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ESTIMATING THE IMPACT OF INCARCERATION ON SUBSEQUENT OFFENDING TRAJECTORIES: DETERRENT, CRIMINOGENIC, OR NULL EFFECT?

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Despite record levels of incarceration and much discussion about the role that incarceration plays in influencing criminal activity, there does not yet exist a sound knowledge base about the extent to which incarceration exhibits a criminogenic, deterrent, or null effect on subsequent individual offending trajectories. This is an unfortunate happenstance since classic criminological theories make vastly different predictions about the role of punishment in altering criminal activity, and life-course criminologists suggest that life events can materially influence subsequent criminal activity. Using arrest histories of a sample of prisoners released from state prisons in 1994 and followed for three years post-release, this Article seeks to address the impact of incarceration on subsequent offending trajectories. Results indicate that a comparison of the counterfactual and actual offending patterns suggests that most releasees were either deterred from future offending (40%) or merely incapacitated by their incarceration (56%). Only about 4% had a criminogenic effect. Future theoretical and empirical research directions are outlined.

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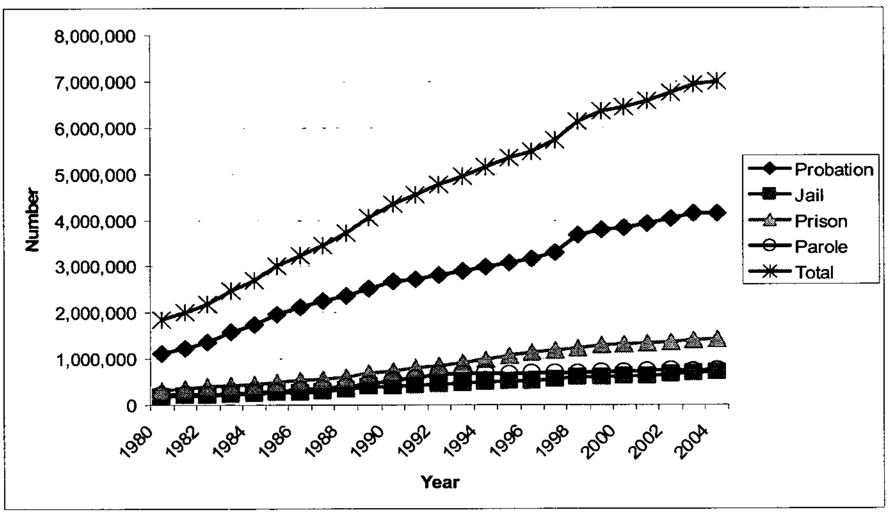
I. INTRODUCTION

There is no doubt that the major crime-reduction strategy since the 1980s has been to increase the use of punishment, especially incapacitation, under the assumption that offenders will be prevented from committing further crimes.[1] Incapacitation strategies seek to reduce crime by interruption, or "taking a slice out of" an individual career.[2] Figure 1 shows the number of individuals under several types of adult correctional supervision between 1980 and 2004. All forms of correctional supervision have been increasing since the 1980s, and especially during the early 1990s when crime rates reached their peak in the United States; by year-end 2004, there were almost seven million individuals under some form of correctional control—2.3% of the U.S. population in 2004. These trends show no signs of waning. As shown in Figure 2, the State of California is projected to add 23,000 new inmates by 2011—totaling 193,000 inmates—a growth being driven largely by increases in new prison admissions and by parolees' new crimes or parole violations.[3]

Figure 1

U.S. Adult Correctional Population, 1980-2004



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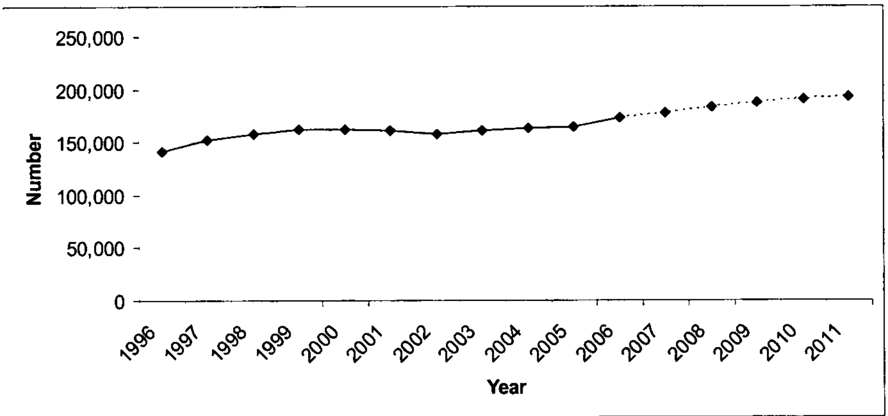
[1] FRANKLIN E. ZIMRING & GORDON HAWKINS, INCAPACITATION (1995); Thomas B. Marvell & Carlisle E. Moody, Jr., *Prison Population Growth and Crime Reduction*, 10 J. QUANTITATIVE CRIMINOLOGY 109 (1994).

[2] Alfred Blumstein, *Incapacitation*, *in* 3 ENCYCLOPEDIA OF CRIME & JUSTICE 873-80 (Sanford H. Kadish ed., 1983). *Accord* Christy A. Visher, *Incapacitation and Crime Control: Does a "Lock 'Em Up" Strategy Reduce Crime?*, 4 JUST. Q. 513 (1987).

[3] Jenifer Warren, *Packed Prisons Brace for New Crush*, L.A. TIMES, Apr. 22, 2006, at A1.

Figure 2

California Current and Projected Institutional Population, 1996-2011



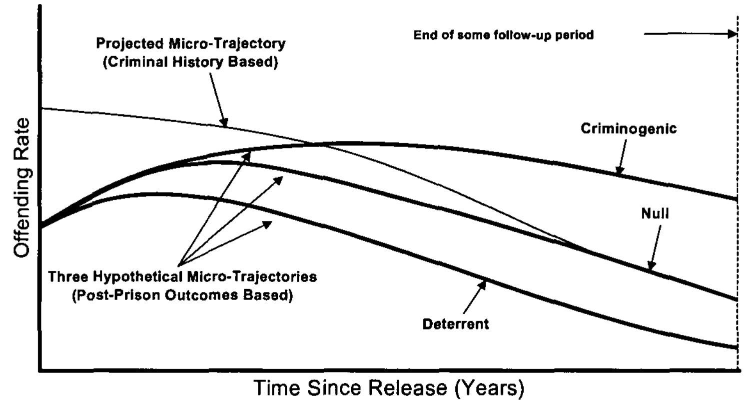
Amidst this backdrop, a very basic but important question to be asked is the extent to which incapacitation affects individuals generally, and their subsequent criminal activity specifically. Of course, for incapacitation strategies to be effective, there is a need to identify the sorts of offenders who are expected to commit crimes at very high rates while free and whose crimes would not be committed by someone else in their absence.[4] As depicted in Figure 3, it could produce three distinct outcomes. First, it could lead to an increase in the rate of subsequent criminal activity: a criminogenic effect. Second, it could lead to a decrease in the rate of subsequent criminal activity: a deterrent effect. Third, it could lead to no change in the rate of subsequent criminal activity: a null effect. Identifying and understanding the effects that incapacitation can have on individuals under different contexts is crucial in: (1) assessing theoretical predictions about the role of punishment in criminal careers, and (2) developing strategies that minimize any criminogenic harm and maximize any deterrent benefits that result from it—a key issue in the reentry discussion.[5]

[4] *See* RUDY HAAPANEN, SELECTIVE INCAPACITATION AND THE SERIOUS OFFENDER: A LONGITUDINAL STUDY OF CRIMINAL CAREER PATTERNS 121 (1990); José Canela-Cacho et al., *Relationship Between the Offending Frequency (λ) of Imprisoned and Free Offenders*, 35 CRIMINOLOGY 133 (1997).

[5] *See* JOAN PETERSILIA, WHEN PRISONERS COME HOME: PAROLE AND PRISONER RE-ENTRY (Michael Tonry & Norval Morris eds., 2003).

