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ORIGINAL PAPER

Estimating the Number of Crimes Averted by Incapacitation: An Information Theoretic Approach

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Abstract This paper presents an information theoretic approach for estimating the number of crimes averted by incapacitation. It first develops models of the criminal history accumulation process of a sample of prison releasees using their official recorded arrest histories prior to incarceration. The models yield individual offending trajectories that are then used to compute the number of crimes these releasees could reasonably have been expected to commit had they not been incarcerated—the counterfactual of interest. The models also afford the opportunity to conduct a limited set of policy simulations. The data reveal a fair amount of variation among individuals both in terms of the number of crimes averted by their incarceration and the responsiveness of these estimates to longer incarceration terms. Estimates were found not to vary substantially across demographic groups defined by offender race, gender, or ethnicity; variations across states and offense types were more pronounced. Implications of the findings and promising avenues for future research are discussed.

Keywords Incapacitation · Information theory · Individual offending trajectories

Introduction

With an abandoning of the rehabilitative ideal in the 1970's, incarceration has increasingly been justified as a means of removing individuals from society and incapacitating them,

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thereby preventing them from committing crimes they otherwise would have, had they been free to do so (Spelman 1994; Zimring and Hawkins 1995). Reliance on this strategy during the 1980's and 1990's resulted in a ballooning prison population with record number of offenders being incarcerated. The number of persons incarcerated in state or federal prisons grew from about 200,000 in 1973 to 1.4 million in 2003 (Pastore and Maguire 2005, p. 500). Before 1970, this number had remained fairly stable since the early 1930's (Blumstein and Cohen 1973).

Without a doubt, incapacitating criminals by imprisoning them does avert some crime (Spelman 2000). Knowing exactly how much crime is averted by incapacitation is, of course, impossible. Since incarcerated individuals cannot be in prison and in society at the same time, any claims about the number of crimes averted by incapacitation must, by definition, be based on counterfactual reasoning–reasoning that runs something like this: Had the individual not been incarcerated for z months, (s)he would have committed x number of crimes over that period. Different ways of estimating the incapacitation effect can, therefore, be seen as alternate ways of generating this counterfactual.

Despite the opposing views regarding incapacitation represented by Blumstein and Piquero (2007), on the one hand, and Miles and Ludwig (2007), on the other, scholars generally agree that there are several practical difficulties in generating this counterfactual, especially if one believes that for policy purposes a single estimate is inadequate. This paper aims to tackle this practical difficulty by generating the counterfactuals at the individual level. This is an important step forward that is needed to perform realistic policy simulations. The emphasis here is on linking the counterfactuals with important attributes like age and criminal history so that computations can take into account when in an offender's life and criminal career this incapacitation occurs. Such details offer clearer insights not only into the anticipated crime reduction benefits associated with various incarceration strategies but also the distribution of the estimated incapacitation effect across offenders.

Although incarceration can, and presumably does, have other effects on crime, for example through general and specific deterrence or deviance amplification, this paper addresses only the incapacitation effect. Applying the framework developed here for recovering the deterrence or criminogenic effects of incarceration at the individual level is possible; those extensions are currently being developed.

The paper begins with a brief review of the literature, with an eye toward motivating this work. That is followed by a non-technical overview of the analytical framework. After describing the data used in this study, the paper then presents the main findings with a discussion of their implications. It concludes with a discussion relating findings reported in this paper with those reported elsewhere in the literature, and enumerates some promising directions for future research.

Background and Motivation

As noted above, all attempts at computing the number of crimes averted by incapacitation are really attempts at generating plausible counterfactuals. Early attempts at generating this counterfactual relied on the mathematical model developed in Avi-Itzhak and Shinnar (1973) and Shinnar and Shinnar (1975). This model combines estimates of the annual offending rate (popularly denoted λ), the probabilities of arrest, conviction, and incarceration (given crime commission), and the expected incarceration term (conditional on being incarcerated). Combination of these quantities with estimates of the typical period for which offenders remain active can yield, under a host of assumptions, estimates of the number of crimes averted by incapacitation (Cohen 1978, 1983; Visher 1987).

One of the crucial inputs into this model is the offending rate while free—the λ. Researchers have used one of two approaches to estimate its value. They have either surveyed samples of offenders directly (Petersilia et al. 1978; Chaiken and Chaiken 1982; DiIulio 1990; Horney and Marshall 1991) or they have used official arrest records to estimate it indirectly (Greenburg 1975; Blumstein and Cohen 1979; Cohen 1986). Both approaches have their benefits and drawbacks (Blumstein et al. 1986). However, both approaches are concerned with estimating a value of a mean (or one that varies by offense categories) so that policy simulations can be conducted using the Avi-Itzhak and Shinar steady-state model.

Despite its mathematical elegance, the steady-state model lacks two realistic features: (i) the heterogeneity of offending rates among individuals and (ii) variations in the offending rate over the life course. Offenders commit crimes at different rates (Nagin and Land 1993; Nagin and Paternoster 2000) and individuals' offending rates evolve over their life course (Sampson and Laub 2005). Therefore, estimating how many crimes are averted (or can be averted under a simulated policy) must depend crucially on when in individuals' lives and at what point in their criminal careers the incarceration occurs. To the extent that realistic models that link offending rates with offenders' ages (i.e., how far along in their life they are) and criminal histories (i.e., how far along in their criminal career they are) can be generated, simulations from these models may provide more detailed and more meaningful estimates of the number and distribution of crimes averted by incapacitation.

This paper develops one such model. A semi-parametric approach is used to estimate the model using detailed dated arrest histories of a sample of prison releasees. Once estimated, the model is used to project a unique offending trajectory for each offender during the period (s)he was actually incarcerated (and thus incapacitated). These projections—the counterfactual micro-trajectories—form the basis for estimating the number of crimes averted by incapacitation. By integrating individuals' projected hazard paths over their incarceration terms, distinct estimates of the number of crimes averted by each individual's incarceration are obtained. When normalized by their respective incarceration lengths, the model produces estimates of the annual number of crimes averted by incapacitation for each individual in the sample.

In addition to providing these estimates, the micro-trajectories allow for a vastly expanded array of policy simulations. For example, by increasing (or decreasing) the incarceration term the models can provide valuable insights into the expected crime reduction benefits that may accrue from various policy choices. Similarly, simulating the responsiveness of individuals' incapacitation effects to varying prison terms can provide an alternate criterion for assessing selective incapacitation strategies.

Chief among the limitations of this analytical strategy is that any estimates obtained from it are generalizable only to a population of prison releasees. If, for example, interest centers on assessing the effects of increasing the incarceration rate—e.g., by relying on incarceration more often than, say, community supervision—then this population is clearly inappropriate. Re-weighting the empirical distributions (reported in this paper) to reflect other relevant populations is possible, but left for future work. If, on the other hand, interest centers on computing the number of crimes averted under current incarceration policies or on simulating the effects of altering current incarceration terms, then the population of releasees is an appropriate one. In this paper, analysis, interpretations and discussion are restricted only to the population of releasees.

The Analytical Framework

In order to simulate counterfactuals at the individual level, what is needed is a dynamic model of the offending rate (or the λ) that is related to appropriate time-indexed variables as well as a set of offender-specific attributes. Links to the time-indexed variables will allow a simulation of the offending hazard as time passes. Links to offender-specific attributes will ensure that this process captures any population heterogeneity in the process. The analytical strategy used in this paper utilizes information available in the criminal history accumulation process—i.e., how individuals were accumulating their respective criminal histories—to estimate the links between the offending hazard, the time-indexed variables, and offender attributes.

Guidance on which time-indexed variables and which offender attributes to use in constructing the model can come either from formal theoretical reasoning or from exploratory empirical analysis. For example, it is a well-established fact in criminology that the rate of offending increases as youthful offenders age but that, at some point, the rate begins to decline. This non-monotonic shape (first increasing then decreasing)—termed the "age-crime curve"—is a very predictable aspect of offending over the life course (Farrington 1986; Brame et al. 2003; Bushway et al. 2004). Hence, the hazard model that we eventually develop must be consistent with this fact—i.e., it should exhibit a non-monotonic evolution with age.

In a similar manner, it is often observed in recidivism studies that there exists duration dependence in criminal recidivism. That is, the hazard of re-offending may decrease (or increase) as time between events—the spell-length—increases (Maltz 1984; Allison 1995). Therefore, another fact that the model should be consistent with is this dependence of the hazard on time since the last arrest event.

Other theoretical guidance or empirical regularities may exist that suggest how the hazard should evolve with time. The crucial question then is: How do we develop a hazard model that exhibits all of these dynamic features?

