CCJ | Women's Justice Commission

What Happens When Women Serve Less Time in Prison? Projected Changes in Arrests, Prison Population, and Costs

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Methodology

This methodology report describes the data, modeling approach, and assumptions used to estimate the public safety, prison population, and cost implications of reducing time served for women released from prison in Illinois and North Carolina, findings that are presented in *What Happens When Women Serve Less Time in Prison? Projected Changes in Arrests, Prison Population, and Costs*. Three years of release data were used from each state to simulate changes in deterrence and incapacitation effects of imprisonment that may stem from reduced time served. Estimates were calculated for changes in corrections costs, costs to victims, and other external costs of women's imprisonment. The main brief presents selected findings focused primarily on a 50% reduction in time served; this supplement provides the full set of results for broad and targeted scenarios based on 10%, 20%, 30%, and 50% reductions in time served.

The central question in this analysis is counterfactual: How would arrests, prison population size, and costs change if women released from prison in Illinois and North Carolina had served less time? Arrest estimates are based on individual-level simulation models that use observed criminal history records both before incarceration and after release. Average daily prison population estimates are based on changes in time served under each scenario. Cost estimates incorporate reductions in incarceration costs and additional costs associated with arrests, law enforcement response, and victimization.

Data Sources and Analytic Sample

This analysis uses release cohorts of women who exited prison in Illinois and North Carolina between January 2018 and December 2021. These states were selected because public release cohort data were available and could be linked to individual-level criminal history records obtained from state authorities following Institutional Review Board review and execution of required data use agreements.

Release Cohort Construction

For Illinois, demographic and correctional information was obtained from the Illinois Department of Corrections' public prison exit data.[1] For North Carolina, a comparable release cohort was constructed using publicly available data from the North Carolina Department of Adult Correction.[2]

The release cohort files included date of birth, prison admission date, prison release date, and sex. These data were used to calculate age at admission, age at release, and time served.

Criminal History Records

After the release cohorts were constructed, individual-level criminal history records were requested from the Illinois Criminal Justice Information Authority and the North Carolina State Bureau of Investigation. These records provided dated arrest histories before incarceration and after release.

The linked criminal history records were obtained following Institutional Review Board review and execution of required data use agreements. Human subjects approval was granted by Solutions IRB. These linked data provide the basis for the arrest trajectory models described below.

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[1] Illinois.Gov. (n.d.). *Prison exit data sets*. https://idoc.illinois.gov/reportsandstatistics/prison-exit-data-sets.html

[2] North Carolina Department of Adult Correction. (n.d.). *Offender public information: Downloads*. https://webapps.doc.state.nc.us/opi/downloads.do?method=view

Final Analytic Sample

The initial release cohorts included 6,527 women in Illinois and 5,561 women in North Carolina. Some records were excluded because of missing data, same-day admission and release dates, or inability to link the release record to a valid state criminal history record. The final analytic sample used in the simulations included 6,419 women in Illinois and 5,552 women in North Carolina.

Table 1 presents descriptive information for the release cohorts in each state. The table includes analytic sample size, age at admission and release, time served, arrests that occurred prior to incarceration, arrests that occurred during the 3-year follow-up window (post-release arrests), and the share of women with at least one post-release arrest.

The Illinois and North Carolina cohorts were similar in size and age. Women in the Illinois analytic sample had an average age of 35.7 years at admission and 36.9 years at release. Women in the North Carolina analytic sample had an average age of 35.1 years at admission and 36.5 years at release.

Average time served was somewhat shorter in Illinois (1.18 years) than in North Carolina (1.42 years). Arrest histories also differed across states. Women in the Illinois sample had more prior arrests, on average, than women in North Carolina (11.6 vs. 7.8) and more post-release arrests during the three-year follow-up period (1.3 vs. 1.0). The three-year rearrest rate was also higher in Illinois (49.1%) than in North Carolina (44.3%).

Table S1. Release Cohort and Analytic Sample Characteristics

	Illinois (*n* = 6,419)	North Carolina (*n* = 5,552)
Age at Admission	35.7	35.1
Age at Release	36.9	36.5
Average Time Served (Years)	1.18	1.42
Average Prior Arrests	11.6	7.8
Average Post-Release Arrests (3 years)	1.3	1.0
Recidivism Rate (3 years)	49.1%	44.3%

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Analytic Strategy

The central question in this analysis is: How would arrests, prison population size, and costs change if women released from prison in Illinois and North Carolina had served less time?

Answering that question requires an individual-level approach. Aggregate analyses can show how prison populations and arrest rates change over time, but they cannot estimate how a reduction in time served would affect women with different ages, sentence lengths, and prior arrest histories. Because the effects of reducing time served may vary across individuals, the analysis uses person-level arrest histories to estimate individual arrest trajectories, and then aggregates those estimates to the cohort level. This approach is grounded in the Criminal Career paradigm,[3] which emphasizes variation in offending patterns over time, including onset, duration, termination, and desistance.[4]

The analysis uses a counterfactual framework. For each woman in the analytic sample, the model estimates an expected arrest trajectory based on observed arrest patterns before incarceration and compares that trajectory with observed arrest patterns after release. This allows the analysis to estimate how incarceration may have affected subsequent arrests. For some people, post-release arrests may be lower than expected based on prior history, suggesting a deterrent effect. For others, post-release arrests may be higher than expected, suggesting a criminogenic effect. For many, post-release arrests may be similar to the expected trajectory, suggesting a neutral effect, beyond incapacitation. This framework builds on prior work using individual micro-trajectories to estimate crimes averted by incarceration and to distinguish deterrent, criminogenic, and null effects.[5]

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[3] National Research Council. (1986). *Criminal careers and "career criminals,"*: Volume I. The National Academies Press. https://doi.org/10.17226/922; National Research Council. (1986). *Criminal careers and "career criminals,"*: Volume II. The National Academies Press. https://doi.org/10.17226/928 ; Piquero, A.R. (2008). Taking stock of developmental trajectories of criminal activity over the life course. In: A. M. Liberman (Ed.), *The Long View of Crime: A Synthesis of Longitudinal Research*, pp. 23-78. Springer. https://doi.org/10.1007/978-0-387-71165-2_2 ; Piquero, A. R., Farrington, D. P., & Blumstein, A. (2003). The criminal career paradigm. *Crime & Justice, 30*, 359-506. https://www.journals.uchicago.edu/doi/abs/10.1086/652234

[4] Bushway, S. D., Piquero, A. R., Broidy, L. M., Cauffman, E., & Mazerolle, P. (2001). An empirical framework for studying desistance as a process. *Criminology*, *39*(2), 491-516. https://doi.org/10.1111/j.1745-9125.2001.tb00931.x

[5] Bhati, A. S. (2007b). Estimating the number of crimes averted by incapacitation: An information theoretic approach. *Journal of Quantitative Criminology*, *23*(4), 355-375. https://link.springer.com/article/10.1007/s10940-007-9034-2; Bhati, A.S. (2010). *Quantifying the specific deterrent effects of DNA databases*. Urban Institute.

The same framework can then be used to simulate reductions in time served. Shortening time served changes the period during which a person is incapacitated in prison and changes the timing of release. The model estimates how those changes affect expected arrests during a fixed three-year follow-up period. Estimated effects are calculated at the individual level and then summed across the analytic sample to estimate changes in arrests under each simulated scenario. Prior applications of this approach have used similar micro-trajectory methods to study the effects of incarceration and related criminal justice interventions, including DNA database deterrence, sentence length simulations, and the public safety implications of shortening lengthy prison terms.[6]

This individual-level approach also allows the analysis to examine how projected effects are distributed across the population. In addition to estimating results for all women in the analytic sample, the simulations estimate effects for cumulative groups based on projected public safety impact. These groupings are described in detail in the Simulation Scenarios section below.

Finally, the analysis uses the simulated changes in time served to estimate changes in the average prison population and associated costs. Cost estimates incorporate reductions in incarceration costs from shorter sentences and the projected costs associated with additional arrests, including law enforcement response, court processing, and victimization costs.

The sections that follow describe the Criminal History Accumulation Process (CHAP) model used to estimate individual arrest trajectories and the simulation approach used to estimate public safety, population, and cost effects.

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https://www.urban.org/sites/default/files/publication/28476/412058-Quantifying-the-Specific-Deterrent-Effects-of-DNA-Databases.PDF; Bhati, A. S., & Piquero, A. R. (2007). Estimating the impact of incarceration on subsequent offending trajectories: Deterrent, criminogenic, or null effect. *Journal of Criminal Law & Criminology*, *98*, 207-253. https://doi.org/0091-4169/07/9801-0207

[6] Bhati, A.S. (2010). *Quantifying the specific deterrent effects of DNA databases.* Urban Institute. http://www.urban.org/url.cfm?ID=412058; Bhati, A.S. (2023). *The public safety impact of shortening lengthy prison terms.* Council on Criminal Justice, https://counciloncj.foleon.com/tfls/long-sentences-by-the-numbers/the-public-safety-impact-of-shortening-lengthy-prison-terms; Bhati, A.S., Austin, J., & Gaes, G. (2011). *How much prison time is enough?* Final report submitted to The Pew Charitable Trusts. https://www.pew.org/-/media/legacy/uploadedfiles/wwwpewtrustsorg/reports/sentencing_and_corrections/prisontimeservedpdf.pdf; Bhati, A.S., & Roman, C. G. (2014). Evaluating and quantifying the specific deterrent effects of DNA databases. *Evaluation Review*, *38*(1), 68-93. https://doi.org/10.1177/0193841X14531415

Modeling Individual Arrest Trajectories: The CHAP Model

Conceptual Overview

The analysis uses the CHAP model[7] to estimate individual arrest trajectories. CHAP links a person's current arrest risk to two core factors: age and accumulated prior arrest history. This framework allows the analysis to estimate how arrest risk changes over time and how those changes vary across individuals.