Figure 3

Potential Effects of Incapacitation on Subsequent Offending Trajectories



Unfortunately, while there is much discussion about whether incapacitation reduces crime at the aggregate- and individual-level of analysis,[6] there have been few assessments about whether incapacitation, as a life-interrupting event, deflects individual criminal careers—either upwardly or downwardly. The purpose of this Article is to examine the effects of incarceration on individual offending trajectories. In so doing, it extends this area of research by proposing and implementing an information-theoretic model applied to a large sample of prisoners. The results of such an effort bear on both theoretical and policy matters, to which we now turn.

II. THEORETICAL CONTEXT

The extent to which incapacitation influences criminal careers bears on two strands of criminological theory: that which focuses on the role of punishment (deterrence, labeling, defiance), and that which focuses on the relationship between past and future criminal activity (life-course).

Incapacitation is a specific form of punishment, and understanding the effects of punishment on individual behavior has been a central feature in

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[6] *See* Thomas J. Miles & Jens Ludwig, *The Silence of the Lambdas: Deterring Incapacitation Research*, 23 J. QUANTITATIVE CRIMINOLOGY (2007); Alex R. Piquero & Alfred Blumstein, *Does Incapacitation Reduce Crime?*, 23 J. QUANTITATIVE CRIMINOLOGY (2007); William Spelman, *What Recent Studies Do (and Don't) Tell Us About Imprisonment and Crime*, 27 CRIME & JUST. 419 (2000).

the study of criminology.[7] At the same time, several classic criminological theories make vastly different predictions about the role of punishment with regard to subsequent behavior. According to the classical perspective, swift, certain, and severe punishment should dissuade future criminal activity by altering sanction threat perceptions. Effectively punished individuals are expected to view the threat of sanctions as more salient and thus be deterred from subsequent criminal activity. The research base regarding the deterrent effect of punishment (typically within the context of a police contact or arrest) on sanction threats and subsequent criminal activity is not conclusive, though tends to suggest that the certainty of punishment exhibits a small but significant deterrent effect.[8]

Contrary to the deterrence perspective, the labeling perspective makes a vastly different prediction. Here, punishment is expected to lead to continued criminal activity because offenders become officially labeled as delinquent or criminal, or they internalize and adopt a criminal label that reinforces a criminal image.[9] This label, and the more general labeling process, serves to sever opportunities to prosocial pathways, leaving the offender with few options, and this is believed to be the case regardless of whether the imposition of the label comes from formal or informal social control agents.[10] Much like the evidence on deterrence, the research base with regard to the effect of punishment on subsequent criminal activity via the labeling perspective is mixed,[11] though some recent research finds evidence for indirect labeling effects.[12]

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[7] *See, e.g.*, FRANKLIN E. ZIMRING & GORDON HAWKINS, DETERRENCE (1973).

[8] *See* Daniel S. Nagin, *Criminal Deterrence Research at the Outset of the 21st Century*, 23 CRIME & JUST. 1 (1998); Raymond Paternoster, *The Deterrent Effect of the Perceived Certainty and Severity of Punishment: A Review of the Evidence and Issues*, 4 JUST. Q. 173 (1987); Greg Pogarsky et al., *Modeling Change and Perceptions About Sanction Threats: The Neglected Linkage in Deterrence Theory*, 20 J. QUANTITATIVE CRIMINOLOGY 343 (2004); Greg Pogarsky & Alex R. Piquero, *Can Punishment Encourage Offending? Investigating the "Resetting" Effect*, 40 J. RES. CRIME & DELINQ. 95 (2003); Douglas A. Smith & Patrick R. Gartin, *Specifying Specific Deterrence: The Influence of Arrest on Future Criminal Activity*, 54 AM. SOC. REV. 94 (1989).

[9] EDWIN M. SCHUR, RADICAL NONINTERVENTION (1973); FRANK TANNENBAUM, CRIME AND THE COMMUNITY (1938).

[10] Ross Matsueda, *Reflected Appraisals, Parental Labeling, and Delinquency: Specifying a Symbolic Interactionist Theory*, 97 AM. J. SOC. 1577 (1992); Ruth A. Triplett & G. Roger Jarjoura, *Theoretical and Empirical Specification of a Model of Informal Labeling*, 10 J. QUANTITATIVE CRIMINOLOGY 241 (1994).

[11] Douglas A. Smith & Raymond Paternoster, *Formal Processing and Future Delinquency: Deviance Amplification as Selection Artifact*, 24 LAW & SOC'Y REV. 1109 (1990); David A. Ward & Charles R. Tittle, *Deterrence or Labeling: The Effects of Informal Sanctions*, 14 DEVIANT BEHAV. 43 (1993).

[12] Jon Bernburg et al., *Official Labeling, Criminal Embeddedness, and Subsequent Delinquency: A Longitudinal Test of Labeling Theory*, 43 J. RES. CRIME & DELINQ. 67

Even further, the defiance perspective advanced by Sherman outlines a series of conditional hypotheses for the effect of punishment on subsequent criminal activity.[13] In defiance theory, punishment can be effective, ineffective, or conditional, depending upon a number of factors, including the context and manner in which the agent delivers the sanction. Because defiance theory is relatively new and requires the collection of original data, the evidence base regarding defiance predictions on the effect of punishment is both indirect and scant.[14]

In short, key theoretical perspectives outline disparate predictions with regard to the role of punishment in deflecting subsequent criminal activity. It is important to recognize that most research conducted with regard to punishment has focused on the role of police contacts or arrest in influencing subsequent behavior.[15] Very few efforts have examined the specific role of incapacitation on subsequent individual patterns of offending.

In a parallel fashion, one of the most consistently documented criminological facts is the link between prior and future criminal activity. Individuals who were criminal in the past have a strong likelihood of being criminal in the future. Although criminologists do not speak with one voice about the explanation for this persistence in, and more interestingly, the divergence from, criminal activity,[16] the theoretical debate underlying this linkage centers on the causal interpretation attributed to the link between past and future crime.[17]

(2006); Jon Bernburg & Marvin D. Krohn, *Labeling, Life Chances, and Adult Crime: The Direct and Indirect Effects of Official Intervention in Adolescence on Crime in Early Adulthood*, 41 CRIMINOLOGY 1287 (2003).

[13] Lawrence W. Sherman, *Defiance, Deterrence, and Irrelevance: A Theory of the Criminal Sanction*, 30 J. RES. CRIME & DELINQ. 445 (1993).

[14] *See* Raymond Paternoster & Alex Piquero, *Reconceptualizing Deterrence: An Empirical Test of Personal and Vicarious Experiences*, 32 J. RES. CRIME & DELINQ. 251 (1995); Alex R. Piquero et al., *Discerning Unfairness Where Others May Not: Low Self-Control and Unfair Sanction Perceptions*, 42 CRIMINOLOGY 699 (2004); Alex R. Piquero & Raymond Paternoster, *An Application of Stafford and Warr's Reconceptualization of Deterrence to Drinking and Driving*, 35 J. RES. CRIME & DELINQ. 5 (1998); Nicole L. Piquero & Leana Allen Bouffard, *A Preliminary and Partial Test of Specific Defiance*, 26 J. CRIME & JUST. 1 (2003).

[15] *See, e.g.*, LAWRENCE W. SHERMAN, POLICING DOMESTIC VIOLENCE (1992).

[16] *See* Alex R. Piquero et al., *The Criminal Career Paradigm*, 30 CRIME & JUST. 359 (2003).

[17] *See* Daniel S. Nagin & Raymond Paternoster, *On the Relationship of Past to Future Participation in Delinquency*, 29 CRIMINOLOGY 163 (1991).