To do so, the first task is to define all of the criterion variables (or outcomes) that the hazard model is being designed to predict. Assume there exists detailed dated information on the arrest sequence of individuals, along with their date of birth. This information allows us to construct a sequence of arrest ages. These sequences tell us exactly at what age the offender was arrested for the first, second, or subsequent time. Harding and Maller (1997) refer to these sequences as offenders' arrest profiles. It is also straightforward to convert these sequences into a variable measuring elapsed time between successive arrest events. In a similar manner, we can develop measures of all the relevant "clocks" that may be needed to accurately describe the evolution of the hazard rate with time. The ultimate goal is to construct a model (for λ) that evolves along these multiple clocks. Such multiple-clock models allow researchers to capture several dimensions of time simultaneously when studying event histories (Yamaguchi 1991, p. 53; Lillard 1993).

Next, we need some way to relate λ to the evidence we have in the sample. If we believe that λ increases or decreases with some variable x (e.g., age, spell-length, arrest number, etc.) then, at a minimum, λ should covary with x. But by how much? Provided that the sample is a random drawing from the population of interest, one may assume that the best estimate of this covariation is to be found in the sample itself. This principle, termed the analogy principle (Manski 1988), suggests that the expected covariance between x and λ should be equal to the actual covariance between x and the timing of arrest events observed in the sample. Such reasoning allows us to derive a set of constraints that the hazards should satisfy, irrespective of their functional form.

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

Information theory, an inter-disciplinary field that uses entropy and entropy-related measures to quantify uncertainty, provides the philosophical justification to make this choice. Edwin Jaynes, a physicist, argued in a series of influential paper that when faced with a problem that has an infinite number of solutions (the so-called ill-posed inversion problems) we should choose the solution that is the least informative (or as close as possible to our prior beliefs, if such beliefs exist) while satisfying what limited evidence we may have observed (Jaynes, 1957a, b). To operationalize such an agnostic approach, Jaynes needed some way to quantify the lack of information. Fortunately, within the context of a problem in communication theory, Shannon (1948) had, just a few years earlier, developed a precise definition of uncertainty and termed it *Information Entropy*. In what has come to be known as the Maximum Entropy formalism, Edwin Jaynes proposed to use Shannon's Entropy as the criterion to maximize, subject to all available constraints, in order to derive conservative inferences from the evidence. The field of *Information and Entropy Econometrics* has grown exponentially over the two decades since econometricians were first introduced to this approach by Arnold Zellner and his colleagues (Zellner and Highfield 1988; Zellner 1991; Ryu 1993).[1]

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

Full mathematical derivation of the solution is provided in Bhati (2007), as are references to the relevant statistics and econometrics literatures. The resulting model that emerges from the approach takes the functional form:

$$\lambda_n(z) = \exp\left(\mathbf{x}_n'\boldsymbol{\theta}_0 + z \cdot \mathbf{x}_n'\boldsymbol{\theta}_1 + z\log z \cdot \mathbf{x}_n'\boldsymbol{\theta}_2 + v(z) \cdot \mathbf{x}_n'\boldsymbol{\theta}_3\right) \quad \forall n \in N \tag{1}$$

where $\mathbf{x}_\mathrm{n}$ is a vector of offender attributes, $\boldsymbol{\theta}_0,\ldots,\boldsymbol{\theta}_3$ are a set of Lagrange Multipliers (a bi-product of solving any constrained optimization problem) that reflect the value of each of the constraints on reducing uncertainty about the process; z captures the evolution of the hazard linearly with age; $z \log z$ captures the non-monotonic shape of the hazard (provided that $\boldsymbol{\theta}_2$ have the opposite sign of the corresponding $\boldsymbol{\theta}_1$); and $v(z)$ captures the dependence of the hazards on the time since last arrest (provided that $\boldsymbol{\theta}_3$ are non-zero).

The semi-parametric nature of the approach stems from the fact that rather than make assumptions about the form of the hazard function, we recover the functional form *from the imposed constraints* directly. Therefore, any arbitrary set of constraints may be imposed. If they are irrelevant, then the corresponding Lagrange Multipliers will be close to zero. As

[1] For more recent theoretical and empirical developments in this field, see the 2002 special issue of the *Journal of Econometrics* (Vol 107, Issues 1&2), Chapter 13 of Mittelhammer et al. (2000), Fomby and Hill (1997), and the Golan et al. (1996) monograph. See also Maasoumi (1993), Soofi (1994), and Golan (2002) for historical discussions and general surveys.

with fully parametric models, asymptotic standard errors can be derived for these parameters and they can be subjected to standard statistical significance testing (Kullback 1959).

It is important to note that this approach differs, both conceptually and empirically, from existing methods of modeling repeated events (Allison 1984; Blossfeld et al. 1989; Mayer and Tuma 1990). Application of the information theoretic approach yields the form of the hazard trajectories as well as estimates for the parameters $\boldsymbol{\theta}_0,\ldots,\boldsymbol{\theta}_3$. Moreover, under certain restrictive assumptions the information theoretic approach can yield functional forms and inferences identical to fully-parametric repeated event models. As such, the approach can yield models that encompass one or more fully-parametric models as special cases. The key conceptual distinction is that, in the information theoretic approach, the point of departure is the theoretical or empirical guidance regarding multiple clocks or moments.

Once the θ parameters are recovered by solving the optimization problem, simulating the evolution of the hazard with age or time since last arrest, conditional on a given set of offender attributes, is simply a matter of plugging in the appropriate quantities into Eq. 1 and computing the hazard micro-trajectories for each individual.

Since the data typically available to analysts contains dated arrest sequences, the approach described above would yield, unless modified, estimates of the micro-trajectories of arrest hazards. Our main interest, however, is in estimating the number of *crimes* averted by incapacitation. Therefore, we need some way to estimate offending hazard paths from observed arrest events. In order to do so, following Blumstein and Cohen (1979), a correction factor (denoted c) was first defined. With it, the analytical framework sketched above can be extended in a straightforward way to recover offense-specific trajectories of offending hazards rather than arrest hazards.[2] Data on number of charges (h) of crime category l (available for each arrest event), the crime clearance rate (b) for various years during which arrest histories are observed (available annually by crime categories), the crime reporting rate (e) by age of offender and crime categories, as well as crime category-specific co-offending rates (o) can be used to compute the correction factor as follows:

$$c = \frac{h}{b \times e \times o}. \tag{2}$$

Auxiliary data sources used to obtain each of these quantities (for this study) are detailed in the next section.

In the final models, what distinguishes each of the trajectories of different crime categories are the estimated parameters (now denoted $\hat{\boldsymbol{\theta}}_{0l},\ldots,\hat{\boldsymbol{\theta}}_{3l} \forall l \in L$). Once these parameters are estimated, the total number of crimes of type l averted by incapacitating an individual (denoted $\hat{s}_{nl}$) between the ages of $\underline{z}_n$ and $\bar{z}_n$ can be estimated by integrating the hazard trajectory over that range. i.e.,

$$\hat{s}_{nl} = \int_{\underline{z}_n}^{\bar{z}_n} \hat{\lambda}_{nl}(z)\,\mathrm{d}z = \int_{\underline{z}_n}^{\bar{z}_n} \exp\left(\boldsymbol{x}'_n\hat{\boldsymbol{\theta}}_{0l} + z \cdot \boldsymbol{x}'_n\hat{\boldsymbol{\theta}}_{1l} + z\log z \cdot \boldsymbol{x}'_n\hat{\boldsymbol{\theta}}_{2l} + v(z)\cdot \boldsymbol{x}'_n\hat{\boldsymbol{\theta}}_{3l}\right)\mathrm{d}z \quad \forall n,l \tag{3}$$

[2] It should be noted here that the strategy entails adjusting the event histories by this correction factor (at the micro-level) before estimating λ and not adjusting the crimes averted estimates after their computation. See Bhati (2007) for complete details.

Furthermore, dividing this number by the time spent in prison, i.e., $\bar{z}_n - \underline{z}_n$, yields an estimate of the annual number of crimes averted by incapacitation for each individual in the sample.

More interesting are the prospects of conducting detailed policy simulations. Simulating the effects of increasing (or decreasing) the prison term for each individual can be computed by altering the upper limit of integration by an appropriate amount. Given that the hazard's solution is of an exponential form, increasing (decreasing) the range of integration is guaranteed to increase (decrease) the crimes averted estimates by some amount. The question of interest is: by how much?