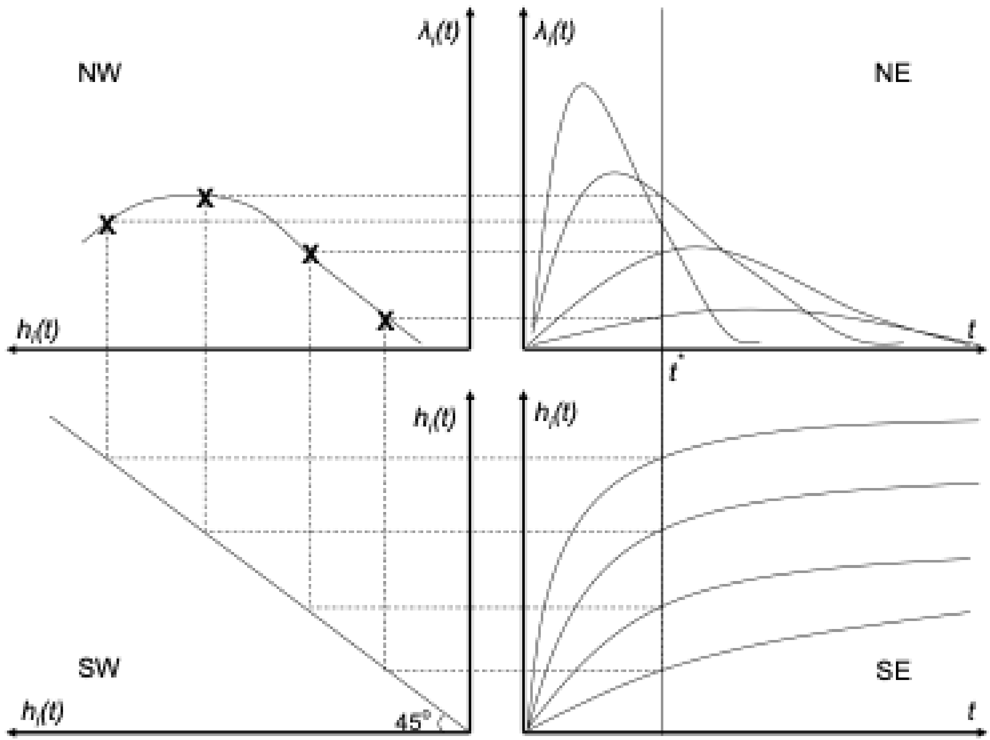
The model builds on the well-established age-crime relationship: Arrest risk generally changes over the life course. But age alone does not capture individual differences in behavior. Two people of the same age may have very different arrest histories, and those histories provide important information about how arrest risk is likely to evolve. CHAP incorporates age and accumulated prior arrest history to estimate individual-level trajectories.

In this framework, arrest histories are treated as dynamic. Individuals are not assumed to follow fixed or predetermined paths. Instead, the model allows estimated arrest risk to change as people age and as their arrest histories accumulate. This makes it possible to generate individual micro-trajectories that reflect both life-course patterns and prior system involvement.

Figure S1 illustrates the basic logic of the CHAP model. The figure shows how different arrest trajectories (shown in the NE quadrant) accumulate into different arrest histories over time (shown in the SE quadrant). CHAP links these concepts by estimating arrest risk as a function of both age (the NE quadrant) and accumulated prior arrests (the NW quadrant). This allows the analysis to estimate and simulate individual arrest trajectories rather than apply a single average age-crime curve to everyone.

[7] Bhati, A.S. (2007a). *An information theoretic method for estimating the number of crimes averted by incapacitation.* Urban Institute. https://www.urban.org/url.cfm?ID=411478

Figure S1. Relationship Between Age, Prior Arrest History, and Arrest Risk



Note: The figure illustrates the conceptual relationship underlying the CHAP model. Arrest risk is estimated as a function of age and accumulated prior arrest history.

The core relationship underlying CHAP can be expressed as:

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

where $\lambda_i(t)$ represents the estimated arrest hazard, or arrest risk, for individual i at time t; $h_i(t)$ represents that person's accumulated prior arrest history at time t; and t captures age or time. In plain terms, the model estimates a person's arrest risk at a given point in time as a function of both age and accumulated arrest history (up to that point).

To estimate these trajectories, the model uses dated arrest sequences and date of birth to identify the age at which each arrest occurred and the time between successive arrests. These sequences are used to estimate the relationship between age, accumulated arrest history, and the timing of arrest events.

Because many possible trajectories could be consistent with the observed arrest histories, CHAP uses a maximum entropy framework to select the least-informative set of trajectories that satisfies the constraints observed in the data. In practical terms, this approach produces conservative estimates: The model does not impose more structure than the data support.

Formally, CHAP models the arrest hazard as a function of age, accumulated arrest history, and individual attributes. The exact functional form may include linear and nonlinear transformations of age and arrest history. Once model parameters are estimated, the equation can be used to compute a person's arrest trajectory conditional on age and prior arrest history.

The resulting model produces an estimated arrest hazard trajectory for each person in the analytic sample. These trajectories provide the basis for estimating the number of arrests expected during incarceration and after release, and projecting how those estimates change under simulated reductions in time served.

Data Inputs and Model Estimation

Estimating CHAP models requires two core inputs for each person in the analytic sample: date of birth and a dated sequence of arrests. Together, these data make it possible to identify the individual's age at which each arrest occurred and to measure the time between successive arrest events.

These dated arrest sequences are used to construct individual arrest profiles. Each profile reflects how arrests accumulate over time, including the timing of first arrest, subsequent arrests, and periods without arrests. Prior research refers to these sequences as arrest profiles.[8]

The model then uses observed patterns in the analytic sample to estimate the relationship between arrest risk, age, and accumulated prior arrest history. This estimation relies on the principle that the expected relationship between arrest risk and factors such as age, time since last arrest, or accumulated arrest history should be consistent with the relationship observed in the sample. This logic follows the analogy principle,[9] which uses observed sample patterns to inform the constraints the model must satisfy.

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[8] Harding, R. W., & Maller, R. A. (1997). An improved methodology for analyzing age-arrest profiles: Application to a western Australian offender population. *Journal of Quantitative Criminology*, *13*(4), 349-372. https://link.springer.com/article/10.1007/BF02221046
[9] Manski, C. (1988). *Analog estimation methods in econometrics*. London: Chapman and Hall.

Those constraints narrow the set of possible arrest trajectories, but they do not identify a single trajectory. Many different trajectories could be consistent with the observed arrest histories. To select among them, CHAP uses a maximum entropy framework. In this context, maximum entropy means selecting the least-informative trajectory consistent with the observed data and model constraints. This approach follows the information-theoretic framework developed by Jaynes and Shannon and produces conservative estimates by avoiding assumptions not supported by the data.[10]

The full mathematical derivation of the solution can be found in Bhati (2007).[11] 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 $\lambda_i(t)$ represents the estimated arrest hazard for individual i at time t; $\bar{\lambda}_i(t)$ reflects a prior belief about λ, if any; x is a vector of individual 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 offender attributes, is done by plugging in the appropriate quantities into the main equation and computing the micro-arrest trajectories for that person.

These individual trajectories are the basis for the next step in the analysis: estimating the number of arrests expected during incarceration, the number expected after release, and how those estimates change under simulated reductions in time served.

[10] Jaynes, E. T. (1957). Information theory and statistical mechanics. *Physical Review*, *106*(4), 620. https://journals.aps.org/pr/abstract/10.1103/PhysRev.106.620; Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379-423. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6773024

[11] Bhati, 2007a; 2007b.

Model Outputs

The CHAP model produces an estimated arrest hazard trajectory for each woman in the analytic sample. Each trajectory represents the expected rate at which arrests accumulate over time, conditional on age, accumulated prior arrest history, and other available attributes.

These trajectories are integrated over specific periods to estimate expected arrests during incarceration and during the three-year follow-up period after release. Expected arrests during the incarceration period are used to estimate incapacitation effects. Expected and observed arrest patterns during the post-release period are used to estimate whether incarceration was associated with deterrent, criminogenic, or neutral effects.

The same individual-level trajectories are used in the simulation analysis. Under each scenario, time served is reduced by a specified amount, the release date is shifted earlier, and the model simulates how arrests, prison population size, and associated costs change relative to observed time served.

Estimating Incapacitation and Post-Release Effects

The modeling strategy described above allows the analysis to estimate two related effects of incarceration: the incapacitation effect and the post-release effect. The incapacitation effect reflects arrests expected to have been averted while a person was in prison. The post-release effect reflects whether the person's arrest trajectory after release was lower than, higher than, or similar to what would have been expected based on pre-incarceration arrest patterns.

Incapacitation effects are computed by simulating each person's micro-trajectory during the incarceration period—from age at prison admission to age at prison release. For example, the incapacitation effect (*INC*) of being incarcerated between ages 35 and 37 can be computed as the accumulation of the estimated arrest hazard $\lambda(t)$ between those ages:

$$INC = \int_{35}^{37} \lambda(t)\, dt$$

In similar fashion, the pre-incarceration arrest trajectory can be projected over a fixed follow-up period after release. This projected trajectory serves as the counterfactual: it represents the arrest trajectory expected if the person had continued along the pre-incarceration pattern.

Next, using the counterfactual as a prior belief about λ—that is, the $\bar{\lambda}_i(t)$ defined above—the model is re-estimated using arrest data from the post-release follow-up period. The updated trajectory reflects how the person's micro-trajectory changed after incarceration. Comparing the counterfactual trajectory with the post-release trajectory allows the analysis to assess whether post-release arrests were lower than, higher than, or similar to what would have been expected based on pre-incarceration arrest patterns.

The specific deterrent effect (*SDE*) of the same incarceration episode can be computed as the difference between the accumulated counterfactual trajectory over the follow-up period and the updated post-release trajectory. For a person released at age 37 and followed through age 40, this can be written as:

$$SDE = \int_{37}^{40} \bar{\lambda}(t)\,dt - \int_{37}^{40} \lambda(t)\,dt$$

where $\bar{\lambda}(t)$ is the pre-incarceration-based, counterfactual arrest trajectory and $\lambda(t)$ is the post-release trajectory estimated using follow-up data. Under this formulation, a positive *SDE* indicates that post-release arrests were lower than expected, suggesting a deterrent effect. A negative *SDE* indicates that post-release arrests were higher than expected, suggesting a criminogenic effect. An SDE close to zero indicates a neutral effect beyond incapacitation.

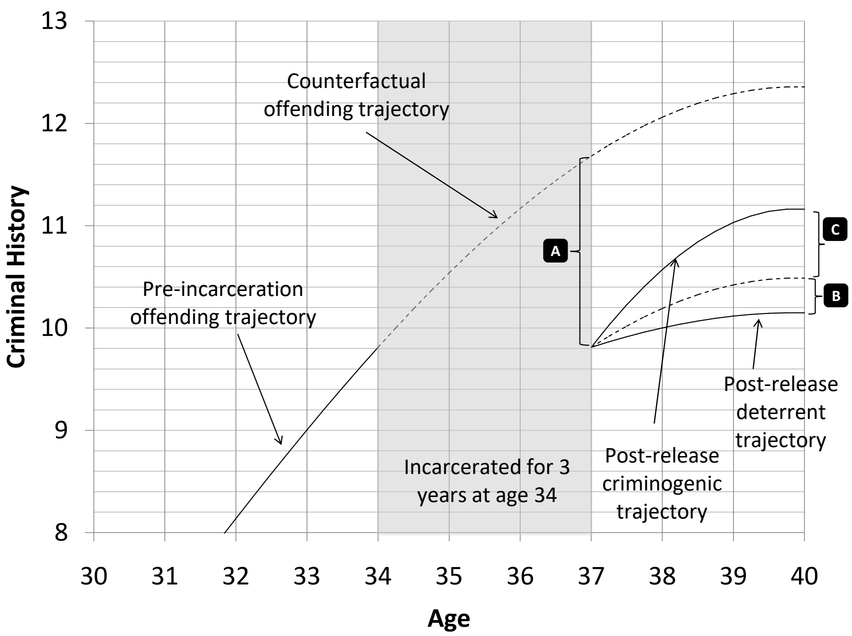
The net effect of incarceration is estimated as the sum of the incapacitation effect and the specific deterrent effect (or, post-release effect):

$$Net\ Effect = INC + SDE$$

This value can be positive, negative, or close to zero. Because the calculations integrate λ over time, the estimates reflect the amount by which a person's accumulated arrest history would be higher or lower at the end of the three-year follow-up period under the observed incarceration episode, compared with the counterfactual trajectory. The sign and magnitude of the effect depend on several factors, including the person's age, pre-incarceration arrest trajectory, post-release arrest trajectory, and time served.