Some criminologists argue that this link is simply a manifestation of a constant and unchanging criminal propensity.[18] Such stable individual differences in criminal propensity are believed to manifest in and across a variety of domains over the life course. Here, individuals who commit offenses at one point in time are more likely than non-offenders to commit crimes at a later point in time. According to this population heterogeneity perspective, there is heterogeneity within the population in a time-stable characteristic that affects the probability of antisocial behavior early in the life course and at all subsequent points thereafter.[19] Others argue that the link between past and future crime reflects the fact that the act of committing a crime transforms the offender's life circumstances in such a way that it alters the probability that subsequent criminal acts will occur, commonly referred to as state dependence. According to Nagin and Paternoster, this process is one of contagion in which an offender's current activities make their life circumstances worse, accelerating the probability of future crime.[20] Involvement in crime could lead to changes in affiliation with delinquent peers, failure in school, etc. which, in turn, lead to subsequent criminal activity. Even further, other scholars argue for some sort of mixed explanation, which allows for both stable individual differences in criminal propensity and for the fact that criminal behavior can causally alter the risk of future crime.[21]

Thus far, the collective research findings appear to indicate that individual differences in criminal propensity are more important than previously thought and that events and experiences that occur after individual differences in criminal propensity have formed also seem to have important consequences for subsequent criminal activity.[22] In short, evidence for a mixed model of population heterogeneity and state dependence is growing.

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[18] *See, e.g.*, MICHAEL R. GOTTFREDSON & TRAVIS HIRSCHI, A GENERAL THEORY OF CRIME (1990).

[19] Daniel S. Nagin & Raymond Paternoster, *Population Heterogeneity and State Dependence: State of the Evidence and Directions for Future Research*, 16 J. QUANTITATIVE CRIMINOLOGY 117 (2000).

[20] *Id.*

[21] JOHN H. LAUB & ROBERT J. SAMPSON, SHARED BEGINNINGS, DIVERGENT LIVES: DELINQUENT BOYS AT AGE 70 (2003); Raymond Paternoster et al., *Generality, Continuity, and Change in Offending*, 13 J. QUANTITATIVE CRIMINOLOGY 231 (1997).

[22] *See* Julie D. Horney et al., *Criminal Careers in the Short-Term: Intra-Individual Variability in Crime and Its Relation to Local Life Circumstances*, 60 AM. SOC. REV. 655 (1995); John H. Laub et al., *Trajectories of Change in Criminal Offending: Good Marriages and the Desistance Process*, 63 AM. SOC. REV. 225 (1998); Alex R. Piquero et al., *Crime in Emerging Adulthood*, 40 CRIMINOLOGY 137 (2002).

The policy relevance of the aforementioned debate is obvious: To the extent that an individual's relative criminal propensity is "fixed," incarceration can and should play only an incapacitative role, with the rate of subsequent criminal activity resuming at the same point as before incapacitation. If, on the other hand, an individual's relative criminal propensity is not "fixed," then incarceration could serve as a deterrent and possible turning point to desistance from crime. Whether incapacitation influences the relationship between past and future crime is an important but under-researched question. On this point, Nagin and Paternoster have noted that additional work is needed with regard to identifying the specific events and experiences that can lead persons into and out of crime. One of these is the extent to which institutionalization in the criminal justice system may lead to a deeper involvement in crime, perhaps by "knifing off" conventional opportunities.

III. EXTANT RESEARCH

The study of incapacitation and its role in altering criminal activity is a central policy question underlying the criminal career framework.[23] Scholars have examined the effect of incapacitation on crime through the lens of both individual criminal careers and aggregate crime rates.[24] Given the purpose of the current study, we briefly highlight four relevant studies with regard to the effects of incapacitation on micro-, or individual-level criminal careers.

Haapanen used data from a sample of California Youth Authority offenders to compare aggregate offense rates in the four-year period before and four-year period after their current sentence.[25] As reproduced in Figure 4, the offense rates showed a drop immediately after release from the current sentence, with some continuing decline after that point. Specifically, the four-year average prior to the current sentence was 3.95 arrests, while the four-year average after the current sentence was 2.00 arrests.[26] None of the arrest rates in the four-year post-sentence periods approaches any of the arrest rates in the four-year pre-sentence periods.[27]

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[23] ALFRED BLUMSTEIN ET AL., CRIMINAL CAREERS AND "CAREER CRIMINALS" (1986).

[24] *See* Miles & Ludwig, *supra* note 6; Piquero & Blumstein, *supra* note 6; Spelman, *supra* note 6.

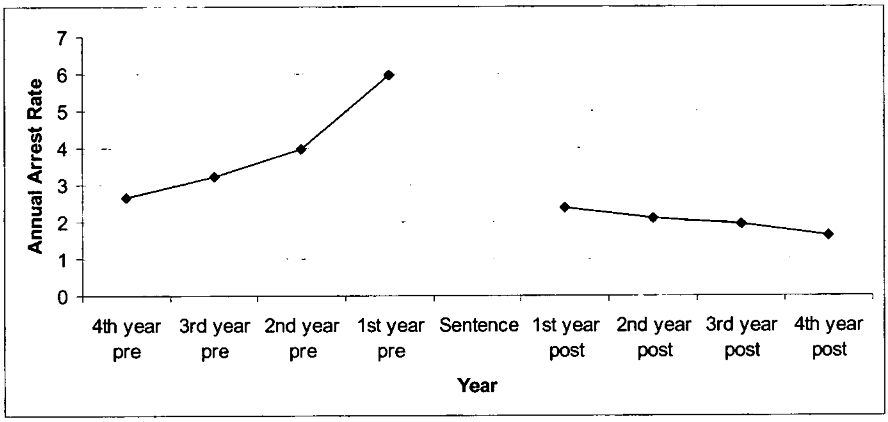
[25] *See* HAAPANEN, *supra* note 4.

[26] It is also worth pointing out that arrest rates increased shortly before the current sentence, which is consistent with research showing that offenders' criminal activity is highest just prior to their current sentence.

[27] Of course, such simple before/after comparisons are not without their limitations, see Michael D. Maltz et al., *An Artifact in Pretest-Posttest Designs: How It Can Mistakenly Make Delinquency Programs Look Effective*, 4 EVALUATION REV. 4 (1980), and a more

Figure 4

Average Annual Arrest Rate, Four Years Pre- and Four Years Post-Sentence[28]



In a series of companion studies using data from a classic longitudinal study of 500 Boston-area delinquents, Laub and Sampson found that incarceration as a juvenile and as a young adult had a negative effect on later job stability, which was negatively related to continued involvement in crime over the life course (by age thirty-two).[29] In a more recent study using an extension of the Glueck data through age seventy, Laub and Sampson undertook an in-depth quantitative and qualitative study of incarceration experiences and how such experiences influenced criminal activity and other aspects of the men's lives.[30] Two specific themes emerged from their interviews. The first was that most men viewed the criminal justice system as corrupt and disinterested in helping them move away from a life of crime. For example, for "Boston Billy," who had spent about half his life in prisons and jails, institutions were horrible places that toughened people up "to a point that you don't care."[31] For Billy and other persistent offenders, prison was no turning point, as it failed to serve any sort of deterrent effect. Moreover, it may have produced a criminogenic effect, since prisons rarely offered skill training, and offenders instead

rigorous examination would require a determination of what would have happened to these arrest rates if the sentences had not been imposed.

28 Figure reproduced from HAAPANEN, *supra* note 4, at 93 fig.7.1.

29 John H. Laub & Robert J. Sampson, *Turning Points in the Life Course: Why Change Matters to the Study of Crime*, 31 CRIMINOLOGY 301 (1993).

30 *See* LAUB & SAMPSON, *supra* note 21.