The answer will depend on who the individual is (i.e., the set of attributes) and when during the career this increase takes place. If, as has been argued elsewhere (Blumstein and Piquero 2007), the enhanced incapacitation happens at a time when the offender would not have been active (or had a very low value of λ), then we should expect to see negligent increases in the number of crimes averted. To investigate this issue, the paper presents the percent increase in the estimated number of crimes averted, had individuals served an additional 1% of their current incarceration term—the elasticity of the incapacitation effect to altered prison terms ($\hat{\eta}$). This quantity, a unit-free measure of the responsiveness of the incapacitation effect to altered incarceration terms, is defined as

$$\hat{\eta}_{nl} = \frac{\int_{\underline{z}_n}^{\bar{z}_n+\delta_n} \hat{\lambda}_{nl}(z)\,\mathrm{d}z}{\int_{\underline{z}_n}^{\bar{z}_n} \hat{\lambda}_{nl}(z)\,\mathrm{d}z} \quad \forall n, l \tag{4}$$

where δ_n represents 1% of the individual's current incarceration term, i.e., $\left(\bar{z}_n - \underline{z}_n\right)/100$. Because individuals in a prison release cohort will have served varying lengths of prison terms prior to release, elasticities are a convenient way to standardize and compare the simulated effects of policy choices.

The Data

The data used in this research effort is available to the public from the National Archives of Criminal Justice Data (NACJD), at the Inter-University Consortium for Political and Social Research (ICPSR), University of Michigan, Ann Arbor, MI. It is archived as study # 3355 (*Recidivism of Prisoners Released in 1994* [*United States*]) (BJS 2002).

The data were collected by the Bureau of Justice Statistics (BJS). BJS tracked a sample of 38,624 prisoners released from 15 state prisons in 1994 for a period of 3 years. The vast majority of the archived database consists of information on each releasee's entire officially recorded arrest history. This includes all recorded adult arrests through the end of the follow-up period. These data were obtained from state and FBI automated RAP sheets which include arrest, adjudication, and sentencing information. Each arrest event includes information on adjudication and sentencing related to that event, if such action was taken. Unfortunately, however, the data do not contain detailed information on when these individuals were released from prison, if they were imprisoned after a particular arrest event. Prison admission and release dates are only available for the incarceration that resulted in offenders' being released in 1994. This implies that the data are unable to calculate street time—a serious limitation of these data. However, ill-effects of this limitation are addressed during the model estimation stage (explained more below).

In addition, the database contains a limited amount of demographic data about offenders (e.g., date of birth, race, ethnicity, and gender) and some information pertaining to the current incarceration (e.g., sanction imposed, offenses for which incarcerated, type of release from prison, and type of admission to prison).

Before conducting the analysis, diagnostic checks were performed on the data to ensure they were compatible with model requirements. All individuals whose arrest sequences either had gaps in them, had inappropriate ages (e.g., negative or below 15), or had inappropriate chronological ordering (e.g., first arrest is at an age after a subsequent arrest) were dropped from the analysis. Also dropped from this analysis were all individuals excluded (for a variety of reasons) from the original analysis reported by BJS (Langan and Levin 2002, p. 14).

Since the sample for California releasees was very large (nearly 60,000 person-arrests before prison admission) a random subset of 2,500 individuals (21,792 person events) was used from the California sample for estimating the criminal history accumulation process. For the simulation analysis, however, all individuals from California were included in the study. In addition, data for releasees from two states—Delaware and Maryland—were completely dropped from the analysis. Delaware's sample was too small and convergence problem were encountered in estimating some of the models. Maryland, on the other hand, lacked offense specific charge information. Since this information was crucial in estimating offense category-specific models, all records from Maryland were dropped.

The final pre-incarceration sample used in the analysis consisted of a total of 175,490 arrest events for 24,998 individuals across 13 states.[3] Arrest records for these persons were re-structured into a hierarchical person-event level file. In addition to the key criterion variables—age at arrest, duration since last arrest, and number of charges for specific offense types at each arrest event—the data were also manipulated to create a set of individual-level attributes. The key independent variables (the x) used in estimating the criminal history accumulation process included the (i) arrest number, (ii) age at first arrest, and (iii) age at last arrest. The last two of these were set to 0 for the first arrest event. The same basic set of attributes were used in all of the models.

To account for the lack of information on prior incarceration spells, a flag was included indicating whether or not the previous arrest event resulted in some confinement. If it is the case that, on average, individuals confined after an arrest are off the street for some time, this would manifest itself as a reduced hazard of rearrest following such events (relative to arrests that did not result in confinement). Including such a flag in all models is one way of accounting for this temporary drop in rearrest hazard that results not from any behavioral tendencies, but a misspecified model. Hence, any negative duration dependence uncovered in the model will be net of the effect of this misspecification.[4]

Admission and release dates (for the 1994 prison release) were used to construct the amount of time served in prison as well as the ages at admission and release. These variables were used in constructing the interval over which the hazard paths were integrated to compute the estimated number of crimes averted by incapacitation.

To construct the correction factor (c) data published in a variety of sources were used. The number of charges of offense type l that were associated with each arrest event were available in the BJS data itself. Year and offense-type specific clearance rates were

[3] These include Arizona, California, Florida, Illinois, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Texas, and Virginia.

[4] While simulating the counterfactual, however, this flag was set to 0 for all individuals, in effect, simulating the micro-trajectory "as if" the individual had not been confined.

obtained from Table 4.20 in Pastore and Maguire (2005, p. 377). Reporting rates were computed from data provided in Hart and Rennison (2003). Cooffending rates of 2 for property crimes and 1.5 for crimes against persons were used (Reiss 1988). Based on this additional data, Eq. 2 was used to compute a correction factor for each individual at each arrest event and for each of the offense types analyzed.

Findings

Because states vary in their penal policies and practicies, separate models were estimated for each of the 13 states included in this study. Separate models were also developed for crimes against persons, property related crimes, and all crimes combined. Although the parameter point estimates from these models varied considerably (both across states and offense type) their signs were largely consistent across samples. Hence, detailed estimates and interpretation of parameter signs are provided for only one model (all crime types for the California sample). Table 1 provides estimates of $\hat{\theta}$ as well as their asymptotic standard errors.[5]

To get an intuition for what the parameter signs mean, consider the effects of age at first arrest on the process. Starting the criminal career later in life implies a permanently lower hazard (a negative $\hat{\theta}_0$), with a steeper rise in offending hazard with age (a positive $\hat{\theta}_1$), but for a shorter career (a negative $\hat{\theta}_2$) relative to someone who starts offending much earlier. Moreover, starting the criminal career later in life implies stronger negative duration dependence—i.e., hazard drops more rapidly as time since the last arrest increases—relative to someone who starts their career earlier (a negative $\hat{\theta}_3$).

In a similar manner, being confined at the last arrest reduces the hazard permanently (a negative $\hat{\theta}_0$) but also reduces the amount of negative duration dependence (a positive $\hat{\theta}_3$). These signs are consistent with a process where individuals are not at risk of being rearrested for a period after an arrest event that resulted in some confinement. By setting this variable to 0 for all individuals in the sample while simulating their micro-trajectories, we are able to account for, albeit in a very rudimentary way, the lack of precise information on prior incarceration spells.

To provide more clarity on what these model estimates imply, a graphical depiction of the counterfactual micro-trajectory for a hypothetical offender profile is presented in Fig. 1. Consider a man who was arrested for the first time at age 19, was re-arrested at age 25 at which point he was incarcerated for 10 years. Had he not been incarcerated (between ages 25 and 35) what would his offending trajectory have looked like? Given the parameter estimates in Table 1, and these attributes, one can plot the counterfactual micro-trajectory for this individual. This plot, along with its two clock components, appears in Fig. 1. The two individual clock components are defined by re-writing Eq. 1 as follows:

$$\lambda_n(z) = \overbrace{\exp\left(\boldsymbol{x}_n'\boldsymbol{\theta}_0 + v_n(z)\cdot\boldsymbol{x}_n'\boldsymbol{\theta}_3\right)}^{\text{spell}-\text{basedclock}}\overbrace{\exp\left(z\cdot\boldsymbol{x}_n'\boldsymbol{\theta}_1 + z\log z\cdot\boldsymbol{x}_n'\boldsymbol{\theta}_2\right)}^{\text{age}-\text{basedclock}}\quad \forall n\in N \tag{5}$$

[5] Since the samples include multiple arrest events per individual, standard errors need to be corrected for this clustering. The modified sandwich variance estimator (Ezell et al. 2003)—a modified version of sandwich estimators (Huber 1967; White 1980) that account for this clustering—is used here.