Figure S2 illustrates how these computations are conducted. The example involves a person who enters prison at age 34, is released at age 37, and is observed for three years after release. Using the person's prior arrest history, the model first estimates a pre-incarceration arrest trajectory. In the example, that trajectory shows approximately 10 prior arrests at the time of prison admission. The pre-incarceration trajectory is then projected through the incarceration period and the follow-up period, forming the counterfactual arrest trajectory. The difference between the number of arrests the person would have been expected to accumulate during the incarceration period had they remained in the community is indicated by marker A; this is the incapacitation effect. After release, a post-release trajectory is estimated using observed arrest data through age 40. If post-release arrests accumulate more slowly than the counterfactual trajectory, the difference is indicated by marker B, representing a deterrent effect. If post-release arrests accumulate more quickly than the counterfactual trajectory, the difference is indicated by marker C, representing a criminogenic effect. The net effect of incarceration is then calculated by combining the incapacitation effect (A) with either the deterrent effect (B) or the criminogenic effect (C), depending on the observed post-release pattern.

Figure S2. Calculating Incapacitation, Deterrent, Criminogenic, and Neutral Effects



Estimating Incapacitation and Post-Release Effects

The CHAP model was used to estimate incapacitation and post-release effects for each woman in the Illinois and North Carolina analytic samples. Because some records could not be used in the simulation analysis due to missing or incomplete data, all results in this section are based on the final analytic samples of 6,419 women in Illinois and 5,552 women in North Carolina.

For each woman, the model estimates two related quantities. The first is the incapacitation effect, or the number of arrests expected to have been averted during the period she was incarcerated. The second is the post-release effect, which compares observed post-release arrest patterns with the arrest trajectory expected based on pre-incarceration arrest history.

Post-release effects can be deterrent, criminogenic, or null. If observed post-release arrests are lower than expected, the effect is classified as deterrent. If observed post-release arrests are higher than expected, the effect is classified as criminogenic. If observed arrests are similar to the expected trajectory, the effect is classified as null. These post-release classifications are mutually exclusive; each woman can have only one. Incapacitation effects are estimated separately and are always non-negative because arrest hazards cannot be negative.

Figures S3 and S4 show the distribution of estimated incapacitation and post-release effects for women released from prison in Illinois and North Carolina. In each figure, the left panel shows the estimated incapacitation effect, while the right panel shows the estimated post-release effect. Estimates are sorted from lowest to highest and plotted by percentile of the state's release cohort.

In Illinois, estimated incapacitation effects ranged from 0 to about 8 arrests, with half of the women in the analytic sample having an estimated incapacitation effect of less than one arrest. The post-release effects were also generally small. Most women had estimated post-release arrest patterns that were lower than expected based on their pre-incarceration trajectories, suggesting a deterrent effect. Less than 10% had higher-than-expected post-release arrest patterns, suggesting a criminogenic effect. For a majority of the sample, the deterrent effect ranged between +/- 5 arrests whereas the incapacitation effect ranged between 0 and 5.

The North Carolina results followed a similar pattern. Estimated incapacitation effects ranged from 0 to nearly 15 arrests, with half of the women in the sample having an estimated incapacitation effect of less than one arrest. As in Illinois, fewer than 10% of women had estimated criminogenic effects, while most had post-release arrest patterns that were slightly lower than expected based on their pre-incarceration trajectories. These findings are not surprising given that women of all risk levels and all lengths of stay are included in the simulation analysis.

Figure S3. Estimated Incapacitation and Post-Release Effects for Women Released from Prison in Illinois

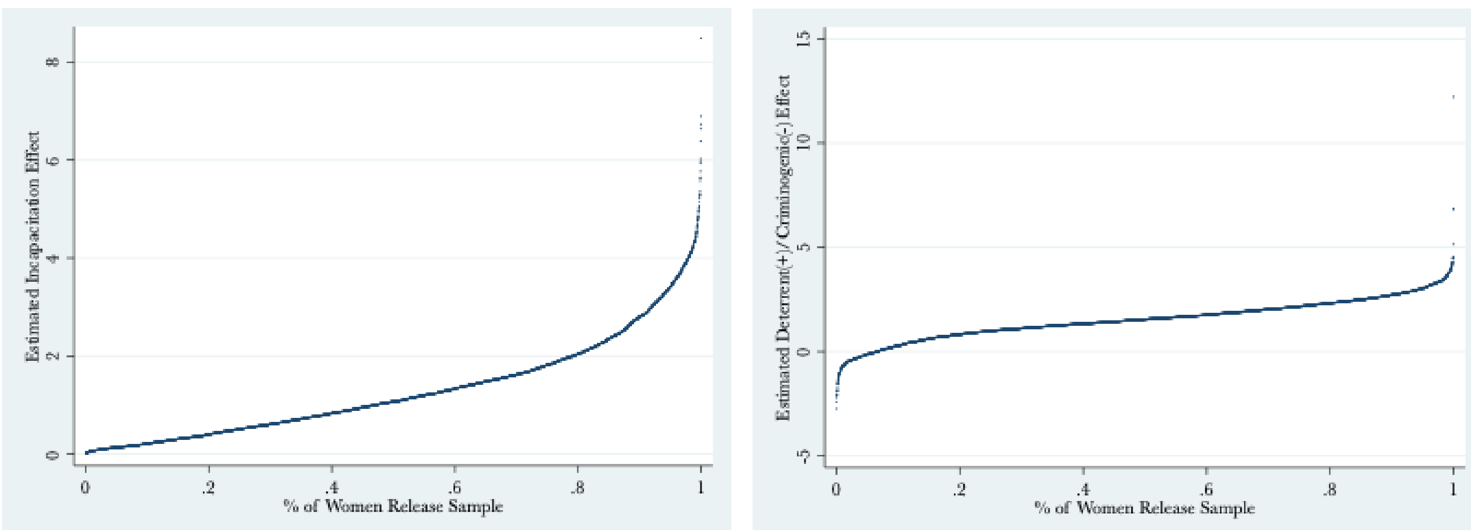
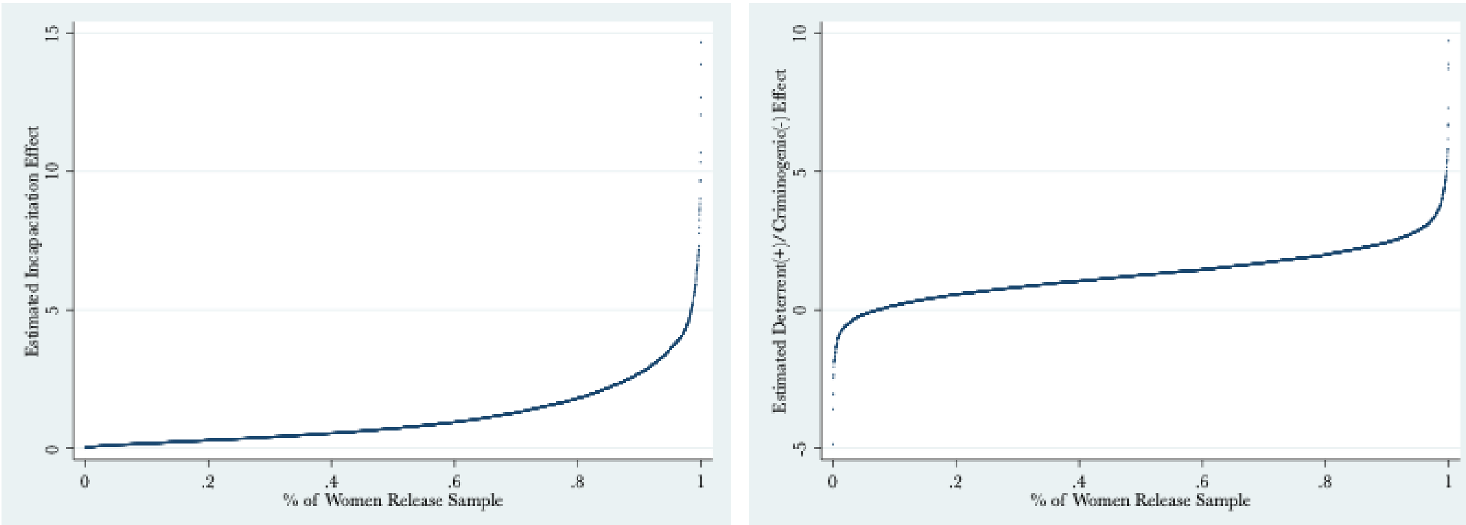


Figure S4. Estimated Incapacitation and Post-Release Effects for Women Released from Prison in North Carolina



Relationship Between Time Served and Estimated Effects

Figures S5 and S6 examine whether the estimated effects are associated with the amount of time women actually spent in prison before release. In each figure, the left panel plots estimated incapacitation effects against time served, while the right panel plots estimated post-release effects against time served.

In both states, estimated incapacitation effects generally increase with time served, but the relationship is not linear. Variation in incapacitation effects grows as time served increases, and the relationship appears to flatten for women serving longer terms. This pattern suggests that, for some women serving longer terms, the primary incapacitation effects may accrue earlier in the incarceration period.

The relationship between incapacitation effects and time served is more varied in North Carolina than in Illinois. The Illinois scatter plot is more clustered, particularly among women who served less than five years, while the North Carolina plot shows greater dispersion. This suggests more variation in the estimated relationship between time served and incapacitation effects in the North Carolina sample.

The relationship between time served and post-release effects is also varied. In both states, deterrent effects are concentrated among women with relatively short time served, particularly those serving less than one year. As time served increases from one to about five years, estimated deterrent effects decline, and more women appear to experience criminogenic effects, meaning post-release arrests were higher than expected based on pre-incarceration arrest patterns. Among women serving longer terms—roughly five to seven years or more—estimated post-release effects are generally close to null, meaning there is little estimated deterrent or criminogenic effect.

These figures are descriptive and should not be interpreted as showing that time served alone causes differences in estimated effects. Women who served one to two years may differ in important ways from women who served five to 10 years. The purpose of these figures is not to explain those differences, but to show how the model-estimated incapacitation and post-release effects are distributed across the observed release cohorts and how they relate to time served before the simulation scenarios reducing time served are applied.

These distributions are important for interpreting the simulations that follow. The estimates show that incarceration effects vary across individuals. Some women have higher estimated incapacitation effects, while others have very low estimated incapacitation effects; some have lower-than-expected post-release arrests, while a smaller share have higher-than-expected post-release arrests. Because the simulation analysis is conducted at the individual level, these differences are carried forward into the time-served reduction scenarios.

