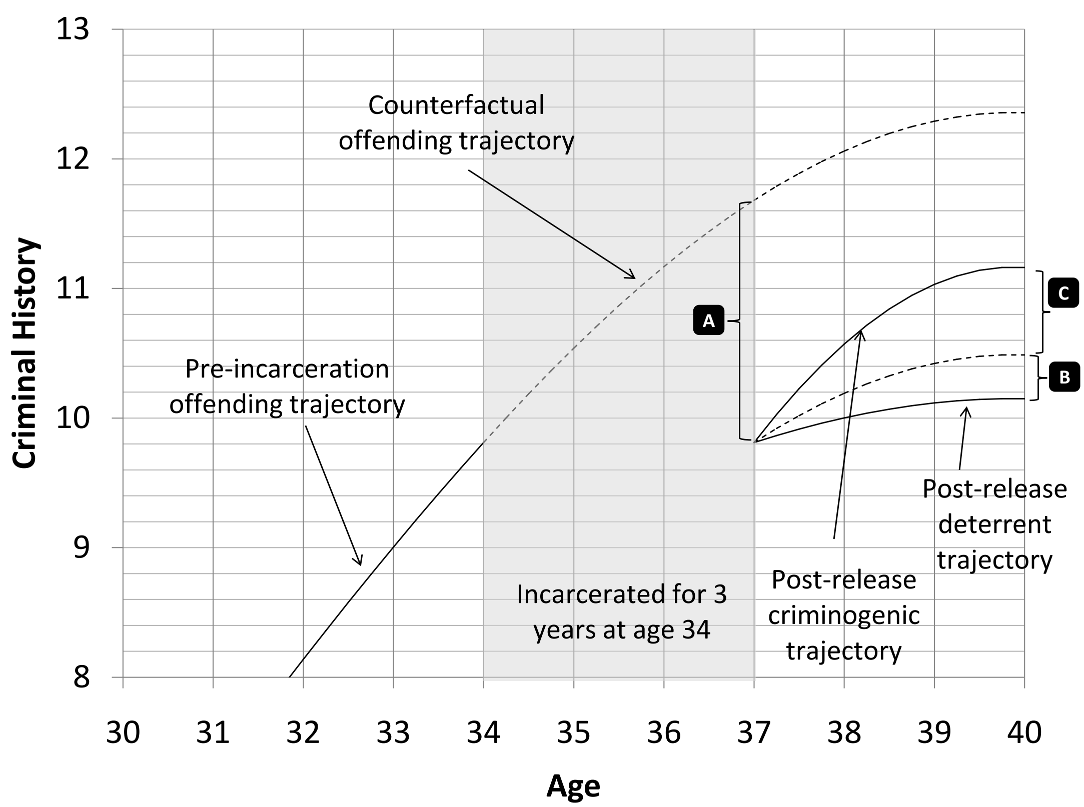
The specific deterrent effects (SDE) of the same incarceration episode may be computed as the difference between an accumulation of $\lambda(t)$ over a fixed follow-up period (post release) and the updated offending trajectory during the follow-up period. I.e., SDE= $\int_{37}^{40} \lambda(t)\, dt - \int_{37}^{40} \bar{\lambda}\ (t) dt$ 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%

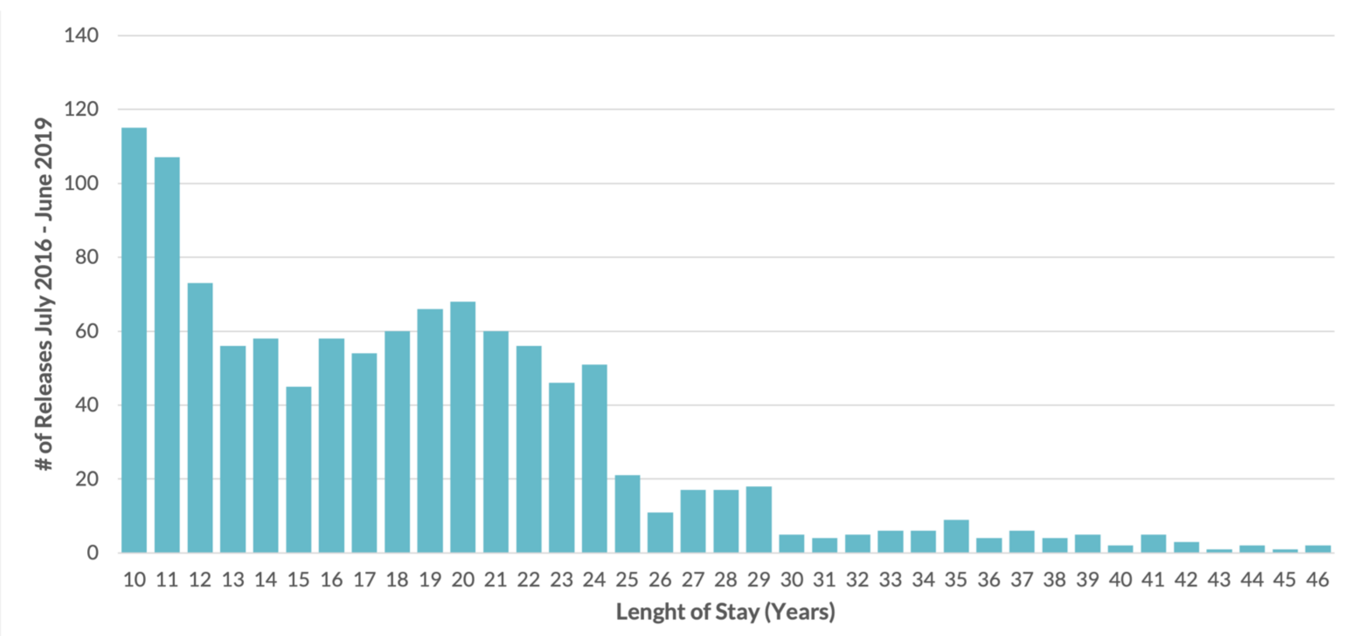
MSR violator, New sentence	3,730	8.4%	66.7%		97	8.5%	47.4%
Parole violator, New sentence	2	0.0%	50.0%		7	0.6%	57.1%
Return additional mittimus	223	0.5%	67.3%		6	0.5%	66.7%
Transferred from juvenile	90	0.2%	75.6%		19	1.7%	47.4%
Exit Type	**Short Time Served (< 10 yrs)**				**Long Time Served (≥ 10 yrs)**		
	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

[1] Bhati, A.S., 2010. *Quantifying the Specific Deterrent Effects of DNA Databases*, Final report submitted to the National Institute of Justice, Washington, DC. (http://www.urban.org/url.cfm?ID=412058). Bhati, A.S., and Roman, C.G. 2014. "Evaluating and Quantifying the Specific Deterrent Effects of DNA Databases" *Evaluation Review*, 38(1): 68 - 93.
[2] Bhati, A.S., Austin, J., and Gaes, G. 2011. *How Much Prison Time is Enough?* Final report submitted to PEW Charitable Trusts, Washington, DC.
[3] Harding, R.W., and Maller, R.A. 1997. "An Improved Methodology for Ana- lyzing Age-Arrest Profiles: Application to a Eastern Australian Offender Population." *Journal of Quantitative Criminology* 13(4):349-372.
[4] Manski, C. 1988. *Analog Estimation Methods in Econometrics*. London: Chapman and Hall.
[5] Jaynes, E.T. 1957a. "Information Theory and Statistical Mechanics." *Physics Review* 106:620–630.
[6] Shannon, C.E. 1948. "A Mathematical Theory of Communication." *Bell System Technical Journal* 27:379-423.
[7] Bhati, A.S., 2007. *An Information Theoretic Method for Estimating the Number of Crimes Averted by Incapacitation*, Final report submitted to the National Institute of Justice, Washington, DC. (http://www.urban.org/url.cfm?ID=411478)
[8] These computations were conducted and presented in Bhati (2007) and Bhati and Piquero (2008).