Table 1 Parameter estimates for simulating the criminal history accumulation process of releasees in California, all crime types

Covariates	$\hat{\theta}$	a.s.e[a]	χ^2	*p*-value
θ_0: *Fixed*				
Intercept	2.444	0.494	24.46	0.00
Arrest number	0.051	0.051	0.99	0.32
Age at first arrest	−0.797	0.043	339.44	0.00
Age at last arrest	0.292	0.018	249.98	0.00
Confined at last arrest	−0.151	0.032	22.93	0.00
θ_1: *Age (linear)*				
Intercept	0.777	0.075	108.12	0.00
Arrest number	−0.010	0.007	2.19	0.14
Age at first arrest	0.070	0.005	191.49	0.00
Age at last arrest	−0.035	0.003	172.66	0.00
θ_2: *Age (non-linear)*				
Intercept	−0.218	0.019	132.76	0.00
Arrest number	0.003	0.002	2.89	0.09
Age at first arrest	−0.014	0.001	167.13	0.00
Age at last arrest	0.008	0.001	162.39	0.00
θ_3: *Time Since Last Arrest (linear)*				
Intercept	−0.462	0.038	146.21	0.00
Arrest number	−0.028	0.004	59.54	0.00
Age at first arrest	−0.007	0.003	4.55	0.03
Age at last arrest	0.019	0.003	45.27	0.00
Confined at last arrest	0.047	0.019	6.04	0.01

[a] Modified sandwich estimates

The plots in Fig. 1 show that, had this person not been incarcerated for 10 years at the age of 25, his offending rate would have continued to drop from about 3.5 to about 0.5 by age 35. This drop is expected due to two stochastic processes at work. First, there is the anticipated age-crime curve effect (as shown in Fig. 1 by the age-based clock component, displayed with hollow circles). This individual's anticipated age-based offending trajectory had almost peaked when he was arrested and incarcerated. However, the stronger effect is with spell length (as shown by the spell-based clock in Fig. 1, depicted by the filled circles).

If this individual had not been incarcerated at age 25, then as time elapsed, the two stochastic processes would have jointly applied a negative pressure. Initially, though, the offender was young enough so that the slight upward pressure of the age-based clock was competing with the downward pressure from the spell-length clock. When combined, however, the two components represent a fairly dramatic downward trend in the offending trajectory expected for this individual between the age of 25 and 35. Much of the 10 years he was actually incarcerated for may have been inefficient use of prison space: at least for the last 5 of those 10 years (age 30–35), his offending rate was expected to be negligible in any case.

Integrating this individual's multiple-clock hazard path between ages 25 and 35 suggests that a total of 23.9 crimes were averted by his incarceration. This translates into an

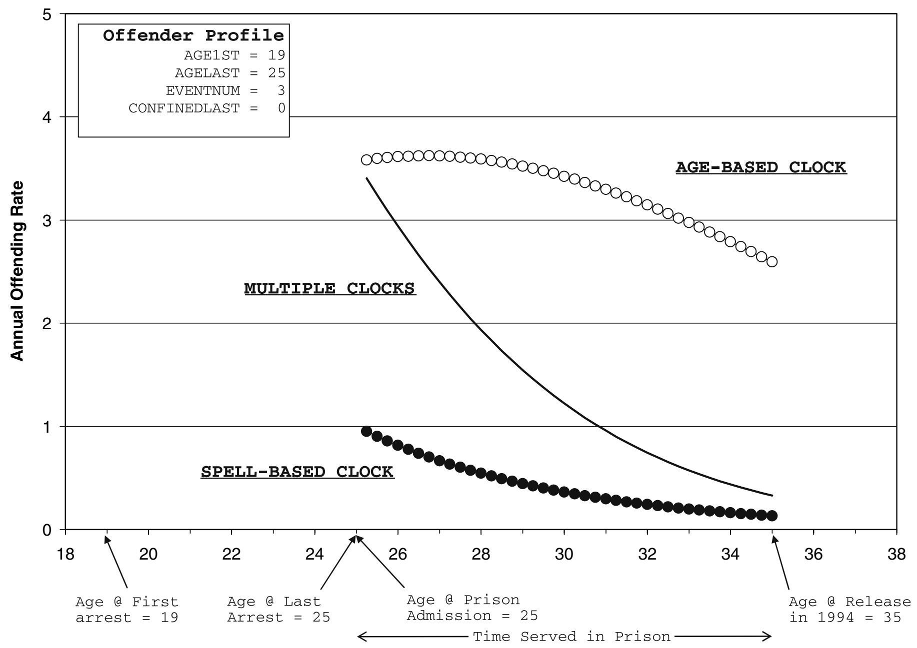

Fig. 1 The composite and clock-specific offending micro-trajectories for a specific offender profile from California, all crimes

annual crimes averted by incapacitation estimate of 2.39 since he was incarcerated for 10 years. Note that this number represents the number of crime averted (not the number of arrests) since a correction factor has already been introduced into the modeling exercise.

Based on model estimates and offenders' attributes, it is possible to plot such trajectories and perform such computations for each individual in the sample. The results are discussed in the next section.

Crimes Averted by Incapacitation Estimates

Based on the simulated micro-trajectories, the integrated counterfactual, normalized by the incarceration terms, were computed for each individual in the sample for the 3 offense types (crimes against persons, property related crimes and all crimes).

Figure 2 shows the distribution of the annual number of crimes against persons averted by incapacitating the offenders released from all 13 states. As is expected, there is a distinct skew in the distribution of crimes averted by incapacitation with a mean of 1.93 and a median of 1.41. Only about 5% of the releasees would have committed more than five crimes against persons annually.

In a similar manner, Fig. 3 shows the distribution of property related crimes averted by incapacitation. The distribution is, as expected, on a higher level with a mean of 8.47 and a median of 5.75 but the skew is still prominent. Only about 5% of the releasees would have committed an estimated 30 or more property related crimes annually, while most (roughly 75%) of them were expected to commit less than 10 property related crimes annually.

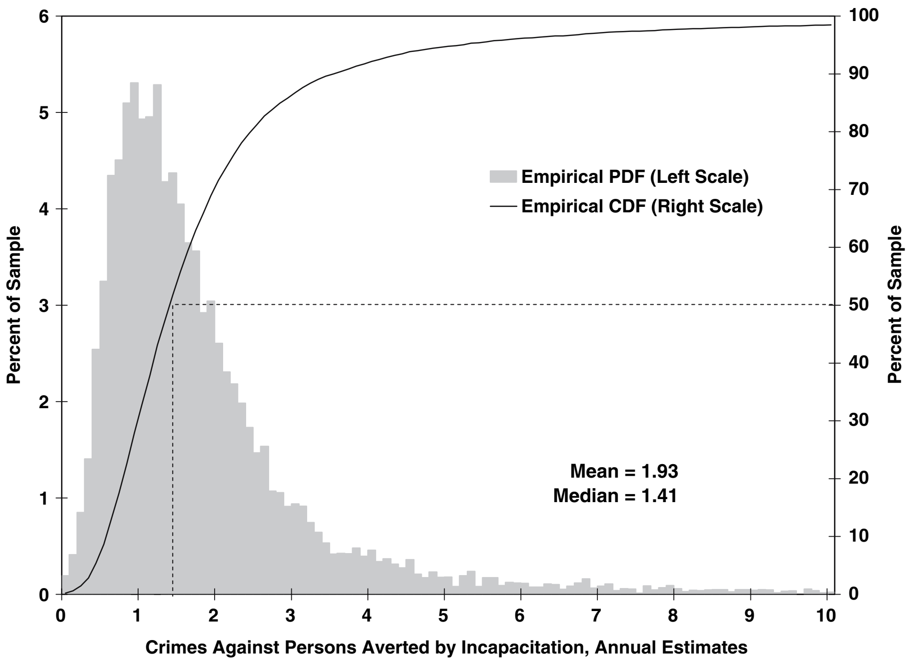

Fig. 2 Distribution of the estimated number of crimes against persons averted annually by incapacitation

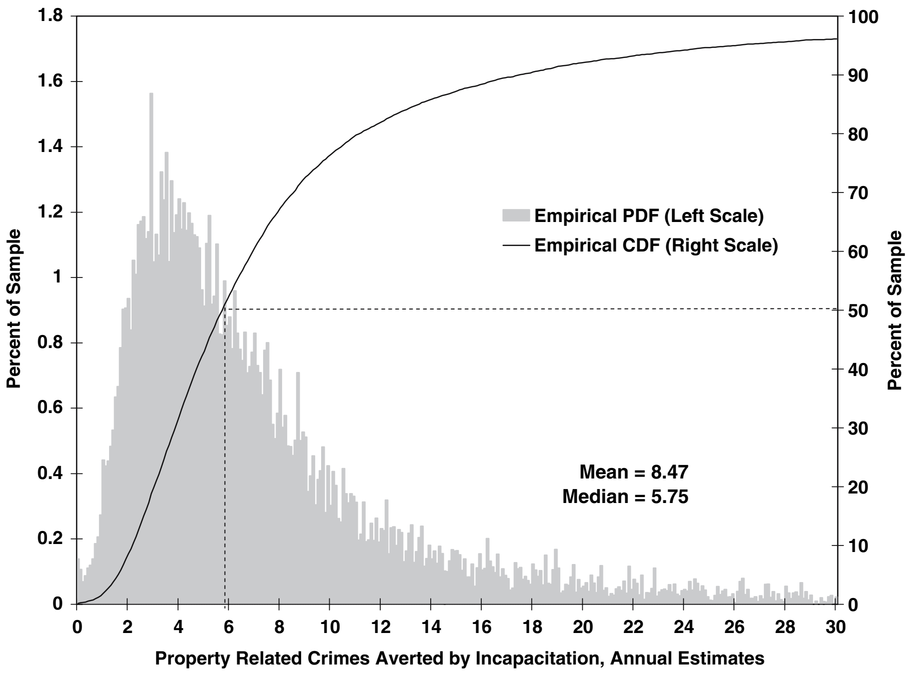

Fig. 3 Distribution of the estimated number of property related crimes averted annually by incapacitation