Figure S5. Time Served and Estimated Incarceration Effects for Women Released from Prison in Illinois

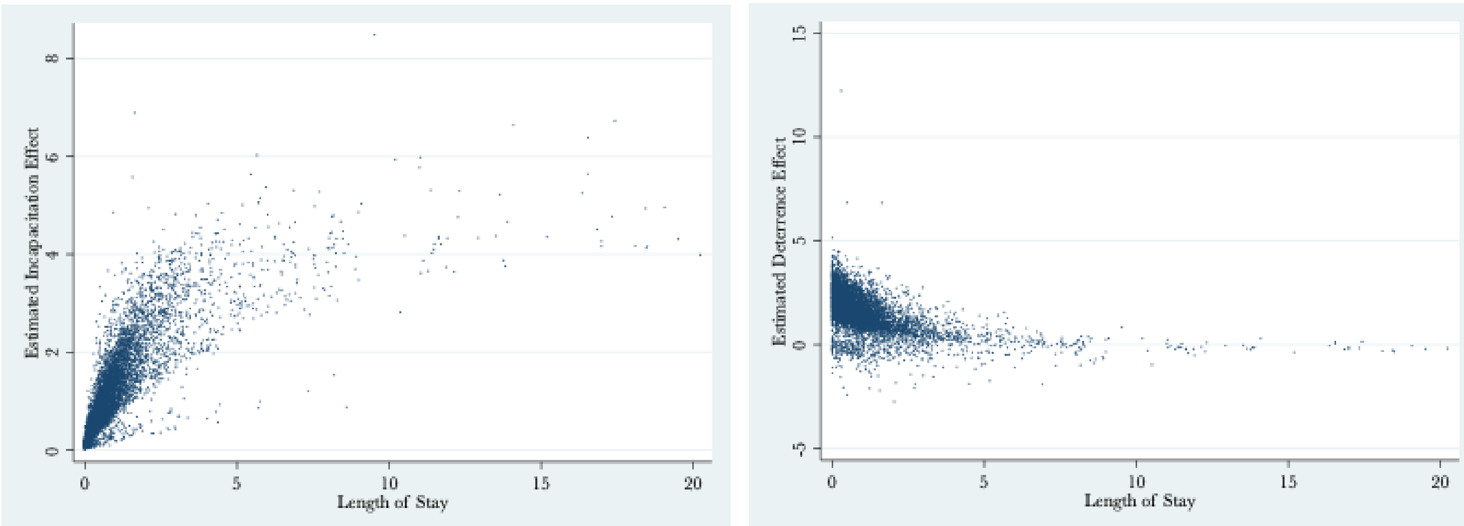
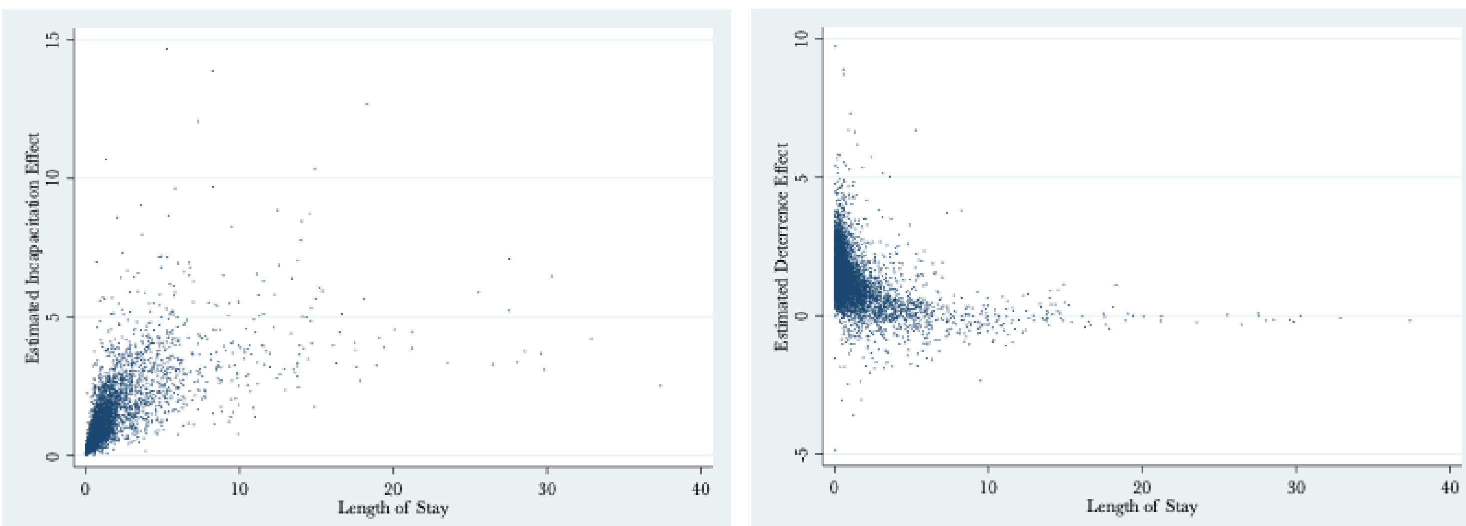


Figure S6. Time Served and Estimated Incarceration Effects for Women Released from Prison in North Carolina



Simulation Scenarios

The CHAP models described above are used to estimate how arrests, prison population size, and costs would change if time served were reduced. The simulations do not model a specific statute, release mechanism, or program. Instead, they estimate the effects of hypothetical reductions in time served under a defined set of scenarios.

The prior section showed that estimated incapacitation and post-release effects vary across individuals and are not explained by time served alone. As a result, the effect of reducing time served is difficult to anticipate without simulation. Shortening time served changes several components of the model at once: It reduces the period of incapacitation, shifts the age at release, and changes the period during which post-release arrests may occur. The effect depends on each woman's age, prior arrest history, time served, and estimated arrest trajectory.

This is especially important because the public safety value of incarceration may vary over the course of a person's sentence. For some women, expected incapacitation effects may accrue earlier in the incarceration period; for others, shortening time served may have a larger effect. Similarly, post-release effects may be deterrent, criminogenic, or null depending on how observed post-release arrests compare with the expected trajectory. The simulations are designed to quantify these effects under several policy-relevant scenarios.

The scenarios presented here are not exhaustive. Once individual trajectories are estimated, many possible time-served reductions could be simulated. This report focuses on a limited set of reductions designed to show how results change as reductions become larger and are applied more broadly across the population.

The simulations vary along two dimensions: the magnitude of the reduction in time served and the share of the release cohort to which the reduction applies.

Reductions in Time Served

The analysis simulates reductions in time served of 10%, 20%, 30%, and 50%. For each scenario, the observed time served for each person included in the scenario is reduced by the specified percentage. The model then estimates how the earlier release date changes expected arrests during the period of incarceration and the three-year follow-up period, and how this reduction in time served affects the average prison population.

For example, a 50% reduction in time served means that a person who served 18 months in prison is modeled as having served 9 months. Because observed time served varies across individuals, the number of months reduced also varies.

Groups Based on Simulated Effect Size

Because the simulations are estimated at the individual level, the analysis can examine how projected public safety effects are distributed across the release cohort. For each simulated reduction in time served, the model estimates the projected change in arrests for each woman in the analytic sample. Those individual estimates are then used to group women by projected public safety impact.

The groups are cumulative. The lowest 25% includes the quarter of women with the smallest projected increase in arrests under the simulated reduction in time served. The lowest 50% includes the bottom half of the distribution, including the lowest 25% plus the next quarter. The lowest 75% includes the bottom three-quarters of the distribution, and the lowest 90% includes nearly the full sample, except the highest 10% based on projected public safety impact. The "all women" scenario applies the reduction to the full analytic sample.

Each time-served reduction—10%, 20%, 30%, and 50%—is simulated for each of these cumulative groups. This structure makes it possible to compare how results change when reductions are applied narrowly, broadly, or to the full cohort.

These groupings are based on simulation results that use observed pre-incarceration and post-release arrest histories. They should not be interpreted as formal risk classifications. They do not account for offense severity, institutional behavior, program participation, health status, caregiving responsibilities, or other factors that may be relevant to individual release decisions.

Because the groupings are created from the simulation results, they identify which groups contribute more or less to projected public safety impacts after the model is estimated. That does not mean the same groups could be identified prospectively with the same precision in actual policy implementation. The targeted scenarios should therefore be interpreted as an analytic exercise showing how public safety impacts vary across the sample, not as a ready-made release rule.

Interpreting the Simulation Results

For each scenario, the model estimates the change in arrests relative to observed time served. Because the model is estimated at the individual level, projected changes in arrests can be summed across individuals to estimate the total effect for each scenario.

The results are reported both as total estimated changes over the three-year follow-up period and as annualized estimates. Annualized estimates convert the three-year total into an average yearly value; this makes it easier to compare projected additional arrests with annual statewide arrest totals.

The same simulated reductions in time served are also used to estimate changes in the average prison population. These estimates reflect reductions in the total time served across the system, rather than the number of people released. In other words, a reduction in the average prison population results from many people spending less time in prison, not from a one-to-one reduction in the number of people incarcerated.

Finally, the simulation results are used to estimate costs. Public safety costs are estimated by applying cost assumptions to projected additional arrests, including the extra expenses related to law enforcement response, court processing, and victimization. Incarceration cost reductions are estimated using changes in the average prison population and per-woman incarceration cost assumptions.

Public Safety Estimates

The first set of simulations estimates how reducing time served would affect arrests during the three-year follow-up period. For each state, results are shown across four reductions in time served—10%, 20%, 30%, and 50%—and across cumulative groups based on projected public safety impact.

The rows show the share of the analytic sample to which the reduction is applied. These groups range from the lowest 25% of women based on projected public safety impact to the full analytic sample of all women. The columns show the size of the reduction in time served.

As noted above, the groupings are based on model-estimated changes in arrests under each scenario, not observed arrest counts or formal risk classifications. Because they are cumulative, the lowest 50% includes the lowest 25% plus the next quarter of women based on projected public safety impact; the lowest 75% includes the bottom three-quarters, and the lowest 90% includes nearly the full sample except the highest 10%.

As expected, larger reductions in time served and broader application across the sample produce larger estimated increases in arrests. The tables report projected additional arrests over the full three-year follow-up period. To provide statewide context, the tables also show the annualized projected increase as a share of total arrests reported statewide. This percentage is calculated by dividing the three-year projected increase by three and comparing that annualized value with the total number of arrests reported in the state. This makes it possible to assess the projected increase relative to each state's overall volume of arrest activity.

Illinois

Table S2 presents the simulated public safety effects of reducing time served for women in the Illinois analytic sample. The cohort's average observed time served was 1.18 years.

For a typical annual release cohort of 1,605 women (based on 6,419 releases over four years), the model estimates 4,557 total expected arrests over a three-year follow-up period (or 1,519 arrests per year across the cohort). These projected totals account for incapacitation, deterrence, and criminogenic effects. The simulated arrest counts presented below represent additional arrests relative to this baseline.