31 *Id.* at 151-72.

learned about others' successful involvement in crime.[32] The second theme that emerged was that the effects of incarceration across multiple life domains was variable; that is, incarceration appeared to work for some offenders in deterring them away from continued crime, while it failed to help other offenders. For example, the reform school experience was perceived as a positive turning point for some desisters. As articulated by Bruno, getting sent to the Lyman School for Boys "was positive, it was good,"[33] and for three other desisters, Angelo, Leon, and Henry, institutionalization in the Lyman School acted "as a turning point."[34] This rare deterrent effect notwithstanding, the portrait of long-term incarceration among the interviewed men, especially the persistent offenders, was "overwhelmingly negative."[35]

Rosenfeld and his colleagues used recidivism data from the Bureau of Justice Statistics Multiple State Data Set to assess the effect of released prisoners on state crime rates, focusing on: (1) the number of released prisoners, (2) differences among them in re-offending risk, and (3) the effects on re-offending of post-release supervision.[36] After removing some cases and states from the analysis due to data problems, they focused on three large categories of crime types (violent, property, and drug crimes) during one- and three-year periods following release. Regarding their first question, ex-prisoners' contribution to crime, they found that ex-prisoners had a small but non-trivial impact on crime rates. With respect to the correlates of recidivism, Rosenfeld et al. found results similar to previous research; prior arrests were associated with recidivism, while age was inversely associated with recidivism (older offenders were less likely to recidivate). Additionally, males were more likely to be re-arrested (for

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[32] *Id.* at 169, 188.

[33] *Id.* at 128.

[34] To be sure, the Lyman School experience was not the same for all the males, nor did it have the same sort of outcome for all of the males. Unlike the generally positive, deterrent experiences for Angelo, Leon, and Henry, David described the Lyman School experience as horrible, and Ralph encountered a labeling effect that caused his high school principal to target him for "things he didn't do." *Id.* at 232-35. Further, Laub and Sampson noted that it was difficult to understand why among those men who had adverse experiences, like Victor, some did not react negatively by committing further crime or failing in adult roles. *Id.* at 131.

[35] *Id.* at 291. Using a longer time series of the same data, Wimer et al. found that imprisonment was associated with higher rates of arrest, but that the criminogenic effect of arrest was fragile when they applied specific methods for causal inference with non-experimental data. Christopher Wimer et al., *A New Approach to Estimating Time-Varying Causes and Outcomes, With Applications to Incarceration and Crime*, *in* APPLIED DATA ANALYTIC TECHNIQUES FOR TURNING POINTS RESEARCH (Pat Cohen et al. eds., 2008).

[36] Richard Rosenfeld et al., *The Contribution of Ex-Prisoners to Crime Rates*, *in* PRISONER REENTRY IN AMERICA (Jeremy Travis & Christy Visher eds., 2005).

violence) than females, while black ex-prisoners were re-arrested more often than whites for all crime types. In contrast, they found that the number of months served in prison was not associated with incidence of re-arrest. After finding that discretionary parole release was associated with lower recidivism, the authors undertook a supplemental simulation analysis that examined the overall incidence of re-arrest if prisoners were shifted from discretionary parole to unconditional release. This analysis indicated that shifting prisoners from discretionary parole to unconditional release would produce small increases in the percentage of re-arrests. In their final analysis, the authors examined the "net" impact of incarceration on crime rates, and their findings indicated that, when extrapolating admission and release trends, many more persons will be leaving prisons and returning to the community than entering prison over time, and that those persons are predicted to add many thousand more crimes when they are released. In short, there will be a larger number of ex-prisoners returning to the community as they exit from prison, and resources need to be devoted to their successful transition and re-integration. Further, evidence from their analysis also supports the expanded use of discretionary parole supervision in the community.

Nieuwbeerta et al. used data from the Netherlands-based Criminal Career and Life-Course Study to examine the effect of first-time imprisonment at ages twenty-six to twenty-eight on the conviction rates in the three years immediately following the year of the imprisonment.[37] After combining group-based trajectory modeling with propensity score matching in order to achieve balance across different groups of individuals, the authors found that first-time imprisonment led to an increase in criminal activity in the three-year follow-up period, and that this effect was not sensitive to crime type (i.e., the results held for property, violent, and other crimes) or age at first imprisonment (i.e., the results held for imprisonment at ages twenty-one to twenty-three and thirty-one to thirty-three as well). Further, the results revealed that the imprisonment effect was observed for three different offending trajectory groups, and was largest for the comparison of the imprisoned versus the not-convicted at ages twenty-six to twenty-eight, but somewhat smaller (but still significant) for the comparison of the imprisoned versus the convicted but not imprisoned at ages twenty-six to twenty-eight.

The importance of their study is without question, but some limitations should be noted. First, they limited their analysis to persons who had not

[37] Paul Nieuwbeerta et al., The Relationship Between First Imprisonment and Criminal Career Development: A Matched Samples Comparison (2007) (unpublished manuscript, on file with Netherlands Institute for the Study of Crime and Law Enforcement).

been imprisoned prior to age twenty-six. Second, their sample experienced very little imprisonment, and among those who were imprisoned, the average term was four months, and 78% were imprisoned for less than six months. Clearly, the Dutch imprisonment experience is not much like that experienced in the United States. Nevertheless, their study is important as it stands as one of the first sets of studies to deal with the vast methodological problems that permeate the incapacitation and crime research area.

In sum, it should be clear that a summary statement regarding the effect of incarceration on subsequent criminal activity at the individual level is far from being realized. Punishment experiences such as incarceration tend to have varied effects on offenders, for some operating as a deterrent, for others as criminogenic, and for others as irrelevant. Further, the type of effect garnered by incarceration may vary at different points in the life course; for example, serving as a deterrent early in life and as criminogenic later in life. More generally, summary conclusions are difficult to realize because very few studies have actually examined the effect of imprisonment on subsequent offending trajectories, and almost none have involved any sort of random assignment procedure, leaving scholars to study the question as best they can, non-experimentally. What we ideally wish to see is the effect of imprisonment on recidivism and a counterfactual rate, recidivism if one was not incarcerated.

IV. CURRENT FOCUS: EXTENDING THE LITERATURE

The extent to which criminal justice sanctions, especially incarceration, foster recidivism or help lead to the termination of criminal activity is a central one in criminology, and takes on even more importance given the recent incarceration increases in the United States. In an effort to provide some evidence on this issue, the current research builds on prior recidivism research generally and post-prison recidivism research in particular, although with a slightly different emphasis. Our goal is to estimate and compare a releasee's actual post-prison offending trajectory with his or her criminal history-based counterfactual offending trajectory for the purpose of answering the question: "How, if at all, has this incarceration experience deflected the trajectory the offender was on?" Since the offender in question was incarcerated and had his or her career interrupted, the pre-prison offending micro-trajectory is termed a counterfactual because we never actually observe what this individual would have done had he or she not been incarcerated. The strategy developed in this Article is a flexible way of using all available knowledge about prior offending patterns to make inferences about post-prison offending trajectories.

In theory, this idea is not necessarily novel, but in practice it is. Bushway et al. note that "pre-existing rates of offending at the time of incarceration would be a perfect control for individual heterogeneity."[38] However, two individuals with exactly the same pre-incarceration offending rates may have been on differently sloped trajectories at the time of incarceration and, given varying lengths of time served in prison, could be released at very different times in their lives or careers. The analytical strategy developed in this Article, in utilizing a projected counterfactual for each and every individual, is a flexible and robust means of explicitly taking these differences into account.

Of course, the methodological challenge lies in developing this counterfactual and in assessing whether, and to what extent, the (actual) post-prison offending trajectory deviates from the counterfactual sufficiently. To do so, we rely on an information-theoretical approach that can be used for developing these micro-trajectories—dynamic counterfactuals—using detailed information about past arrest patterns. Furthermore, we use this approach for testing whether the post-release trajectory is, in some sense, better, worse, or about the same as the counterfactual. Thereafter, the effects of incarceration are classified based on whether it has deflected "sufficiently" an individual from his or her own counterfactual and if so, whether this deflection is for the better or worse.