Table 2 Annual number of crimes averted by incapacitation, distributed across states, crime types, and select demographic attributes

	All		Males		Females		Blacks		Non-blacks		Hispanics		Non-Hisp.	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
Number of all crimes averted annually by incapacitation														
AZ	17.01	13.55	17.05	13.57	16.60	13.40	16.71	13.99	17.07	13.49	16.04	12.33	17.44	14.14
CA	23.63	17.37	23.73	17.50	22.64	14.89	25.54	18.66	22.69	16.66	22.37	16.02	24.22	17.98
FL	13.64	11.55	13.59	11.48	14.03	12.98	13.25	11.25	14.16	11.93	13.13	8.80	13.66	11.61
IL	13.83	11.14	13.91	11.23	12.63	10.42	14.28	11.23	12.97	11.01	13.31	10.28	13.88	11.15
MI	6.51	5.36	6.63	5.43	4.99	4.50	6.52	5.37	6.50	5.35	…	…	6.51	5.36
MN	11.58	9.94	11.59	9.98	11.46	9.73	11.76	10.00	11.50	9.93	…	…	11.62	9.98
NJ	16.35	14.02	16.40	14.05	15.76	13.63	16.63	14.45	15.78	13.61	15.96	13.91	16.43	14.11
NY	16.24	14.19	16.37	14.30	14.57	12.08	16.65	14.82	15.74	13.46	15.69	13.46	16.52	14.66
NC	24.14	18.25	24.03	18.29	24.87	18.13	24.00	18.47	24.37	17.91	…	…	24.16	18.29
OH	10.22	7.89	10.23	7.92	…	…	9.47	7.37	10.90	8.44	…	…	10.27	7.92
OR	24.48	16.03	24.15	15.66	…	…	28.68	20.43	23.70	15.53	18.52	12.45	25.12	16.75
TX	9.19	7.69	9.24	7.72	8.61	7.28	9.28	7.63	9.09	7.79	8.77	7.83	9.30	7.68
VA	11.33	9.65	11.42	9.76	10.35	8.71	11.32	9.72	11.34	9.62	…	…	11.34	9.72
Number of crimes against persons averted annually by incapacitation														
AZ	1.81	1.45	1.80	1.45	1.91	1.35	1.61	1.27	1.85	1.47	1.76	1.40	1.84	1.47
CA	2.61	1.96	2.62	1.97	2.52	1.84	2.70	1.99	2.57	1.94	2.47	1.82	2.68	2.02
FL	0.80	0.71	0.81	0.71	0.75	0.68	0.77	0.68	0.85	0.76	0.85	0.70	0.80	0.71
IL	1.60	1.37	1.62	1.37	1.36	1.23	1.59	1.34	1.63	1.39	1.62	1.37	1.60	1.37
MI	0.94	0.59	0.95	0.60	0.70	0.48	1.01	0.60	0.84	0.58	…	…	0.94	0.59
MN	1.56	1.29	1.55	1.29	1.70	1.36	1.39	1.16	1.63	1.34	…	…	1.56	1.29
NJ	1.34	1.14	1.35	1.14	1.22	1.09	1.34	1.15	1.36	1.09	1.34	1.10	1.34	1.14
NY	2.14	1.53	2.19	1.56	1.49	1.21	2.29	1.62	1.96	1.42	1.93	1.36	2.24	1.61
NC	1.68	1.21	1.66	1.21	1.84	1.18	1.66	1.22	1.73	1.17	0.94	0.84	1.69	1.21
OH	2.16	1.43	2.17	1.43	…	…	2.01	1.28	2.28	1.57	…	…	2.16	1.43
OR	1.07	0.78	1.06	0.77	…	…	1.20	0.87	1.05	0.77	…	…	1.09	0.79
TX	0.95	0.79	0.96	0.79	0.82	0.78	0.96	0.78	0.95	0.79	0.89	0.79	0.97	0.79
VA	1.29	1.09	1.30	1.10	1.11	0.95	1.30	1.09	1.26	1.09	…	…	1.29	1.09
Number of property related crimes averted annually by incapacitation														
AZ	7.69	5.78	7.82	5.83	6.47	5.41	8.07	6.08	7.62	5.64	7.15	5.24	7.94	6.00
CA	9.83	6.56	9.84	6.59	9.71	6.04	10.93	7.15	9.29	6.25	9.39	6.05	10.03	6.85
FL	5.05	4.16	5.00	4.09	5.51	4.80	4.91	4.09	5.24	4.31	4.67	3.33	5.06	4.17
IL	7.22	5.05	7.21	5.10	7.34	4.85	7.63	5.25	6.43	4.78	6.63	4.20	7.27	5.10
MI	2.93	2.17	2.95	2.21	2.70	1.78	2.95	2.18	2.91	2.17	…	…	2.93	2.17
MN	6.67	5.67	6.70	5.74	6.16	4.68	7.18	6.06	6.44	5.47	…	…	6.69	5.69
NJ	8.71	7.29	8.70	7.31	8.85	7.12	8.95	7.51	8.23	6.86	8.21	6.85	8.82	7.38
NY	7.67	5.97	7.69	6.02	7.46	5.44	7.90	6.31	7.40	5.58	7.46	5.94	7.78	5.99
NC	15.26	11.60	15.31	11.80	14.88	10.52	15.09	11.78	15.54	11.44	…	…	15.27	11.60
OH	4.33	3.23	4.31	3.28	…	…	4.19	3.28	4.45	3.20	…	…	4.35	3.28
OR	7.37	4.42	7.30	4.37	…	…	8.99	5.27	7.07	4.27	5.55	3.29	7.57	4.60
TX	4.30	3.41	4.32	3.40	4.06	3.41	4.38	3.42	4.22	3.40	4.08	3.26	4.36	3.42

Table 2 continued

	All		Males		Females		Blacks		Non-blacks		Hispanics		Non-Hisp.	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
VA	6.24	5.05	6.27	5.06	5.93	4.96	6.21	5.06	6.28	4.94	…	…	6.24	5.06

... Fewer than 100 observations

In each of the distributions it is interesting to see that there are small proportions of releasees that were not anticipated to commit any crime.

Although the graphical presentation of the distribution of crimes averted by incapacitation provides some insights, it would be interesting to see if there are any systematic differences among various offender sub-groups. Towards that end, Table 2 presents detailed state-and demographic sub-group-specific estimates of the annual incapacitation effects. In general, there seems to be little systematic difference among the various groups. With few exceptions, the annual number of crimes averted by incapacitating males is slightly higher than females. There are little or no discernible differences between groups based on race and ethnicity.[6]

There is, however, a fair amount of variation across states. For example, incarceration averted a lot of property related crimes in North Carolina annually—the most among all states. On the other hand, the most number of crimes against persons were averted in California.[7]

Incapacitation Effect Elasticities

The results discussed above were for estimated number of crime averted by the current incarceration periods. In what follows, the estimated model is used for simulating the effects of increasing prison terms for all individuals in the sample by 1% each and computing the elasticities as defined in Eq. 4. Figure 4 shows the distribution, across sample members, of the elasticities for crimes against persons and Fig. 5 shows the same for property related crimes.

An increase of a prison term by 1% can be expected to bring about a roughly proportional increase in the number of crimes against persons averted. Although there are individuals on both tails of the distribution, it is interesting to note that the skew is in fact in the other direction—the mean is smaller than the median. However, the number of persons for whom the increased prison term would more than compensate for an increase in the crimes averted estimate is still small. Only 15% of the sample had an estimated elasticity greater than 1 (i.e., a 1% increase in their prison term would yield an increase in the estimated number of crimes averted by more than 1%).

A very different story emerges when assessing the distribution of the incapacitation effect elasticities for property related crimes. Here, we find that nearly everyone (about 98%) had an elasticity of less then 1. Moreover, among these the distribution shows a very

[6] These statements are based on a casual review of the estimates in Table 2 and not on rigorous statistical testing.