Table S2. Simulated Public Safety Effects of Reducing Time Served for Women in Illinois

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Simulated Increase in Arrests Over 3 Years	Targeting the lowest 25% of the distribution	0	1	4	7
	Targeting the lowest 50% of the distribution	7	18	28	48
	Targeting the lowest 75% of the distribution	24	50	76	132
	Targeting the lowest 90% of the distribution	39	81	124	215
	All women	57	117	179	315
Simulated Increased Arrests as a Share of Annual Female Arrests	Targeting the lowest 25% of the distribution	< 0.001%	0.001%	0.004%	0.007%
	Targeting the lowest 50% of the distribution	0.007%	0.017%	0.027%	0.047%
	Targeting the lowest 75% of the distribution	0.023%	0.048%	0.074%	0.128%
	Targeting the lowest 90% of the distribution	0.038%	0.078%	0.120%	0.208%
	All women	0.055%	0.113%	0.174%	0.305%

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Across all modeled scenarios, estimated increases in arrests remain modest. For example, reducing time served by 20% for the lowest 50% of women based on prior arrest history is estimated to result in 18 additional arrests over the three-year follow-up period.

The largest simulated increase occurs when time served is reduced by 50% for all women in the Illinois sample. Under that scenario, the model estimates 315 additional arrests over three years, or approximately 105 additional arrests per year. Compared with the 130,943 arrests of women reported statewide in Illinois in 2022, this represents an increase of approximately 0.31% of annual female arrests—or less than one-third of one percent.

Under the scenarios, average time served in Illinois declines from 1.18 years to 1.06 years with a 10% reduction, to 0.94 years with a 20% reduction, to 0.82 years with a 30% reduction, and to 0.59 years with a 50% reduction.

North Carolina

Table S3 presents the same simulations for women in the North Carolina analytic sample. The cohort's average observed time served was 1.42 years.

As in Illinois, larger reductions in time served and application of the reduction to more women produce larger estimated increases in arrests. The magnitude of that effect, however, is small relative to statewide arrest activity.

For a typical annual release cohort of 1,388 women (based on 5,552 releases over four years), the model estimates 3,379 total expected arrests over a three-year follow-up period (or 1,126 arrests per year across the cohort). These projected totals account for incapacitation, deterrence, and criminogenic effects. The simulated arrest counts presented below represent additional arrests relative to this baseline.

Table S3. Simulated Public Safety Effects of Reducing Time Served for Women in North Carolina

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Simulated Increase in Arrests Over 3 Years	Targeting the lowest 25% of the distribution	0	2	6	10
	Targeting the lowest 50% of the distribution	5	15	23	41
	Targeting the lowest 75% of the distribution	18	39	59	102
	Targeting the lowest 90% of the distribution	32	65	99	171
	All women	53	107	164	287
Simulated Increased Arrests as a Share of Annual Female Arrests	Targeting the lowest 25% of the distribution	< 0.001%	0.001%	0.003%	0.005%
	Targeting the lowest 50% of the distribution	0.002%	0.008%	0.012%	0.021%
	Targeting the lowest 75% of the distribution	0.009%	0.020%	0.030%	0.051%
	Targeting the lowest 90% of the distribution	0.016%	0.033%	0.050%	0.086%
	All women	0.027%	0.054%	0.083%	0.145%

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Under the largest scenario—a 50% reduction in time served applied to all women—the model estimates 287 additional arrests over three years, or approximately 96 additional arrests per year. Compared with the 65,602 arrests of women reported statewide in North Carolina in 2022, this represents an increase of approximately 0.15% of annual female arrests.

The percentage increase is slightly larger in North Carolina than in Illinois because total statewide arrest volumes are lower, even though the estimated number of additional arrests is somewhat smaller.

Under the scenarios, average time served in North Carolina declines from 1.42 years to 1.28 years with a 10% reduction, to 1.14 years with a 20% reduction, to 0.99 years with a 30% reduction, and to 0.71 years with a 50% reduction.

Prison Population Estimates

The same simulated reductions in time served are also used to estimate changes in the states' average daily prison population (ADP). These estimates reflect changes in the total amount of time served across the system, not fluctuations in the number of people released.

In practical terms, reducing time served lowers the average prison population because it means many people spend less time in prison. For example, if multiple people each serve several months less than they otherwise would have, the cumulative reduction in prison time translates into a lower average population over time.

The prison population estimates are calculated by comparing the average population under observed time served with the average population under each simulated reduction. Because the simulations reduce time served, all scenarios result in lower estimated average prison populations.

Rows in Tables S4 and S5 show the cumulative groups to whom the reduction is applied. Columns show the size of the reduction in time served. As with the public safety estimates, larger reductions and broader application produce larger changes.

Illinois

Table S4 presents estimated reductions in the average prison population for the Illinois analytic sample.

Under observed time served, the estimated ADP for the Illinois release cohort is 1,851 women, closely aligned with the average year-end female prison population of 1,847 reported by NCRP for 2018–2021.

Reducing time served by 50% for all women in the cohort is estimated to reduce the average population by 925 women. Because this scenario cuts time served in half for the full cohort, the estimated population also declines by roughly half.

More targeted scenarios produce smaller population reductions because they apply to fewer women. For example, reducing time served by 30% for the lowest 75% of women based on prior arrest history is estimated to reduce the ADP by 159 women, or about 9% of the observed average population.

These estimates reflect changes in total time served across the cohort, rather than a one-to-one reduction in the number of people in custody. Because people serve varying lengths of time, reductions in time served do not translate directly into equivalent reductions in the population at a single point in time.

The table also illustrates how different combinations of scale and targeting can produce similar population effects. Larger reductions applied to smaller groups, for example, may yield population changes comparable to smaller reductions applied more broadly.

Table S4. Simulated Effects of Reducing Time Served on the Average Prison Population in Illinois

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Simulated Reductions in Average Daily Population (ADP)	Targeting the lowest 25% of the distribution	9	16	25	35
	Targeting the lowest 50% of the distribution	41	65	95	152
	Targeting the lowest 75% of the distribution	83	159	231	373
	Targeting the lowest 90% of the distribution	129	248	367	597
	All women	185	370	555	925

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North Carolina

Table S5 presents the same estimates for the North Carolina analytic sample.

Under observed time served, the estimated ADP for the North Carolina cohort is 1,967 women, slightly lower than the average year-end female prison population of 2,395 reported by NCRP for 2018–2021.

As in Illinois, larger reductions in time served and broader application across the sample produce larger decreases in the ADP. Because average time served is somewhat longer in North Carolina, reductions in time served can produce substantial population effects even when applied to more targeted groups.

These estimates should be interpreted in the same way as the Illinois results: They reflect changes in total time served across the cohort, not a one-to-one reduction in the number of women in custody. Because time served varies across individuals, population reductions are distributed over time rather than occurring as a single, proportional decrease.

The results also demonstrate that different combinations of scale and targeting can produce similar population effects, depending on how reductions are applied across the cohort.

Table S5. Simulated Effects of Reducing Time Served on the Average Prison Population in North Carolina

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Simulated Reductions in Average Daily Population (ADP)	Targeting the lowest 25% of the distribution	9	22	31	45
	Targeting the lowest 50% of the distribution	42	64	91	142
	Targeting the lowest 75% of the distribution	87	158	226	361
	Targeting the lowest 90% of the distribution	130	253	376	613
	All women	197	393	590	984

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Estimating Cost Impacts

Reducing time served affects costs in two directions.

First, when women leave prison earlier, some additional arrests are projected to occur. Those arrests create new costs for the criminal justice system, including those related to law enforcement response, investigation, arrest, court processing, and supervision. Some arrests also create costs for victims, particularly when the underlying offense involves violence or property loss.

Second, reducing time served lowers incarceration costs by reducing the total amount of time women spend in prison. Those cost reductions reflect lower average prison populations and fewer prison days. Reducing time served may also cut other costs associated with incarceration, including health care, staffing, and facility-related expenses.

The analysis estimates both sides of this ledger: additional costs associated with projected crime and arrests, and reductions in incarceration costs associated with lower average prison populations.

The cost estimates should be interpreted as modeled estimates rather than realized budget effects. In practice, correctional costs are not strictly linear. Some costs change only when population reductions reach thresholds such as the closure of a housing unit, reductions in staffing posts, or closure of an entire facility. The estimates below therefore reflect the expected value of reduced prison time and projected arrest-related costs, rather than immediate budget savings.

Costs Associated with Additional Arrests

Projected additional arrests generate costs for the criminal justice system and, for some offenses, costs to victims. To estimate these amounts, the analysis converts projected arrests into estimated crime and victimization costs by offense category.

The process uses five inputs: offense category allocation, clearance adjustments, reporting adjustments, law enforcement costs, and victimization costs. Table S6 summarizes the parameters used in these calculations. Charge allocations and clearance rates are state specific; reporting rates, law enforcement costs, and victimization costs are based on national estimates. As a result, the final cost multiplier varies by state because the projected arrests differ in offense mix and clearance rates. Detailed derivations are provided below in Appendix A.

First, projected arrests are allocated across four offense categories: violent, property, drug, and other. These allocations are based on the observed distribution of post-release arrests in each state's analytic sample, so they reflect the offense mix among women included in the analysis, rather than a national distribution. In Illinois, a randomly selected post-release arrest had an 11.8% chance of being violent, 27.1% chance of being property-related, 19.5% chance of being drug-related, and 41.6% chance of falling into the other category. In North Carolina, the corresponding probabilities were 9.0%, 27.0%, 31.5%, and 32.5%. These percentages are used to allocate projected additional arrests into offense categories. For example, if a scenario produces 100 additional arrests in Illinois, the observed distribution for that state means that about 12 would be allocated to violent offenses, 27 to property offenses, 20 to drug offenses, and 42 to other offenses.

Second, each offense-category-specific arrest is adjusted using clearance rates. Clearance rates are applied inversely to estimate the number of reported crimes implied by each arrest. This step captures reported crimes that generate investigative costs and, for violent and property offenses, potential victimization costs, even when those crimes do not result in an arrest. For example, if the clearance rate for an offense category is 50%, then 100 arrests imply approximately 200 reported crimes, since 50% of those reported crimes would be expected to result in an arrest. Offense- and jurisdiction-specific clearance rates were obtained from state sources, where available. Illinois 2024 clearance rates were obtained from the Illinois State Police and North Carolina 2024 clearance rates were obtained from the North Carolina State Bureau of Investigation.[12]

Third, reported crimes are adjusted using victimization reporting rates from the National Crime Victimization Survey.[13] Reported crimes do not capture all victimizations because not all victimizations are reported to law enforcement. Reporting rates are therefore used to estimate victimization costs from unreported crimes. Because unreported crimes do not come to the attention of law enforcement, they do not generate criminal justice system costs for investigation, arrest, or prosecution in this analysis. Violent and property reporting rates are available directly. Placeholder values are used for drug and other categories, but these do not affect victimization cost estimates because those offense categories are assigned $0 for such costs. Victimization reporting is assumed to be the same across both states.