In short, this Article seeks to examine whether the experience of being incarcerated affects post-release offending behavior, to classify these effects, and investigate the factors associated with them. In so doing, it will speak to matters related to both theory and policy. As noted earlier, estimates of the effect of punishment, specifically incarceration, on subsequent criminal activity is a question at the center of criminology, for its supposed relation is expected to vary according to at least three key criminological theories. Moreover, the extent to which incarceration influences the strong relationship between prior and future offending also bears relevance for the study of life-course criminology and criminal careers, specifically as an example of a potential but largely under-investigated local life circumstance or turning point. Regarding policy, knowing "what to do" about offender reentry after incarceration remains a major issue. The process of reentry into society after a period of incarceration is riddled with questions of individual sustainability, vulnerability, and fear of failure.[39] Therefore, identifying and

[38] Shawn Bushway et al., *Connecting Desistance and Recidivism: Measuring Changes in Criminality over the Lifespan*, *in* AFTER CRIME AND PUNISHMENT: PATHWAYS TO OFFENDER REINTEGRATION 97 (Shadd Maruna & Russ Immarigeon eds., 2004).

[39] JEREMY TRAVIS & CHRISTY VISHNER, PRISONER REENTRY AND CRIME IN AMERICA (2005).

understanding the effects that incarceration can have on offenders across contexts is crucial to developing strategies that minimize any criminogenic harm, and maximize any deterrent benefits, that result from it. Further, identifying and understanding the correlates of these distinct experiences should be of tremendous help to correctional authorities in reentry planning. Knowledge about the types of releasees likely to experience criminogenic or deterrent effects as a result of their incarceration, for example, could be used in the development of support systems designed to foster positive reentry experiences. They could be a crucial ingredient to individual successes, and ultimately to the promotion of public health and safety. This Article attempts to shed some light on these issues by examining the effects of incarceration on subsequent criminal activity.

V. DATA

The data used in this research effort come from a larger study, *Recidivism of Prisoners Released in 1994*.[40] They were collected by the Bureau of Justice Statistics ("BJS") primarily for the purposes of studying recidivism of a nationally representative cohort of persons released from state prisons and updating findings of another similar recidivism study undertaken a decade earlier by BJS.[41] The current data collection effort tracked a sample of 38,624 prisoners released from fifteen state prisons in 1994 over a period of three years. The vast majority of the archived database consists of information on each releasee's entire officially recorded criminal history, and includes all recorded adult arrests (including felonies and misdemeanors) through the end of the follow-up period.[42] These data were obtained from state and federal automated RAP sheets that 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. This omission implies that the data cannot be used to calculate street time;[43] however, the data do provide information on the adjudication outcome at each successive arrest event that we utilize in our models.

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[40] PATRICK A. LANGAN & DAVID J. LEVIN, RECIDIVISM OF PRISONERS RELEASED IN 1994 (2002).

[41] ALAN J. BECK & B.E. SHIPLEY, RECIDIVISM OF PRISONERS RELEASED IN 1983 (1989).

[42] To be sure, our measure of prior arrests is reflective of only one component of an offender's prior criminal history.

[43] Alex R. Piquero et al., *Assessing the Impact of Exposure Time and Incapacitation on Longitudinal Trajectories of Criminal Offending*, 16 J. ADOLESCENT RES. 54 (2001).

It should be noted that the BJS data collection effort was intended mainly to construct valid criminal history measures as well as to accurately assess recidivism. The data collection effort was never intended to be a longitudinal dataset recording offending over the life course. However, given the variations in prison admission and release ages in this dataset, the data are amenable to manipulation and restructuring to measure individual offending patterns. Consequently, one of the chief benefits this data set offers, besides its coverage (fifteen states), is the availability of dated arrest events as well as dates of birth of each of the individuals in the sample that make it possible to restructure the data for a repeated event-history analysis.

In addition, the database also contains a limited amount of demographic and related information. Demographic measures available include date of birth, race, ethnicity, and gender. Some detail is available about the type of release from prison (e.g., parole, mandatory release) and about the type of admission into prison (e.g., new court commitment and new court commitment with a violation of conditions of release). However, this information is available only for the 1994 release and not for all prior (or future) arrest events.

Before conducting the analysis, some diagnostic checks were run on the data to ensure they were compatible with the model requirements. Since the data are based on official records and possible disparate sources of date information (e.g., date of birth obtained from the state data and from the FBI data could differ), we first computed the ages for each of the arrests in the data. Then we checked for the chronology of these dates to see if the age variable was well-defined. We created flags for any individuals with records not in proper chronological order or whose ages were incorrect or impossible (e.g., negative or below fifteen). In addition, we created flags that identified any individuals with missing information on all ages or that had gaps in their age variable. For example, individuals that had appropriate ages for the first and second arrest events but were missing age on the third event and again had appropriate ages for all subsequent arrests were flagged as potentially problematic. After creating these flags, we performed a list-wise deletion of records—i.e., all records for individuals with any problem (as determined by the various flags) were dropped from the analysis set.

Additionally, the data contain a variable ANALYSIS that flags all records that were included in the BJS report.[44] In our analysis, we also excluded all persons that were not included in BJS's report (i.e., persons flagged as ANALYSIS=0).

[44] *See* LANGAN & LEVIN, *supra* note 40, at 14.

After removing persons who either had some problem in their arrest histories or were not included in the BJS report, the remaining sample consisted of 32,628 persons across fifteen states. In addition, since the sample for California releasees was very large (nearly 60,000 person-events before prison release), we used a random subset of 2500 individuals (21,838 person-events) from the California sample for estimating the pre-prison criminal history accumulation process. For the analysis of the post-release data, however, all individuals from California were included in the study. The final pre-release dataset, therefore, consisted of 21,226 individuals across the fifteen states whereas the post-release data consisted of the 32,628 individuals.

Arrest records for these persons were next re-structured into a hierarchical person-event level file. That is, arrest events of each person were all clustered in chronological order. Arrest histories were next truncated after the first post-release re-arrest event. As will be discussed in the next section, for the post-release period, we only examined the first re-arrest event. For persons not arrested after release, the arrest age was set to the age at censoring (i.e., release age + three years).

Table 1 provides a list of measures used in the analysis that follows, with brief descriptions for all the variables. The main criterion (outcome) variable was age at arrest. In addition, the data were also manipulated to create a set of individual-level fixed covariates as well as covariates changing over time. The key independent variables used in estimating the pre-release criminal history accumulation process included the arrest number (EVENTNUM), the age at first arrest (AGE1ST), whether the individual was confined as a result of the previous arrest event (CONFLAST), and a measure of the number of years taken to reach each arrest event cumulated through the last arrest event (CARAGE). AGE1ST and CONFLAST were set to 0 for the first arrest event.

Table 1

List of Variables Used in the Analysis

Variable Name	Variable Label and Name
Variables used for modeling the pre- and post-release criminal history accumulation process	
ARRESTAGE	Age at each successive arrest event
EVENTNUM	Arrest number (in the sequence of all arrests for a particular individual)
AGE1ST	Age at which an individual was first arrested for the first time
CARAGE	A variable capturing the offending heterogeneity among sample members, as they age
CONFLAST	A flag indicating whether or not the individual was confined as a result of the last arrest

Variable Name	Variable Label and Name
Additional variables used to examine variations in how incarceration affected different individuals	
RELAGE	Age at which offender was released from prison in 1994
BLACK	Offender's race (reference category is Non-Black)
MALE	Offender's sex (reference category is Female)
VIOLENT	Most serious offense for which incarcerated and released in 1994=Violent (Homicide, Kidnapping, Rape, Other Sexual Assaults, Robbery, Assault, and Other Violent Offenses)
PROPERTY	Most serious offense for which incarcerated and released in 1994=Property (Burglary, Larceny/Theft, Motor Vehicle Theft, Arson, Fraud, Stolen Property, and Other Property)
DRUG	Most serious offense for which incarcerated and released in 1994=Drug (Possession, Trafficking, Other Drug-Related Offenses)
PAROLE	Type of release from prison in 1994=Discretionary release to parole supervision
MANDATORY	Type of release from prison in 1994=Mandatory release to conditional supervision
CONDITIONAL	Type of release from prison in 1994=Some form of conditional release

Besides CARAGE, the variables used in this part of the analysis are self-explanatory. CARAGE was defined as a measure that captures the evolution of the heterogeneity in the sample members as they aged, defined as:

$$CARAGE_{rn} = \sum_{j=1}^{r} \frac{a_{jn}}{j} \qquad \forall r, n,$$

where a_{jn} is the age of the n^{th} individual at her or his j^{th} arrest event. This measure captures variation in past criminal history up to the current arrest in such a way that it distinguishes people who are closer to their past arrest "clusters" from those that are further. Table 2 shows hypothetical past arrest histories of two individuals and demonstrates the calculation of CARAGE at each arrest event. Note that both individuals have the same CARAGE until their second arrest because they follow the same path. As they differ in their arrest patterns, CARAGE begins to record this heterogeneity. In fact, individual A gets a higher CARAGE on his third arrest because he is "closer" to his past arrest cluster at age thirty than individual B is at age thirty-five. After that, both individuals are re-arrested at age forty but their CARAGE continues to record their heterogeneous pasts. In this sense, the variable records heterogeneity in past offending patterns and, all else being equal, assigns a higher score to those that are closer to their past arrest clusters. In the modeling stage, a lagged value of this measure is included in the hazard model. As with the other lagged variables, CARAGE=0 for the first arrest event.