[7] Examining the causes of the state variation uncovered here is left for future work as it would require careful modeling not only of state policy levers, but also variation in relevant offender attributes across states. The sample of offenders vary considerably across states with respect to attributes like age at release or age at first arrest that are included in the models.

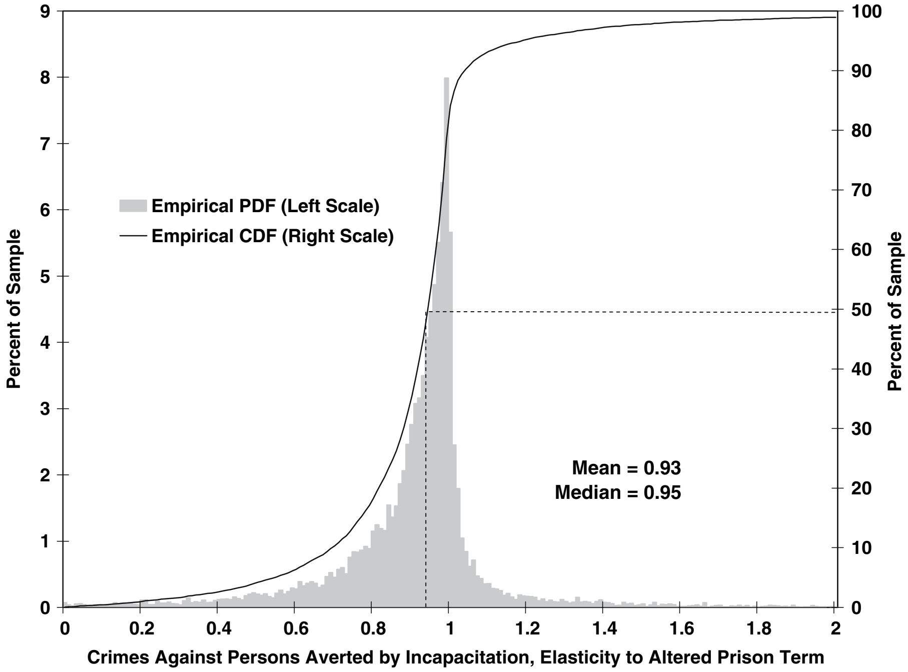

Fig. 4 Estimated elasticity of crimes against persons averted to enhanced sanctions, distributed across sample members

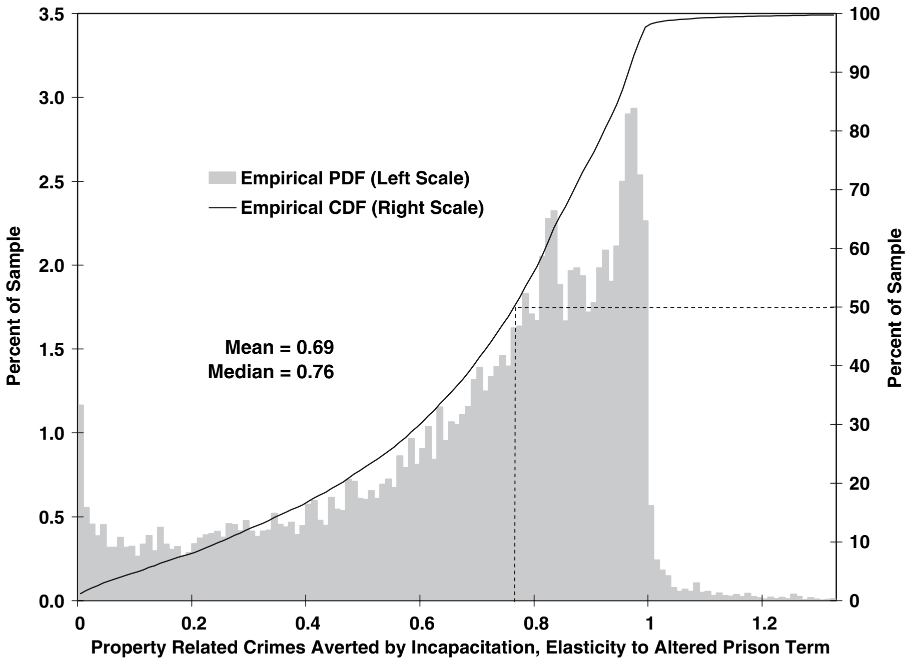

Fig. 5 Estimated elasticity of property related crimes averted to enhanced sanctions, distributed across sample members

Table 3 Estimated elasticity of crimes averted by incapacitation to enhanced sanctions, distributed across states, crimes types, and select demographic attributes

	All		Males		Females		Blacks		Non-blacks		Hispanics		Non-Hisp.	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
Estimated elasticity of all crimes averted to enhanced sanctions														
AZ	0.84	0.91	0.84	0.91	0.89	0.91	0.79	0.86	0.85	0.92	0.84	0.91	0.84	0.91
CA	0.85	0.89	0.85	0.89	0.87	0.92	0.84	0.88	0.86	0.90	0.85	0.88	0.86	0.90
FL	0.65	0.74	0.64	0.72	0.70	0.82	0.61	0.66	0.70	0.80	0.77	0.86	0.64	0.74
IL	0.77	0.82	0.76	0.81	0.85	0.90	0.76	0.81	0.80	0.84	0.79	0.81	0.77	0.82
MI	0.93	0.95	0.92	0.94	0.96	0.97	0.93	0.94	0.92	0.95	...	...	0.93	0.95
MN	0.83	0.87	0.83	0.87	0.87	0.93	0.79	0.84	0.84	0.88	...	...	0.83	0.87
NJ	0.84	0.88	0.83	0.88	0.86	0.90	0.83	0.87	0.85	0.89	0.87	0.90	0.83	0.87
NY	0.60	0.63	0.58	0.61	0.74	0.79	0.55	0.58	0.65	0.72	0.66	0.72	0.56	0.59
NC	0.93	0.97	0.92	0.96	0.96	0.98	0.93	0.96	0.93	0.97	...	...	0.93	0.97
OH	0.86	0.92	0.85	0.92	...	...	0.86	0.91	0.86	0.94	...	...	0.86	0.92
OR	0.64	0.70	0.63	0.69	...	...	0.68	0.78	0.63	0.69	0.67	0.72	0.64	0.70
TX	0.88	0.92	0.88	0.92	0.93	0.95	0.89	0.93	0.87	0.92	0.88	0.92	0.88	0.93
VA	0.76	0.83	0.76	0.82	0.83	0.88	0.76	0.83	0.76	0.82	...	...	0.76	0.83
Estimated elasticity of crimes against persons averted to enhanced sanctions														
AZ	0.87	0.93	0.87	0.93	0.89	0.92	0.84	0.90	0.88	0.94	0.87	0.93	0.87	0.93
CA	0.90	0.94	0.90	0.94	0.90	0.95	0.89	0.93	0.91	0.94	0.90	0.93	0.90	0.94
FL	0.79	0.88	0.79	0.87	0.81	0.91	0.76	0.84	0.83	0.91	0.91	0.95	0.78	0.88
IL	0.90	0.93	0.90	0.93	0.93	0.96	0.89	0.92	0.93	0.94	0.91	0.93	0.90	0.93
MI	1.20	1.06	1.21	1.06	1.11	1.03	1.22	1.06	1.17	1.06	...	...	1.20	1.06
MN	0.92	0.95	0.91	0.94	0.93	0.97	0.90	0.93	0.93	0.95	...	...	0.92	0.95
NJ	0.93	0.94	0.94	0.94	0.93	0.95	0.93	0.94	0.95	0.95	0.97	0.96	0.93	0.94
NY	1.00	0.95	1.00	0.95	0.99	0.97	0.99	0.93	1.02	0.97	1.02	0.96	0.99	0.94
NC	0.97	0.98	0.97	0.98	0.99	0.99	0.97	0.98	0.97	0.99	...	...	0.97	0.98
OH	1.11	0.99	1.12	0.99	...	...	1.19	1.01	1.03	0.97	...	...	1.11	0.99
OR	0.76	0.83	0.76	0.82	...	...	0.79	0.87	0.76	0.82	0.79	0.85	0.76	0.82
TX	0.99	0.99	0.99	0.99	1.00	0.99	0.99	0.99	0.98	0.98	0.96	0.99	0.99	0.99
VA	0.88	0.93	0.88	0.92	0.89	0.95	0.88	0.93	0.87	0.91	…	…	0.88	0.93
Estimated elasticity of property related crimes averted to enhanced sanctions														
AZ	0.83	0.90	0.82	0.90	0.90	0.94	0.79	0.85	0.84	0.91	0.83	0.90	0.83	0.90
CA	0.74	0.79	0.74	0.78	0.79	0.83	0.73	0.78	0.75	0.79	0.74	0.78	0.74	0.79
FL	0.62	0.71	0.61	0.69	0.67	0.78	0.58	0.63	0.67	0.77	0.73	0.82	0.61	0.70
IL	0.63	0.68	0.62	0.68	0.75	0.81	0.62	0.67	0.66	0.71	0.65	0.67	0.63	0.68
MI	0.70	0.73	0.68	0.71	0.85	0.84	0.68	0.72	0.71	0.74	...	...	0.70	0.73
MN	0.72	0.77	0.72	0.77	0.79	0.87	0.69	0.75	0.73	0.79	...	...	0.72	0.77
NJ	0.69	0.74	0.68	0.74	0.73	0.81	0.68	0.74	0.70	0.76	0.72	0.79	0.68	0.74
NY	0.39	0.35	0.37	0.34	0.56	0.61	0.35	0.31	0.43	0.43	0.45	0.47	0.35	0.31
NC	0.87	0.92	0.86	0.92	0.91	0.95	0.87	0.92	0.87	0.93	...	...	0.87	0.93
OH	0.72	0.81	0.70	0.78	...	...	0.68	0.77	0.75	0.85	...	...	0.72	0.81
OR	0.61	0.67	0.61	0.66	...	...	0.65	0.75	0.61	0.66	0.63	0.66	0.61	0.67