Fourth, each projected arrest is assigned a law enforcement cost. These costs reflect response, investigation, and arrest-related expenses and vary by offense category. Violent arrests are assigned higher costs because they generally involve more intensive response and investigation. Property arrests are assigned lower costs, and drug and

[12] Illinois State Police. (2026). *Crime in Illinois online-Group A offense report.* https://ilucr.nibrs.com/Report/GroupACrimeReport; North Carolina State Bureau of Investigation. (2026). *Summary-based reporting: Index offenses and clearances, 2024*. https://www.ncsbi.gov/SSRV?report=/UCR/IndexOffensesAndClearances

[13] Tapp, S.N., & Coen, E.J. (2025). *Criminal victimization, 2024* (NCJ 310547). Bureau of Justice Statistics. https://bjs.ojp.gov/document/cv24.pdf

other arrests use the property-crime arrest cost as a proxy. Law enforcement costs per arrest are assumed to be the same across both states.

Fifth, victimization costs are applied by offense category. Victimization costs are assigned to violent and property offenses. Drug and other offenses are not assigned victimization costs, but they are not treated as cost-neutral because each arrest still carries law enforcement costs.

The result is a state-specific expected cost for each additional arrest that is projected. This does not treat every arrest as if it were simultaneously violent, property, drug, and other. Rather, projected arrests are first distributed across offense categories, and category-specific costs are then weighted by each category's share of arrests. For example, in Illinois, the violent offense cost assumptions apply only to the estimated share of additional arrests that are for violent crimes, while assumptions for property, drug, and other offenses apply to their respective shares.

These components are combined into a charge-specific multiplier using the following equation:

$$M_c = V_c * \frac{a_c}{l_c * r_c} + J_c * a_c$$

where V_c is the victimization cost per crime for charge category c, J_c is the justice system cost per arrest for charge category c, a_c is the arrest allocation percentage for charge category c, l_c is the clearance rate for charge category c, r_c is the reporting rate for crime category c, and M_c is the multiplier for charge category c.

The first term captures victimization costs implied by each projected arrest, adjusted for clearance and reporting rates. The second term captures law enforcement costs directly associated with each projected arrest. The multipliers for all charge categories are then summed to produce a single state-specific dollar estimate for the cost associated with each projected additional arrest.

Table S6. Parameters Used to Convert Projected Arrests Into Estimated Costs

		Illinois	North Carolina
Charge Allocations	Violent	11.8%	9.0%
	Property	27.1%	27.0%
	Drug	19.5%	31.5%
	Other	41.6%	32.5%
Clearance Rates	Violent	29.0%	26.3%
	Property	11.2%	12.9%
	Drug	75.5%	75.0%
	Other	52.7%	50.0%
Reporting Rates	Violent	47.9%	47.9%
	Property	30.5%	30.5%
	Drug	25.0%	25.0%
	Other	25.0%	25.0%
Law Enforcement Costs Per Arrest	Violent	$8,580	$8,580
	Property	$643	$643
	Drug	$643	$643
	Other	$643	$643
Victimization Costs Per Crime	Violent	$64,286	$64,286
	Property	$3,961	$3,961
	Drug	$0	$0
	Other	$0	$0
Charge-Specific Multiplier Per Arrest	Violent	$55,493	$46,659
	Property	$31,472	$27,385
	Drug	$126	$203
	Other	$268	$209
Final Multiplier Per Arrest		$87,357	$74,455

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The final state-specific cost multipliers shown in Table S6 are applied to the annualized number of projected additional arrests under each simulated time-served reduction scenario. This produces an annual estimate of the additional law enforcement and victimization costs associated with each scenario.

Tables S7 and S8 present these estimates for Illinois and North Carolina, respectively. For each scenario, the projected number of additional arrests over the three-year follow-up period is divided by three to produce an annualized estimate, which is then multiplied by the relevant state-specific cost multiplier.

Illinois

For example, in Illinois, the public safety simulations estimate 315 additional arrests over three years under the scenario reducing time served by 50% for all women in the analytic sample. Annualized, this equals 105 additional arrests per year. Applying the Illinois cost multiplier of $87,357 produces an estimated annual cost of about $9.17 million in additional law enforcement and victimization costs.

Table S7. Simulated Annual Costs Associated With Projected Additional Arrests Among Women Released From Prison in Illinois

	Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	$0	$30,844	$106,944	$217,432
Targeting the lowest 50% of the distribution	$196,416	$513,594	$808,572	$1,410,550
Targeting the lowest 75% of the distribution	$685,741	$1,447,156	$2,225,002	$3,838,394
Targeting the lowest 90% of the distribution	$1,144	$2,358,182	$3,612,372	$6,266,718
All women	$1,658,139	$3,394,928	$5,224,197	$9,167,967

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North Carolina

Table S8 applies the same calculation to the North Carolina simulations. Estimates differ across states because the projected number of additional arrests, post-release arrest offense distribution, and clearance rates differ across the Illinois and North Carolina samples. Reporting rates, victimization costs, and law enforcement cost assumptions are held constant across states.

Applying the North Carolina cost multiplier of $74,455 to the estimated 96 additional arrests per year under the 50% time-served reduction scenario produces an estimated annual cost of about $7.12 million in additional law enforcement and victimization costs.

Table S8. Simulated Annual Costs Associated With Projected Additional Arrests Among Women Released From Prison in North Carolina

	Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	$0	$52,212	$138,155	$250,855
Targeting the lowest 50% of the distribution	$114,238	$379,789	$582,051	$1,014,727
Targeting the lowest 75% of the distribution	$455,639	$962,890	$1,466,736	$2,523,908
Targeting the lowest 90% of the distribution	$795,203	$1,611,450	$2,454,765	$4,246,840
All women	$1,313,889	$2,660,109	$4,072,858	$7,124,560

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Correctional Cost Reductions From Lowering the Average Daily Population

The prior section estimated the additional expenses associated with projected increases in arrests, including law enforcement costs and costs borne by victims. This section estimates a separate cost effect: the correctional cost reductions associated with prison population drops caused by women spending less time in prison.

To estimate these correctional cost reductions, the analysis applies per-woman cost estimates for incarceration and community supervision to the projected reductions in

ADP. The annual cost of incarcerating women is estimated to range from $87,305 to $122,227, based on figures developed in a prior Council on Criminal Justice analysis.[14]

Reductions in prison ADP do not eliminate system costs entirely, as people released earlier are assumed to be supervised in the community. The annual cost of community supervision is estimated at $10,609 per person, based on the same Council on Criminal Justice analysis referenced above. As a result, each one-person reduction in prison ADP, paired with a corresponding increase in community supervision, yields a net savings of $76,696 to $111,618 per person per year.

These per-woman correctional cost reductions are applied to the simulated reductions in ADP to estimate annual correctional cost reductions under each scenario. The estimates reflect reduced prison costs offset by increased community supervision costs. They do not subtract the arrest- and victimization-related costs shown in Tables S7 and S8.

Illinois

For example, under the scenario reducing time served by 50% for all women in Illinois, the model estimates a reduction in prison ADP of 925 women. After accounting for the added cost of community supervision for women released earlier, this ADP reduction translates into an estimated correctional cost reduction of about $71.0 million to $103.3 million (Table 9).

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[14] Roman, J. K., Bhati, A. S., & Kennedy, S. (2026). *The rising cost of women's justice system involvement: Projected growth in system size and costs through 2035*. Council on Criminal Justice. https://counciloncj.org/the-rising-cost-of-womens-justice-system-involvement/

Table S9. Estimated Annual Correctional Cost Reductions Under Time-Served Scenarios, Illinois

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	Lower bound	$680,840	$1,248,160	$1,923,064	$2,714,251
	Upper bound	$990,847	$1,816,485	$2,798,693	$3,950,132
Targeting the lowest 50% of the distribution	Lower bound	$3,176,761	$4,955,206	$7,322,271	$11,635,679
	Upper bound	$4,623,236	$7,211,461	$10,656,321	$16,933,754
Targeting the lowest 75% of the distribution	Lower bound	$6,351,288	$12,164,337	$17,703,072	$28,622,648
	Upper bound	$9,243,221	$17,703,127	$25,763,815	$41,655,402
Targeting the lowest 90% of the distribution	Lower bound	$9,904,013	$19,013,209	$28,124,852	$45,800,567
	Upper bound	$14,413,608	$27,670,497	$40,930,945	$66,654,946
All women	Lower bound	$14,193,676	$28,387,360	$42,581,036	$70,968,395
	Upper bound	$20,656,485	$41,312,980	$61,969,465	$103,282,446

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North Carolina

A similar calculation is applied to the North Carolina scenarios. Under a 50% reduction in time served for all women, the model estimates a reduction in prison ADP of 984 women. After accounting for the added cost of community supervision for women released earlier, this ADP reduction translates into an estimated correctional cost reduction of $75.4 million to $109.8 million (Table S10).

Table S10. Estimated Annual Correctional Cost Reductions Under Time-Served Scenarios, North Carolina

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	Lower bound	$713,010	$1,676,618	$2,371,406	$3,422,167
	Upper bound	$1,037,665	$2,440,032	$3,451,178	$4,980,382
Targeting the lowest 50% of the distribution	Lower bound	$3,229,711	$4,912,390	$6,994,867	$10,887,187
	Upper bound	$4,700,296	$7,149,149	$10,179,841	$15,844,452
Targeting the lowest 75% of the distribution	Lower bound	$6,634,657	$12,143,023	$17,356,160	$27,708,124
	Upper bound	$9,655,616	$17,672,108	$25,258,944	$40,324,469
Targeting the lowest 90% of the distribution	Lower bound	$9,987,381	$19,435,743	$28,803,788	$47,019,926
	Upper bound	$14,534,937	$28,285,423	$41,919,022	$68,429,517
All women	Lower bound	$15,088,243	$30,176,486	$45,264,737	$75,441,216
	Upper bound	$21,958,375	$43,916,751	$65,875,137	$109,791,877

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Net Cost Changes

The preceding tables estimate two parts of the cost equation separately. Tables S7 and S8 estimate the added expenses associated with projected increases in arrests, including law enforcement and victimization costs. Tables S9 and S10 estimate correctional cost reductions from lower prison ADP, accounting for the fact that women released earlier are assumed to be supervised in the community.

Tables S11 and S12 combine these two estimates to show the net annual cost change under each time-served reduction scenario. In each scenario, the estimated arrest- and victimization-related costs are subtracted from the estimated correctional cost reductions.

Because correctional cost reductions are estimated using lower- and upper-bound per-person incarceration costs, the net estimates are also presented as a range. The lower bound reflects the more conservative incarceration cost estimate, while the upper bound reflects the higher incarceration cost estimate.

Illinois

For example, under a 50% reduction in time served applied to all women in Illinois, the model estimates a range of $71.0 million to $103.3 million in annual correctional cost reductions and $9.2 million in added arrest- and victimization-related costs. After subtracting the added costs, the estimated net annual cost change is $61.8 million to $94.1 million.