Table 2

An Example of Computing CARAGE for Two Arrest Profiles

Individual A				Individual B			
r	a_r	a_r/r	CARAGE	r	a_r	a_r/r	CARAGE
1	20	20.0	20.0	1	20	20.0	20.0
2	25	12.5	32.5	2	25	12.5	32.5
3	30	10.0	42.5	3	35	11.7	44.2
4	40	10.0	52.5	4	40	10.0	54.2

The same set of basic variables were used to model the past criminal history accumulation process as well as the recidivism process. We define and model recidivism as the age at first re-arrest event after release. This was done in order to ensure that any deviations among the trajectories are attributable to the two different age segments of the releasee's life. Comparisons of these trajectories produced the δ measure for each individual (defined in the next section) that was used for classifying their experience. To understand what variables predicted the deviation of the counterfactual and post-release paths, we included, in addition to the variables listed above, demographic characteristics, the type of release, the age at release, and the most serious offense for which incarcerated. Tables 3 and 4 provide a summary of the sample used in the analysis.

Table 3

Sample Means (Unless Otherwise Noted) of All Variables from the Pre-Release Data Used in the Analysis

	AZ	CA	DE	FL	IL	MD	MI	MN
Pre-Release Sample								
Number of Person-Events	10,920	21,838	10,184	25,729	19,209	12,509	9917	12,196
Number of Persons	1418	2500	659	2554	2299	1588	1939	1728
ARRESTAGE	26.93	26.61	23.87	27.86	25.60	26.67	26.25	25.86
EVENTNUM	8.15	8.72	11.75	9.39	8.84	6.99	5.05	6.86
AGE1ST	20.58	20.58	16.67	20.64	19.35	21.11	20.33	20.02
CARAGE	46.24	47.35	48.33	51.30	45.20	44.97	35.02	41.12
CONFLAST	0.25	0.27	0.10	0.22	0.17	0.28	0.33	0.45

Table 3 (continued)

Sample Means (Unless Otherwise Noted) of All Variables from the Pre-Release Data Used in the Analysis

	NJ	NY	NC	OH	OR	TX	VA
Pre-Release Sample							
Number of Person-Events	17,136	22,616	12,424	4424	19,780	15,541	14,649
Number of Persons	2128	2390	2047	1100	1465	2410	2001
ARRESTAGE	25.90	25.66	26.84	26.42	28.71	27.33	27.07
EVENTNUM	8.30	9.19	5.78	4.51	10.94	6.00	7.14
AGE1ST	20.08	19.89	20.84	21.73	20.09	20.24	20.93
CARAGE	44.74	47.00	39.44	32.38	55.70	39.47	44.37
CONFLAST	0.30	0.37	0.44	0.25	0.34	0.24	0.03

Table 4

Sample Means (Unless Otherwise Noted) of All Variables from the Post-Release Data Used in the Analysis

	AZ	CA	DE	FL	IL	MD	MI	MN
Post-Release Sample								
Number of Persons	1418	6902	659	2554	2299	1588	1939	1728
EVENTNUM[a]	8.70	9.66	16.45	11.07	9.36	8.88	6.11	8.06
AGE1ST	21.96	23.62	17.98	22.46	20.83	22.14	22.15	21.68
CARAGE	56.17	60.26	64.56	64.97	54.58	59.09	48.45	54.01
CONFLAST	0.51	0.50	0.52	0.26	0.46	0.63	0.82	0.86
RELAGE	33.49	34.78	31.19	34.30	31.60	32.86	34.02	31.01
BLACK	0.17	0.27	0.68	0.47	0.57	0.73	0.49	0.32
VIOLENT	0.33	0.61	0.30	0.53	0.51	0.40	0.45	0.42
PROPERTY	0.27	0.14	0.14	0.20	0.22	0.23	0.25	0.40
DRUG	0.26	0.16	0.38	0.18	0.18	0.26	0.20	0.15
PAROLE	0.77	0.00	0.08	0.70	0.00	0.44	1.00	0.21
MANDATORY	0.02	1.00	0.00	0.01	0.98	0.47	0.00	0.77
CONDITIONAL	0.79	1.00	0.08	0.70	0.98	0.91	1.00	0.98
CENSORED	0.38	0.46	0.14	0.35	0.30	0.33	0.61	0.40
RECIDIVISTS	0.62	0.54	0.86	0.65	0.70	0.67	0.39	0.60
RECIDAGE[b]	33.09	33.38	31.12	33.04	30.85	32.39	33.32	30.38
CENSORAGE[c]	38.82	40.56	39.79	41.44	38.40	38.59	38.28	36.56

[a] Average re-arrest number at risk of upon release
[b] Only computed for those that recidivated within the follow-up period
[c] Only computed for those that did not recidivate within the follow-up period

Table 4 (continued)

Sample Means (Unless Otherwise Noted) of All Variables from the Post-Release Data Used in the Analysis

	NJ	NY	NC	OH	OR	TX	VA
Post-Release Sample							
Number of Persons	2128	2390	2047	1100	1465	2410	2001
EVENTNUM[a]	9.05	10.46	7.07	5.02	14.50	7.45	8.32
AGE1ST	21.59	21.85	22.86	24.51	22.18	22.13	22.36
CARAGE	55.87	59.93	54.12	45.28	73.85	55.65	56.93
CONFLAST	0.73	0.71	0.85	0.37	0.79	0.78	0.02
RELAGE	32.79	33.55	31.51	34.06	35.50	34.39	33.14
BLACK	0.60	0.49	0.62	0.38	0.15	0.42	0.61
VIOLENT	0.41	0.44	0.40	0.60	0.55	0.47	0.34
PROPERTY	0.24	0.22	0.26	0.16	0.21	0.23	0.27
DRUG	0.22	0.20	0.24	0.17	0.16	0.20	0.26
PAROLE	0.73	0.54	0.27	0.64	0.63	0.41	0.40
MANDATORY	0.00	0.32	0.67	0.00	0.36	0.39	0.55
CONDITIONAL	0.73	0.85	0.94	0.64	0.99	0.80	0.95
CENSORED	0.42	0.42	0.46	0.73	0.33	0.55	0.41
RECIDIVISTS	0.58	0.58	0.54	0.27	0.67	0.45	0.59
RECIDAGE[b]	31.94	32.85	30.57	32.71	34.48	33.28	32.96
CENSORAGE[c]	38.38	38.87	36.90	37.99	42.07	39.24	37.95

[a] Average re-arrest number at risk of upon release
[b] Only computed for those that recidivated within the follow-up period
[c] Only computed for those that did not recidivate within the follow-up period

Note that the variable CONFLAST captures adjudication outcomes at the last arrest event. It would seem, therefore, that this variable must be one for the entire post-release sample. However, this does not need to be the case. Individuals may enter prison for reasons other than being convicted and sanctioned to some amount of confinement. For example, persons released from prison in 1994 could have entered prison for violating existing conditions of a previous release.[45]

With the exception of California, the number of persons in the pre-release sample is exactly equal to the number of persons in the post-release sample. This is because the cohort of interest is a prison release cohort, and this group of individuals must have, at some point in their past, been arrested at least once. As noted above, a sub-sample was taken for the California sample to ease estimation of the models.