Table 3 continued

	All		Males		Females		Blacks		Non-blacks		Hispanics		Non-Hisp.	
	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.	Mean	Med.
TX	0.77	0.83	0.76	0.82	0.85	0.88	0.77	0.83	0.76	0.83	0.77	0.84	0.77	0.83
VA	0.59	0.64	0.57	0.62	0.71	0.75	0.58	0.64	0.59	0.63	...	...	0.59	0.64

... Fewer than 100 observations

fat tail. There is no clustering of individuals around the higher elasticity values. Instead, the empirical cumulative density function rises gradually from 0 to 1. Interestingly enough, almost 10% of the sample has an estimated elasticity of less than 0.2 with about 1% for whom enhancing sanctions would produce absolutely no benefits. This suggests that these individuals were released at a point in their life when their careers had already terminated.

Since the elasticities are normalized they can be compared across persons, states, and offense types. A quick comparison of the two offense types suggests that in a large portion of the sample, the point of diminishing returns has been reached with respect to crimes against persons. There still exist some unutilized potential reductions in person related crimes that can be accrued if individuals are selectively incapacitated. On the other hand, the analysis of property related crimes suggests that further increases in sanction severity will not yield proportional increases in crimes averted by incapacitation.

Finally, Table 3 shows the estimated elasticities by state and various offender demographic characteristics. As was found with the annual crimes averted by incapacitation estimates, there seem to be no major systematic patterns discernable here along demographic attributes. However, some states (e.g., Michigan, Ohio, and Texas) clearly have a relatively higher potential for reducing crimes against persons by pursuing selective incapacitation strategies. Increasing the prison terms of nearly half the releasees in these states by a percent would yield at least a percent increase in the number of crimes against persons averated.

Conclusion

This paper developed an information theoretic approach for modeling the criminal history accumulation process of a sample of prison releasees. Separate models were estimated for two crime categories—crimes against persons and property related crimes. In addition, a model was estimated for all crimes combined. These sets of models were estimated for each of the 13 states included in the analysis. The estimated parameters were then combined with individual offender attributes to compute counterfactual offending micro-trajectories that one could reasonably expect the offender to have been on, had (s)he not been incarcerated. These counterfactuals were then integrated over the actual incarceration period to obtain estimates of the annual number of crimes averted by incapacitation. Further, the models were used to simulate the anticipated effects of increasing prison terms for all individuals. The resulting elasticities were assessed across offender sub-groups and offense types.

Although a fair amount of heterogeneity was found among offenders, there were few discernable differences across offender sub-groups based on demographic characteristics. With the exception of gender, where incapacitating males was found to avert slightly more crime than incapacitating females, the differences were negligible and inconsistent across race and ethnicity groups. There was a fair amount of variation among the estimated annual crimes averted by incapacitation across various states and across the two offense categories analyzed.

Across all 13 states, the average number of crimes against persons averted annually was 1.93 (with a median of 1.41). The average property related crimes averted annually across these states was 8.47 (with a median of 5.75). These numbers are comparable to estimates reported elsewhere using official arrest data. For example, Blumstein and Cohen (1979, p. 580) report the estimated individual crime rate for aggravated assault to be about 1.7 where as that for burglary, larceny, and auto theft to be between 2.8 and 10. Similarly, Marvell and Moody (1994, p. 118) summarize that between 16 and 25 index crimes are committed annually by incarcerated prisoners. In the present analysis, the estimated mean number of all crimes averted by incapacitation annually (across the 13 states) was 18.5 (with a median of 13.9).

Despite the similarity in these estimates, I hasten to add a cautionary note here since estimates reported in Blumstein and Cohen (1979) and those summarized by Marvell and Moody (1994) were generated from data nearly two decades prior to those used in my analysis. It is unclear whether the less punitive systems of those times should produce similar, larger, or smaller crimes averted estimates than those reported here. What this analysis does suggest is that mean rates reported in earlier studies undoubtedly mask huge variations among individuals. Understanding the source of this variation is crucial to developing efficient policies that do not squander resources. Clearly, since states have different policies and practices, we can expect (and do find in this analysis) a fair amount of variation in the estimates across states. There is still a lot of heterogeneity among individuals that needs to be understood if any strategies are to be devised that will make the best use of limited prison space.

The limited set of analyses simulating the elasticities of the incapacitation effect to an increased prison term suggest that the gains to be made by further increases in prison terms are disproportional. The elasticities of the crimes against persons averted are larger than 1 for a few individuals, but are largely clustered around 0.9. For property related crimes, however, the point of diminishing marginal returns may have been crossed. Simulations suggest that, for most individuals, a 1% increases in prison term will yield a less than a percent increase in the number of crimes averted. Based on these simulations, it is reasonable to conjecture that, at least for property related crimes, reducing the incarceration terms of a large number of inmates may result in little or no reductions in the number of crimes averted by incapacitation. Although the amount of reduction in prison term that may yield little or no reductions in public safety will vary tremendously, as expected, among individuals and will require more detailed analysis, the prospects of reducing incarceration expenses without reducing public safety is very appealing. The analytical framework developed here can provide helpful guidance on early release decisions, if such decisions are contemplated by policy-makers when faced, for example, with prison overcrowding.

Future Research

The use of trajectory-based methods for studying offending over the life-course is not new. Nagin (2005) succintly summarizes what has been learned about this phenomenon to date by applying group-based semi-paramteric methods—first applied to this problem by Nagin and Land (1993). Although the purpose of developing offending trajectories for the present analysis was to project counterfactuals, an interesting avenue for future research would be to compare the substantive predictions made by the present model with those summarized in Nagin (2005).

As was noted in the introductory section of this paper, all inferences derived and discussed here pertain only to the population of releasees. However, incarceration policy may also be altered by increasing or decreasing the incarceration rate without altering the length of the imposed term. In order to empirically assess that set of policy options, it would be necessary to develop weights that would allow the micro-simulations, developed in this paper, to be re-weighted to reflect the unequal probabilities of selection into the current sample of releasees. If such selection weights could be developed satisfactorily, then it may be possible to use the empirical distributions discussed here to provide guidance for those policies choices.

As suggested by a reviewer, it would be interesting to link the state variations uncovered in this study to state policy choices (e.g., the punitiveness of the justice system) since states vary considerably with respect to their penal policies and procedures. Moreover, given their policies, states could already be selectively incapacitating high rate offenders at differential rates. A fruitful avenue for future research, thus, would be to attempt to empirically test competing hypotheses explaining these variations.

Although the modeling exercise conducted here simulated counterfactual trajectories only for the period an individual was incapacitated, nothing precludes us from utilizing this model to simulate a post-release counterfactual. Since the data contain detailed information on the offending patterns of this sample of releasees for a period of 3 years after release, a comparison of the actual offending rate with the simulated counterfactual can be used to study whether, and to what extent, the incarceration has altered the offending patterns of each individual. This approach has been applied elsewhere (Bhati 2006; Bhati and Piquero 2007) and preliminary results indicate that about 40% of the release cohort can be characterized as having been deterred from future offending (specific deterrence), about 56% returned back to offending patterns that were anticipated by their counterfactuals (were merely incapacitated), and about 4% actually experienced criminogenic effects. Similar analysis may be used to compute the number of future crimes averted or caused by incarceration, and what, if any, policy levers can be used to change those outcomes.