Table S11. Estimated Net Annual Cost Changes Under Time-Served Scenarios, Illinois

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	Lower bound	$680,840	$1,217,315	$1,816,120	$2,496,819
	Upper bound	$990,847	$1,785,640	$2,691,749	$3,732,700
Targeting the lowest 50% of the distribution	Lower bound	$2,980,344	$4,441,612	$6,513,698	$10,225,129
	Upper bound	$4,426,819	$6,697,867	$9,847,749	$15,523,204
Targeting the lowest 75% of the distribution	Lower bound	$5,665,547	$10,717,181	$15,478,070	$24,784,253
	Upper bound	$8,557,480	$16,255,971	$23,538,812	$37,817,008
Targeting the lowest 90% of the distribution	Lower bound	$8,759,906	$20,658,913	$24,512,480	$39,533,849
	Upper bound	$13,269,502	$25,312,314	$37,318,573	$60,388,228
All women	Lower bound	$12,535,537	$24,992,431	$37,356,839	$61,800,428
	Upper bound	$18,998,346	$37,918,052	$56,745,268	$94,114,478

North Carolina

In North Carolina, under a 50% reduction in time served applied to all women in North Carolina, the model estimates a range of $75.4 million to $109.8 million in annual correctional cost reductions and $7.1 million in added arrest- and victimization-related costs. After subtracting the added costs, the estimated net annual cost change is $68.3 million to $102.7 million.

Table S12. Estimated Net Annual Cost Changes Under Time-Served Scenarios, North Carolina

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	Lower bound	$713,010	$1,624,405	$2,233,251	$3,171,312
	Upper bound	$1,037,665	$2,387,820	$3,313,023	$4,729,528
Targeting the lowest 50% of the distribution	Lower bound	$3,115,473	$4,532,600	$6,412,816	$9,872,460
	Upper bound	$4,586,058	$6,769,360	$9,597,790	$14,829,724
Targeting the lowest 75% of the distribution	Lower bound	$6,179,018	$11,180,133	$15,889,424	$25,184,216
	Upper bound	$9,199,978	$16,709,218	$23,792,208	$37,800,560
Targeting the lowest 90% of the distribution	Lower bound	$9,192,179	$17,824,293	$26,349,023	$41,824,924
	Upper bound	$13,739,735	$26,673,973	$39,464,256	$64,182,676
All women	Lower bound	$13,774,354	$27,516,377	$41,191,879	$68,316,657
	Upper bound	$20,644,487	$41,256,642	$61,802,279	$102,667,317

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Benefit-Cost Ratios

Tables S13 and S14 present benefit-cost ratios for each time-served reduction scenario. These ratios compare the estimated correctional cost reductions from lower prison ADP with the estimated arrest- and victimization-related costs associated with projected additional arrests.

The ratios are calculated by dividing the correctional cost reductions shown in Tables S9 and S10 by the arrest- and victimization-related costs shown in Tables S7 and S8. The net cost change tables above show the difference between these two values; the benefit-cost ratios show their relative size.

For Illinois, Table S13 divides the annual correctional cost reduction estimates in Table S9 by the annual arrest- and victimization-related cost estimates in Table S7. For North Carolina, Table S14 divides the estimates in Table S10 by the estimates in Table S8. Because correctional cost reductions are presented as lower and upper bounds, the benefit-cost ratios are also presented as ranges.

Benefit-cost ratios are generally higher for scenarios involving smaller reductions in time served or reductions applied to groups with lower projected public safety impacts. These higher ratios should be interpreted alongside the size of the corresponding population reduction. A higher ratio may reflect a relatively small change in system size or a group that would be difficult to identify prospectively in practice.

Across scenarios, benefit-cost ratios are generally higher in North Carolina than in Illinois. This reflects differences in projected additional arrests, offense-category distributions, clearance rates, and prison population reductions.

Illinois

For example, in Illinois, reducing time served by 50% for all women is associated with an estimated annual arrest- and victimization-related cost of about $9.2 million (Table S7) and an estimated annual correctional cost reduction of $71.0 million to $103.3 million (Table S9). This yields a benefit-cost ratio of 7.7 to 11.3 (Table S13). In other words, estimated correctional cost reductions are about 8 to 11 times larger than the estimated costs associated with additional arrests and victimization.

Table S13. Estimated Benefit-Cost Ratios for Time-Served Reduction Scenarios, Illinois

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	Lower bound		40.5	18.0	12.5
	Upper bound		58.9	26.2	18.2
Targeting the lowest 50% of the distribution	Lower bound	16.2	9.6	9.1	8.2
	Upper bound	23.5	14.0	13.2	12.0
Targeting the lowest 75% of the distribution	Lower bound	9.3	8.4	8.0	7.5
	Upper bound	13.5	12.2	11.6	10.9
Targeting the lowest 90% of the distribution	Lower bound	8.7	8.1	7.8	7.3
	Upper bound	12.6	11.7	11.3	10.6
All women	Lower bound	8.6	8.4	8.2	7.7
	Upper bound	12.5	12.2	11.9	11.3

Note: Ratios are not calculated for scenarios with no estimated additional arrest- or victimization-related costs because the denominator is zero.

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North Carolina

In North Carolina, reducing time served by 50% for all women is associated with an estimated annual arrest- and victimization-related cost of about $7.1 million (Table S8) and an estimated annual correctional cost reduction of $75.5 million to $109.8 million (Table S10). This yields a benefit-cost ratio of 10.6 to 15.4 (Table S14), meaning that estimated correctional cost reductions are about 11 to 15 times larger than estimated arrest- and victimization-related costs.

Table S14. Estimated Benefit-Cost Ratios for Time-Served Reduction Scenarios, North Carolina

		Reduce Time Served by 10%	Reduce Time Served by 20%	Reduce Time Served by 30%	Reduce Time Served by 50%
Targeting the lowest 25% of the distribution	Lower bound		32.1	17.2	13.6
	Upper bound		46.7	25.0	19.9
Targeting the lowest 50% of the distribution	Lower bound	28.3	12.9	12.0	10.7
	Upper bound	41.1	18.8	17.5	15.6
Targeting the lowest 75% of the distribution	Lower bound	14.6	12.6	11.8	11.0
	Upper bound	21.2	18.4	17.2	16.0
Targeting the lowest 90% of the distribution	Lower bound	12.6	12.1	11.7	11.1
	Upper bound	18.3	17.6	17.1	16.1
All women	Lower bound	11.5	11.3	11.1	10.6
	Upper bound	16.7	16.5	16.2	15.4

Note: Ratios are not calculated for scenarios with no estimated additional arrest- or victimization-related costs because the denominator is zero.

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Limitations

This analysis has several important limitations.

First, it relies heavily on administrative data systems and is therefore subject to the limitations inherent in those data. In particular, while the analysis seeks to model offending trajectories, the available data reflect arrest histories rather than underlying behavior. Arrests are an imperfect proxy for offending: they typically undercount actual behavior and are shaped not only by individual actions, but also by law enforcement practices and decision-making. As a result, historical arrest data may reflect systemic biases. As with the use of historical arrest data in risk assessment tools, caution is warranted if model outputs are used to target individuals or groups for policy changes.

Second, data limitations affect the precision of key model inputs. For example, jail credit is not fully or consistently captured in the available data. This may lead to underestimates of time served, which in turn could bias estimates of the number of people serving longer prison terms, as well as associated public safety effects and ADP calculations.

Third, the analytical framework is limited in its ability to model charge-specific trajectories. While this does not substantially affect estimates of overall system impacts, it limits the ability to examine how effects may vary across offense types. As a result, the analysis relies on approximate allocation methods when presenting charge-level distributions.

Fourth, the scope of the CHAP model is constrained by available data elements. For example, criminal history data often do not include complete information on case outcomes, such as adjudication or sentencing following arrest. Access to more detailed case processing data could improve the precision and explanatory power of the model.

Finally, as with all simulation-based analyses, results are based on historical data and assumptions about how past patterns will persist. If underlying conditions change, the accuracy of projections may be affected. This is particularly relevant given that the study period overlaps with the COVID-19 pandemic, which disrupted criminal justice system operations and may have altered underlying patterns in ways not fully captured in the data.

Appendix A. Cost Assumptions for Additional Arrests and Victimization

This appendix describes the cost assumptions used to estimate the costs associated with projected additional arrests under simulated reductions in time served. Because the simulation model estimates additional arrests, the cost analysis begins by assigning criminal justice system costs to each projected arrest. The analysis then estimates additional victimization costs for violent and property offenses, using clearance and reporting rates to translate arrests into reported crimes and victimizations. These values are presented together in Table S6 above.

Costs are estimated by offense category: violent, property, drug, and other. All projected arrests are assigned law enforcement costs. Violent and property offenses are also assigned victimization costs. Drug and other offenses are not assigned victimization costs in this analysis; however, they are not treated as cost-neutral because they still generate criminal justice system costs.

A.1 Law Enforcement Cost Assumptions

Projected additional arrests generate criminal justice system costs, including those related to law enforcement response, investigation, and arrests. These costs vary by offense type because some crimes require more intensive response and investigation than others.

The law enforcement cost assumptions are based primarily on estimates from Hunt, Saunders, and Kilmer (2019),[15] which estimate law enforcement costs by crime type for benefit-cost analysis. Costs were inflated to 2025 dollars. Where offense-specific estimates were unavailable, the analysis used the closest available proxy.

Table A1 presents the offense-specific law enforcement cost inputs used to construct the broader cost categories applied in the simulation analysis. Violent offenses generally

[15] Hunt, P. E., Saunders, J., & Kilmer, B. (2019). Estimates of law enforcement costs by crime type for benefit-cost analyses. *Journal of Benefit-Cost Analysis*, *10*(1), 95-123. https://www.cambridge.org/core/journals/journal-of-benefit-cost-analysis/article/abs/estimates-of-law-enforcement-costs-by-crime-type-for-benefitcost-analyses/0A1A55F70324FDBAA947FF1F18AA1B74

carry higher law enforcement costs because they often require more intensive investigation. For example, aggravated assault and sexual assault are assigned costs of $15,426 per arrest, while murder/non-negligent manslaughter is assigned $14,500 and robbery is assigned $4,115. Property crimes generally carry much lower costs, ranging from $151 for larceny/theft to $2,202 for burglary.

Table A1. Offense-Specific Law Enforcement Cost Inputs

Offense	Cost estimate
Murder/Non-Negligent Manslaughter	$14,500
Rape	$15,426
Robbery	$4,115
Aggravated Assault	$15,426
Simple assault	$5,189
Larceny/Theft	$151
Burglary	$2,202
Motor Vehicle Theft	$1,435

Notes: Costs are presented in 2025 dollars. These offense-specific estimates were combined using offense-composition weights to produce the broader violent and property law enforcement cost estimates used in the simulation analysis.

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Because the simulation analysis reports arrests in four broad categories—violent, property, drug, and other—the offense-specific inputs in Table A1 were combined into category-level estimates. The violent category estimate reflects the weighted cost of violent offenses, including assault, sexual assault, robbery, and murder/non-negligent manslaughter. The property category estimate reflects the weighted cost of burglary, larceny/theft, and motor vehicle theft.

No separate estimates were identified for drug and public order arrests. The available literature suggests that many drug and public order arrests are police-initiated or occur at or near the offense event, making them more similar to lower-cost property arrests than to more investigation-intensive violent arrests. For this reason, the property-crime arrest cost is used as a proxy for drug and other arrests.