The three release type variables PAROLE, MANDATORY, and CONDITIONAL are not necessarily mutually exclusive. For some states (California, Delaware, Illinois, and Michigan), release type information was either unavailable or there was insufficient variation to create distinct flags. For some states (Maryland, New York, North Carolina, Texas, and Virginia), enough detail was available to allow a classification of release type in three categories—PAROLE, MANDATORY release to supervision, and unconditional release. For others (Arizona, Florida, New Jersey, and Ohio), the only available information was whether the release was CONDITIONAL or otherwise. Finally, the only available information for Minnesota and Oregon was whether the release was for PAROLE or MANDATORY release. Hence, when analyzing the effects of release type on the likelihood of the prisoner's experience being deterrent or otherwise, separate models were estimated for groups of states to increase statistical power.[46]

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[45] It should be noted, however, that the proportion of cases in Virginia that seem to be recorded as having some confinement as a result of the last arrest is too low (3% in the pre-release sample and 2% in the post-release sample). In all likelihood, this is an error in the data system. Despite that, in this Article, we have used this variable as it is.

[46] The archived data contain numerous errors in this variable. We have incorporated corrections in our analysis that were suggested by the BJS and other researchers. This includes release-type-specific changes made for the states of California and Michigan as well as case-by-case changes made for the North Carolina release cohort. In addition, data from Delaware were missing all conditional-release types. Therefore, when modeling the effect of the release mechanism, we analyzed data by groups of states. Another known problem with these data is that the Maryland cohort is missing detailed offense-level information for each arrest event. For our analysis, since we used all arrest events (irrespective of offense type) in modeling the criminal history accumulation process, we only needed offense information pertaining to the current release (which is available for all observations). Therefore, in our analysis, all known problems with the archived data were accounted for.

Finally, VIOLENT, PROPERTY, and DRUG refer to the most serious offense for which the prisoner was serving time when he or she was released in 1994.

VI. THE ANALYTICAL APPROACH

We begin by explaining the information-theoretic models of offending trajectories developed using detailed dated arrest records of a group of offenders. These models can be applied to retrospective (historical) data as well as prospective sequences of events. The dated arrest histories allow detailed models of the risk of each successive arrest number (e.g., first, second, third, and so forth) at all ages. Once estimated using retrospective criminal histories prior to prison admission, these models then allow projection of the re-arrest risk trajectories for each individual given his age at release and the re-arrest number of which he was then at risk. These projections form the counterfactuals against which the actual re-arrest patterns (post-release) can be assessed.

Given that a prison release cohort is likely to have variation in the age at release *and* variation in the amount of time served in prison, it can be expected that this cohort will have had varying amounts of time to accumulate their criminal histories. However, we have available two sources of variation in the criminal history data—the "amount" of criminal history accumulated prior to prison admission and the "process" by which this criminal history was accumulated. With few exceptions, researchers using criminal history data utilize only the first of these sources of variation in the available data. In the analytical approach developed here, we make full use of the second source of variation—i.e., the criminal history accumulation process—in order to develop models to simulate a counterfactual post-release offending trajectories for each individual.

In order to simulate counterfactuals at the individual level, a dynamic model of the offending rate (or the λ) that is related to appropriate time-indexed variables (like age) is needed, as well as a set of offender-specific attributes. Links to the time-indexed variables will allow a simulation of the offending hazard as offenders age. Links to offender-specific attributes will ensure that this process captures any heterogeneity among offenders.

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. 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. Theory or empirical regularities may suggest other ways in which 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 that 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[47] refer to these sequences as offenders' "arrest profiles." In a similar manner, we can develop measures of other relevant transformations of age that may be needed to accurately describe the non-monotonic evolution of the hazard rate with age. The ultimate goal is to construct a model (for λ) that evolves along these multiple transformations or multiple clocks.[48]

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, 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,[49] 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

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[47] Richard W. Harding & Ross A. Maller, *An Improved Methodology for Analyzing Age-Arrest Profiles: Application to a Western Australian Offender Population*, 13 J. QUANTITATIVE CRIMINOLOGY 349 (1997).

[48] Multiple-clock models allow researchers to capture several other dimensions of time when studying event histories. *See* KAZUO YAMAGUCHI, EVENT HISTORY ANALYSIS (1991); Lee A. Lillard, *Simultaneous Equations for Hazards: Marriage Duration and Fertility Timing*, 56 J. ECONOMETRICS 189 (1993).

[49] CHARLIES F. MANSKI, ANALOG ESTIMATION METHODS IN ECONOMETRICS (1988).

series of influential papers that when faced with a problem that has an infinite number of solutions (the so-called "ill-posed inversion problems"), we should choose the solution that is least informative (or closest to our prior beliefs, if any) while satisfying what limited evidence we may have observed.[50] 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, Claude Shannon had, just a few years earlier, developed a precise definition of uncertainty and termed it Information Entropy.[51] In what has come to be known as the Maximum Entropy formalism, Jaynes proposed using 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.[52]

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 (or lack of information) 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.

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[50] Edwin T. Jaynes, *Information Theory and Statistical Mechanics*, 106 PHYSICAL REV. 620 (1957); Edwin T. Jaynes, *Information Theory and Statistical Mechanics II*, 108 PHYSICAL REV. 171 (1957).

[51] C.E. Shannon, *A Mathematical Theory of Communication*, 27 BELL SYS. TECHNICAL J. 379 (1948).

[52] *See, e.g.*, Arnold Zellner, *Bayesian Methods and Entropy in Economics and Econometrics*, *in* MAXIMUM ENTROPY AND BAYESIAN METHODS (W.T. Grandy, Jr. & L.H. Schick eds., 1991); Hang K. Ryu, *Maximum Entropy Estimation of Density and Regression Functions*, 56 J. ECONOMETRICS 397 (1993); Arnold Zellner & R.A. Highfield, *Calculation of Maximum Entropy Distributions and Approximation of Marginal Posterior Distributions*, 37 J. ECONOMETRICS 195 (1988). For recent theoretic and applied work in this field, see 12 ADVANCES IN ECONOMETRICS: APPLYING MAXIMUM ENTROPY TO ECONOMIC PROBLEMS (T.B. Fomby & R. Carter Hill eds., 1997); AMOS GOLAN ET AL., MAXIMUM ENTROPY ECONOMETRICS: ROBUST ESTIMATION WITH LIMITED DATA (1997); RON C. MITTELHAMMER ET AL., ECONOMETRIC FOUNDATIONS (2000); Amos Golan, *Information and Entropy Economics—Editor's View*, 107 J. ECONOMETRICS (2002); Esfandiar Maasoumi, *A Compendium of Information Theory in Economics and Econometrics*, 12 ECONOMETRIC REV. 137 (1993); Ehsan S. Soofi, *Capturing the Intangible Concept of Information*, 89 J. AM. STAT. ASS'N 1243 (1994).

Building on Ryu,[53] the information implied by the hazards can be computed as

$$H = \sum_{rmn} d_{rmn} \lambda_{rmn} \log\left(\lambda_{rmn} \big/ \lambda^0_{rmn} \right) \quad (1)$$

where λ_{rmn} is an individual's hazard of re-arrest number r at age m; λ^0_{rmn} is an arbitrary non-negative value representing our prior (non-sample) belief about this hazard rate; and d_{rmn} is a flag indicating whether the nth individual was at risk of the rth arrest at the mth age. Minimizing this quantity (the objective function) subject to all data constraints provides a unique solution. Full mathematical derivation of the solution is available from the authors upon request. The resulting model that emerges from the approach takes the functional form:

$$\lambda_{rmn} = \lambda^0_{rmn} \exp\left(z_m \sum\nolimits_k x_{krn}\alpha_k + z_m \log z_m \sum\nolimits_k x_{krn}\beta_k - 1\right) \quad \forall r, m, n \quad (2)$$

where x_{krn} are offender attributes; α_k and β_k are Lagrange Multipliers (a byproduct of solving any constrained optimization problem) that reflect the value of each of the constraints on reducing uncertainty about the process; z_m captures the evolution of the hazard linearly with age; and $z_m \log z_m$ captures the non-monotonic shape of the hazard (provided that β_k have the opposite sign of α_k).