Finally, since the data are at the individual level and since the analysis builds on developing the criminal history accumulation process, one can utilize time varying macro covariates to incorporate general deterrence and replacement effects into the model. For example, to the extent that historic sentencing policies are found to affect the micro-trajectories estimated in this analysis, we will have uncovered general deterrence effects. Similarly, to the extent that historical incarceration rates or changes thereof are found to affect the micro-trajectories, we will have uncovered replacement effects. These extensions are possible, at least in theory. They have yet to be implemented and are promising avenues for future work.

References

Allison PD (1984) Event history analysis. Sage Publications, Beverly Hills, CA

Allison PD (1995) Survival analysis using SAS: a practical guide. SAS Institute Inc., Cary, NC

Avi-Itzhak B, Shinnar R (1973) Quantitative models of crime control. J Crim Just 1:185–217

Bhati AS (2006) Studying the effects of incarceration on offending trajectories: an information-theoretic approach. The Urban Institute, Washington, DC

Bhati AS (2007) An information-theoretic method for estimating the number of crimes averted by incapacitation. The Urban Institute., Washington, DC

Bhati AS, Piquero A (2007) On the effects of incarceration on subsequent individual criminal offending: deterrent, criminogenic, or null effects? Under review

Blossfeld F, Hamerele A, Mayer KU (1989) Event history analysis: statistical theory and applications in the social sciences. Lawrence Erlbaum Association Publishers, Hillsdale, NJ

Blumstein A, Cohen J (1973) A theory of the stability of punishment. J Crim Law Criminol 64(2):198–207
Blumstein A, Cohen J (1979) Estimating the individual crime rates from arrest records. J Crim Law Criminol 70(4):561–585
Blumstein A, Cohen J, Roth JA, Visher CA (1986) Methodological issues in criminal career research. In: Blumstein A, Cohen J, Roth JA, Visher CA (eds) Criminal careers and "career criminals", Vol I. National Academy Press, Washington, DC
Blumstein A, Piquero A (2007) Does incapacitation reduce crime? J Quant Criminol, this issue
Brame R, Bushway S, Paternoster R (2003) Examining the prevalence of criminal desistance. Criminology 41:423–448
Bureau of Justice Statistics (2002) Recidivism of Prisoners Released in 1994, Codebook for Dataset 3355. Downloaded from NACJD in August 2003
Bushway S, Brame R, Paternoster R (2004) Connecting desistance and recidivism: measuring changes in criminality over the lifespan. In: Shadd Murana, Russ Immarigeon (eds) After crime and punishment: pathways to offender reintegration. Willian Publishing, Portland, OR
Chaiken JM, Chaiken MR (1982) Variations in criminal behavior. Rand, Santa Monica, CA
Cohen J (1978) The incapacitation effects of imprisonment: a critical review of the literure. In: Blumstein A, Cohen J, Nagin D (eds) Deterrence and incapacitation: estimating the effects of criminal sanctions on crime rates. National Academy of Sciences, Washington, DC
Cohen J (1983) Incapacitation as a strategy for crime control: possibilities and pitfalls. In: Tonry M, Morris N (eds), Crime and justice: an annual review of research. vol 5, Chicago University Press, Chicago, IL
Cohen J (1986) Research on criminal careers: individual frequency rates and offense seriousness. In: Blumstein A, Cohen J, Roth JA, Visher CA (eds) Criminal careers and "Career Criminals". vol I, National Academy Press, Washington, DC
DiIulio JJ (1990) Crime and punishment in wisconsin, wisconsin policy research institute report, vol 3, no. 7, Wisconsin Policy Research Institute, Milawukee, WI
Ezell ME, Land KG, Cohen LE (2003) Modeling multiple failure time data: a survey of variance-corrected proportional hazard models with empirical applications to arrest data. Sociol Methodol 33:111–167
Farrington D (1986) Age and crime. In: Morris N, Tonry M (ed) Crime and justice 1:289–348. University of Chicago Press, Chicago, IL
Fomby TB, Hill RC (1997) ed. Advances in econometrics: applying maximum entropy to econometric problems, Vol. 12
Golan A (2002) Information and entropy econometrics—editor's view. J Econom 107(1–2):1–357
Golan A, Judge GG, Miller D (1996) Maximum entropy econometrics: Robust estimation with limited data. John Wiley and Sons, Chichester, England
Greenburg DF (1975) The incapacitation effect of imprisonment: some estimates. Law Soc Rev 9(4):541–580
Hart TC, Rennison C (2003) Reporting Crime to the Police, 1992–2000. Special Report, Bureau of Justice Statistics (NCJ 195710), Washington, DC
Harding RW, Maller RA (1997) An improved methodology for analyzing age-arrest profiles: application to a eastern Australian offender population. J Quant Criminol 13(4):349–372
Horney J, Marshall I (1991) Measuring lambda through self-reports. Criminology 29:401–425
Huber PJ (1967) The behavior of maximum likelihood estimators under non-standard conditions. Proceeding of the Fifth Symposium on Mathematical Statistics and Probability 1:221–233
Jaynes ET (1957a) Information theory and statistical mechanics. Phy Rev 106:620–630
Jaynes ET (1957b) Information theory and statistical mechanics II. Phys Rev 108:171–190
Journal of Econometrics (2002) ed. Special Issues on Information, Entropy Econometrics Amos Golan. 107(1–2):1–357
Kullback J (1959) Information theory and statistics. John Wiley, New York, NY
Langan PA, Levin DJ (2002) Recidivism of prisoners released in 1994. Special Report, Bureau of Justice Statistics, New York, NY
Lillard LA (1993) Simultaneous equations for hazards: marriage duration and firtility timing. J Econom 56:189–217
Maasoumi E (1993) A compendium of information theory in economics and econometrics. Econom Rev 12(2):137–181
Maltz MD (1984) Recidivism. Academic Press, Orlando, FL
Manski C (1988) Analog estimation methods in econometrics. Chapman and Hall, London
Marvell TB, Moody CE (1994) Prison population growth and crime reduction. J Quant Criminol 10(2):109–140
Mayer KU, Tuma NB (eds) (1990) Event history analysis in life course research. The University of Wisconsin Press, Madison, EI

Miles T, Ludwig J (2007) Silence of the lambdas: deterring incapacitation research. J Quant Criminol, this issue
Mittelhammer RC, Judge GG, Miller DJ (2000) Econometric foundations. Cambridge University Press, Cambridge, UK
Nagin DS (2005) Group based models of development. Harvard University Press, Boston, MA
Nagin DS, Land K (1993) Age, criminal careers, and population heterogeneity: specification and estimation of a non-parametric, mixed poisson model. Criminology 31:327–362
Nagin DS, Paternoster R (2000) Population heterogeneity and state dependence: state of the evidence and directions for future research. J Quantit Criminol 16:117–144
Petersilia J, Greenwood PW, Lavin M (1978) Criminal careers of habitual Felons. Rand, Santa Monica, CA
Pastore AL, Maguire K (eds) (2005) Sourcebook of criminal justice statistics 2003. U.S. Department of Justice, Bureau of Justice Statistics. USGPO, Washington, DC
Reiss AJ (1988) Co-offending and criminal careers. pages 117–170. In: Tonry M, Morris N (eds) Crime and justice: an annual review of research. Vol. 10, Chicago University Press, Chicago, IL
Ryu HK (1993) Maximum entropy estimation of density and regression functions. J Econom 56:397–440
Sampson RJ, Laub JH (2005) A life-course view of the development of crime. Ann Am Acad Pol Soc Sci 602:6–45
Shannon CE (1948) A mathematical theory of communication. Bell Syst Tech J 27:379–423
Shinnar S, Shinnar R (1975) The effects of the criminal justice system of the control of crime: a quantitative approach. Law Soc Rev 9:581–611
Soofi ES (1994) Capturing the intangible concept of information. J Am Statis Assoc 89(428):1243–1254
Spelman W (1994) Criminal incapacitation. Plenum, New York
Spelman W (2000) What recent studies Do (and Don't) tell us about imprisonment and crime. Crime Just 27:419–494
Visher CA (1987) Incapacitation and crime control: does a "Lock 'Em Up" strategy reduce crime? Just Q 4(4):513–543
White H (1980) A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48:817–830
Yamaguchi K (1991) Event history analysis. Sage Publishing, Inc, Newbury Park, CA
Zellner A (1991) Bayesian methods and entropy in economics and econometrics. In: Grady WT, Schick LH (eds) Maximum entropy and Bayesian methods. Kulwer, Netherlands pp 17–31
Zellner A, Highfield RA (1988) Calculation of maximum entropy distributions and approximation of marginal posterior distributions. J Econom 37:195–209
Zimring F, Hawkins G (1995) Incapacitation: penal confinement and the restraint of crime. Oxford University Press, New York, NY