Table A2 presents the final law enforcement cost assumptions used in the simulation analysis. These values are applied to projected additional arrests by offense category.

Table A2. Final Law Enforcement Cost Assumptions Used in the Simulation Analysis

Offense Category	Law Enforcement Cost per Arrest
Violent	$8,580
Property	$643
Drug	$643
Other	$643

Notes: Costs are presented in 2025 dollars. Drug and other arrests use the property-crime arrest cost as a proxy because separate estimates were not identified.

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A.2 Victimization Cost Assumptions

In addition to law enforcement costs, the analysis assigns victimization costs to violent and property offenses. These estimates are drawn from the harm-to-victims literature and reflect both direct and indirect costs associated with criminal victimization. The estimates rely on prior work that used jury award data and victim loss data from national victimization sources, including Roman's estimates of the cost of criminal victimization and data from the National Crime Victimization Survey. These estimates are developed from jury awards[16] and losses reported by victims to the U.S. Department of Justice in the annual national victimization survey.[17] All values are reprinted with permission.

Victimization costs are assigned only to violent and property offenses. Drug and other offenses are not assigned victimization costs in this analysis. If an offense in these categories involved direct harm to a person or property, it would generally be classified as a violent or property offense. However, drug and other offenses are not treated as cost-neutral because they are still assigned law enforcement costs.

Table A3 presents victimization cost estimates for serious violent crimes. These estimates include direct and indirect costs for murder/non-negligent manslaughter, rape, robbery, and assault. The mean values shown in Table A3 are used to construct the broader violent-offense victimization cost estimate applied in the simulation analysis.

[16] Roman, J. K. (2017). How do we measure the severity of crimes? New estimates of the cost of criminal victimization. In J. MacDonald (Ed.), *Measuring Crime and Criminality* (pp. 37-70). Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9780203785997-3/measure-severity-crimes-new-estimates-cost-criminal-victimization-john-roman

[17] Tapp, S.N., & Coen, E.J. (2025). *Criminal victimization, 2024* (NCJ 310547). Bureau of Justice Statistics. https://bjs.ojp.gov/document/cv24.pdf

Table A3. Price Estimates for Serious Violent Crimes

Crime Type	Mean	Median	Standard Deviation
Murder/Non-Negligent Manslaughter	$1,445,463	$1,380,246	$771,395
Rape	$149,542	$23,143	$355,583
Robbery	$279,085	$88,915	$452,485
Assault	$134,770	$66,644	$212,510

Notes: Costs are presented in 2025 dollars. Victimization cost estimates are based on crime-specific estimates derived from individual-level jury award and injury data from the RAND Institute for Civil Justice, along with offense information from 2000 NIBRS data.. Source: Roman, 2017.

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Table A4 presents victimization cost estimates for serious property crimes, including arson, burglary, motor vehicle theft, forgery, fraud-related offenses, and related categories. These values provide the detailed offense-level inputs used to construct the broader property crime victimization cost estimate.

Table A4. Price Estimates for Serious Property Crimes

Crime type	Mean	90%	75%	Median	25%	10%
Burglary/Breaking & Entering	$4,444	$5,279	$2,210	$782	$222	$12
Motor Vehicle Theft	$15,175	$39,100	$17,000	$6,800	$2,550	$41
Arson	$16,979	$3,621	$1,096	$850	$323	$170
Counterfeiting/Forgery	$8,208	$1,870	$459	$34	$0	$0
Swindle	$4,389	$7,990	$1,771	$170	$2	$0
Extortion/Blackmail	$3,498	$7,700	$1,700	$170	$0	$0
Credit Card Fraud	$973	$1,820	$617	$37	$0	$0
Impersonation	$955	$1,159	$5	$2	$0	$0

Notes: Costs are presented in 2025 dollars. Victimization cost estimates are based on crime-specific estimates derived from individual-level jury award and injury data from the RAND Institute for Civil Justice, along with offense information from 2000 NIBRS data.. Source: Roman, 2017.

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Table A5 presents estimates for property-loss-only crimes, plus indirect costs. These include theft-related offenses, fraud-related offenses, vandalism, embezzlement, and related categories. These estimates supplement the serious property crime estimates and inform the broader property offense victimization cost assumption used in the analysis.

Table A5. Estimates of Harms for Crimes With Property Losses Only, Plus Indirect Costs

Crime type	Mean	Median
Pocket-Picking	$408	$90
Purse-Snatching	$447	$72
Shoplifting	$459	$60
Theft from Building	$6,393	$165
Theft from Coin-Operated Machine	$532	$140
Theft of Motor Vehicle Parts	$408	$210
Theft from Motor Vehicle	$990	$100
All other Larceny	$2,048	$150
Welfare Fraud	$461	$47
Wire Fraud	$1,930	$275
Embezzlement	$9,781	$1,633
Stolen Property Offenses	$3,341	$500
Destruction/Vandalism	$759	$170

Notes: Costs are presented in 2025 dollars. Victimization cost estimates are based on crime-specific estimates derived from individual-level jury award and injury data from the RAND Institute for Civil Justice, along with offense information from 2000 NIBRS data..
Source: Roman, 2017.

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The detailed offense-level estimates in Tables A3 through A5 are used to construct broader victimization cost estimates for the violent and property offense categories used in the simulation analysis. The next section describes how these detailed costs are weighted by offense composition to produce the final category-level victimization cost assumptions.

A.3 Constructing Violent and Property Victimization Cost Estimates

The simulation analysis uses four broad offense categories: violent, property, drug, and other. Because the victimization cost estimates shown above are reported for more specific offense types, those estimates must be converted into category-level assumptions that align with the simulation outputs.

To construct the violent and property victimization cost estimates, offense-specific costs were weighted by the estimated composition of each broader offense category. The composition estimates were developed using FBI Uniform Crime Reports data. Annual counts were calculated using three-year moving averages for each underlying offense type, with more recent years weighted more heavily to better reflect current offense patterns.

For violent offenses, the category-level estimate was constructed using the estimated composition of assault, robbery, rape, and murder/non-negligent manslaughter. For property offenses, the category-level estimate was constructed using the estimated composition of larceny/theft, burglary, and motor vehicle theft.

Table A6 presents the offense composition weights used to construct the violent and property victimization cost estimates.

Table A6. Offense Composition Used to Estimate Violent and Property Victimization Costs

Category	Component Offense	Estimated Share
Violent	Murder/Non-Negligent Manslaughter	1.6%
Violent	Rape	8.6%
Violent	Robbery	31.3%
Violent	Assault	55.6%
Property	Larceny/Theft	72.1%
Property	Burglary	17.4%
Property	Motor Vehicle Theft	10.5%

Notes: Shares are used to construct weighted victimization cost estimates for the violent and property categories. Violent offense shares do not sum to 100% because weapons possession offenses are excluded from the victimization cost calculation.

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These composition weights were applied to the offense-specific cost estimates in Tables A3 through A5 to produce the final category-level victimization cost assumptions. The resulting estimates are $70,254 for violent offenses and $3,961 for property offenses, in 2025 dollars. Drug and other offenses are not assigned a victimization cost, but they remain assigned law enforcement costs as described above.

Table A7. Final Victimization Cost Assumptions Used in the Simulation Analysis

Offense category	2025 Victimization Cost Estimate	Basis
Violent	$70,254	Weighted estimate based on murder/non-negligent manslaughter, rape, robbery, and assault
Property	$3,961	Weighted estimate based on larceny/theft, burglary, and motor vehicle theft
Drug	$0	No victimization cost assigned
Other	$0	No victimization cost assigned

Notes: Costs are presented in 2025 dollars. Drug and other offenses are not assigned victimization costs but are assigned law enforcement costs.

A.4 Clearance and Reporting Adjustments

The simulation model estimates additional arrests. To estimate victimization costs, projected arrests must be translated into estimated reported crimes and victimizations. This requires two adjustments: clearance rates and reporting rates.

Clearance rates are used to estimate the number of reported crimes implied by each projected arrest. Because not every reported crime results in an arrest, each arrest implies a larger number of reported crimes. For example, if the clearance rate for an offense category is 50%, then 100 arrests imply approximately 200 reported crimes.

Clearance rates were applied by offense category. Illinois clearance rates for 2024 were obtained from the Illinois State Police.[18] North Carolina clearance rates for 2024 were obtained from the North Carolina State Bureau of Investigation.[19] Where category-specific rates were unavailable, placeholder values were used as described in the notes below. Because victimization costs are assigned only to violent and property offenses, placeholder rates for drug and other offenses do not affect victimization cost estimates.

Reporting rates are then used to estimate victimizations from reported crimes. Not all victimizations are reported to law enforcement, so reporting rates are used to account

[18] Illinois State Police. (2026). *Crime in Illinois online-Group A offense report.* https://ilucr.nibrs.com/Report/GroupACrimeReport
[19] North Carolina State Bureau of Investigation. (2026). *Summary-based reporting: Index offenses and clearances, 2024.* https://www.ncsbi.gov/SSRV?report=/UCR/IndexOffensesAndClearances

for unreported victimization. Reporting rates for violent and property offenses were drawn from the National Crime Victimization Survey.

Because drug and other offenses are not assigned victimization costs in this analysis, reporting rates for those categories do not affect victimization cost estimates.

Table A8. Clearance and Reporting Rate Assumptions Used to Estimate Victimization Costs

	State	Violent	Property	Drug	Other
Clearance Rates	Illinois	29.0%	11.2%	75.5%	52.7%
	North Carolina	26.3%	12.9%	75.0%	50.0%
Reporting Rates		47.9%	30.5%	25.0%	25.0%

Notes: Clearance rates are applied to convert projected arrests into estimated reported crimes. Reporting rates are applied to convert reported crimes into estimated victimizations. Sources: Clearance rates - Illinois State Police; North Carolina State Bureau of Investigation. Reporting rates - National Crime Victimization Survey.

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The clearance and reporting adjustments are used only in estimating victimization costs. Law enforcement costs are applied directly to projected arrests by offense category.

A.5 Final Cost Parameters Used in the Simulation

The final cost parameters combine offense allocation, law enforcement costs, victimization costs, clearance rates, and reporting rates (available in Table S6 above).

Projected arrests are first allocated across offense categories based on the observed distribution of post-release arrests in each state's analytic sample. This allocation reflects the offense mix among women in the Illinois and North Carolina release cohorts rather than a national offense distribution.

All projected arrests are assigned law enforcement costs by offense category. Violent arrests are assigned the highest law enforcement cost, while property, drug, and other arrests are assigned lower costs.

For violent and property offenses, projected arrests are also converted into estimated reported crimes and victimizations using clearance and reporting rates. Victimization costs are then applied to the estimated number of victimizations. Drug and other offenses are assigned law enforcement costs but no victimization costs.

These components are combined to estimate the annual cost associated with projected additional arrests under each time-served reduction scenario. Table S6 above summarizes the parameters used in these calculations; Tables S7 and S8 apply those parameters to the Illinois and North Carolina simulation results, respectively, producing annual estimates of arrest- and crime-related costs for each scenario.