The semiparametric 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 to the process under study, then the corresponding Lagrange Multipliers will be close to zero. As with fully parametric models, asymptotic standard errors can be derived for these parameters and they can be subjected to standard statistical significance testing.[54] Given the hierarchical nature of the data (multiple arrest events nested within individuals), care needs to be taken in correcting the estimated standard error. In the empirical application in this paper, a modified version of the Huber-White sandwich estimator is used.[55]

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[53] *See* Ryu, *supra* note 52.

[54] *Id.*

[55] Peter J. Huber, *The Behavior of Maximum Likelihood Estimators Under Nonstandard Conditions*, *in* 1 PROCEEDINGS OF THE FIFTH SYMPOSIUM ON MATHEMATICAL STATISTICS AND PROBABILITY 221 (1967); Michael E. Ezell et al., *Modeling Multiple Failure Time Data: A Survey of Variance-Corrected Proportional Hazard Models with Empirical Applications to*

It is important to note that this approach differs, both conceptually and empirically, from existing methods of modeling repeated events.[56] Application of the information-theoretic approach yields the *form* of the hazard trajectories as well as *estimates* for the parameters α_k and β_k. 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.

Once the α_k and β_k 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 simply a matter of plugging in the appropriate quantities into (2) to compute the hazard micro-trajectories for each individual.

We have not yet made any explicit assumptions about the priors λ^0_{rmn}. If we do have some prior knowledge about the evolution of the hazard over time, we can introduce that information in the form of the λ^0_{rmn} so that the final solution is computed as a deviation from this prior. This formulation is particularly relevant for our analysis since we wish to study the deviation of the post-release trajectory from the counterfactual.

One way to construct this counterfactual is to model the links between age, arrest number, and other attributes using the framework described above but by estimating it only with the pre-prison part of the available arrest histories. This model would, therefore, capture the dynamic process by which individuals in the sample had been accumulating their arrest histories prior to prison admission. Next, using the solution (2), we can project a future trajectory (from the age at release onwards) using knowledge about the arrest number this particular individual was at risk of as well as all the other attributes. Let this projected counterfactual be denoted as $\tilde{\lambda}_{rmn}$. These projections trace out the entire evolution of the hazard for the next arrest event over the remaining life of the individual given knowledge about the past criminal history accumulation process. As such, each provides a detailed criminal-history-based counterfactual for assessing future offending patterns, since this is the path we should expect the releasee to have been on at the time of release had he or she not been incarcerated.

Arrest Data, 33 SOC. METHODOLOGY 111 (2003); Halbert White, *A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity*, 48 ECONOMETRICA 817 (1980).

[56] *See, e.g.*, PAUL D. ALLISON, EVENT HISTORY ANALYSIS (1984); HANS-PETER BLOSSFELD ET AL., EVENT HISTORY ANALYSIS: STATISTICAL THEORY AND APPLICATION IN THE SOCIAL SCIENCES (1989); EVENT HISTORY ANALYSIS IN LIFE COURSE RESEARCH (Karl U. Mayer & Nancy B. Tuma eds., 1990).

When we model the post-release offending trajectory—i.e., the hazard of the next event in the sequence of arrests—we simply replace λ^0_{rmn} with $\tilde{\lambda}_{rmn}$ in the objective function (1). This yields a solution exactly like (2) where $\tilde{\lambda}_{rmn}$ replaces λ^0_{rmn}. Note that λ_{rmn} is an updated version of $\tilde{\lambda}_{rmn}$. To the extent that future offending patterns are as predicted by the past, we should see $\lambda_{rmn} \equiv \tilde{\lambda}_{rmn}$. Moreover, the Lagrange Multipliers (α_k and β_k) in the post-release model can be interpreted as "shadow prices" capturing the effects of the various attributes in deflecting the offending trajectories. We still must find a way to decide whether this deflection, for any particular individual, is for the better (lowered trajectory compared to the counterfactual), worse (higher trajectory compared to the counterfactual), or about the same. We derive one such measure next.

Since the objective (1) is defined in terms of the natural log of the ratio of two strictly positive numbers, then

$$\log(\lambda_{rmn}/\tilde{\lambda}_{rmn}) \begin{cases} >0 \text{ if } \lambda_{rmn} > \tilde{\lambda}_{rmn} \\ =0 \text{ if } \lambda_{rmn} = \tilde{\lambda}_{rmn} \\ <0 \text{ if } \lambda_{rmn} < \tilde{\lambda}_{rmn} \end{cases} \forall r, m, n. \tag{3}$$

The problem with this measure, as it stands, is that it is a function of age and therefore it can, and typically will, be different for each m. What we need is a way to aggregate this divergence measure over the entire residual life starting from any point z^*_m (e.g., the date of release).

Ryu showed that the Maximum Entropy solution for any positive quantity could be considered an averaged density if we normalize appropriately. In our case, the quantity of interest is the hazards for all points beyond the date of release.[57] Hence, following Ryu, if we define the term $\lambda^*_{rmn} = \sum_m d_{rmn}\lambda_{rmn}$ for some appropriately redefined d_{rmn}, then we see that

[57] Ebrahimi and Soofi present another way to approach this problem by redefining the hazards into probabilities and noting that the measure reduces to the traditional Kullback-Leibler divergence measure with an appropriate normalization and a ratio of survival functions. Nader Ebrahimi & Ehsan S. Soofi, Presentation at a Conference in Honor of Arnold Zellner: Recent Developments in the Theory, Method, and Application of Information and Entropy Econometrics: Static and Dynamic Information for Duration Analysis (Sept. 19-21, 2003), *available at* http://www.american.edu/cas/econ/faculty/golan/golan/Papers/8_20soofi.pdf; *see also* Ehsan S. Soofi et al., *Information Distinguishability with Application to Analysis of Failure Data*, 90 J. AM. STAT. ASS'N 657 (1995).

$$\pi_{rmn} = \frac{d_{rmn}\lambda_{rmn}}{\lambda^*_{rmn}} = \frac{d_{rmn}\lambda_{rmn}}{\sum_m d_{rmn}\lambda_{rmn}} \tag{4}$$

is a proper probability wherever it is defined (i.e., $\sum_m \pi_{rmn} = 1 \ \forall r,n$ and $\pi_{rmn} \geq 0 \ \forall r,m,n$). This implies that the objective function we are optimizing already contains information about the averaged difference between λ_{rmn} and λ_{rmn}. All we need to do is normalize the objective appropriately. This normalization provides a way to aggregate the various terms in the trajectory (2) across the entire residual life of the individual upon release. This measure is defined as:

$$\delta_{rn} = \sum_m \pi_{rmn} \log(\lambda_{rmn} / \tilde{\lambda}_{rmn}) \tag{5}$$

The δ statistic is an average (expected) log divergence between the projected trajectory (based on knowledge about pre-prison arrest patterns) and the actual post-release offending trajectory. Note that it measures divergence between two entire paths. Moreover, π_{rmn} weights are higher during periods when the hazard is relatively higher. That is, in the aggregation of (5), periods in the individual residual life when he or she is projected to offend frequently are given larger weight when computing the average log divergence between the counterfactual and the actual micro-trajectories. Also, since π_{rmn} are a set of proper probability, we can compute the standard deviation of the log divergence as well. The standard deviation of each δ_{rn} statistic can be computed as:

$$\sigma_{rn} = \sqrt{\sum_m \pi_{rmn}\left[\log(\lambda_{rmn}/\tilde{\lambda}_{rmn})\right]^2 - \left[\sum_m \pi_{rmn} \log(\lambda_{rmn}/\tilde{\lambda}_{rmn})\right]^2} \tag{6}$$

Finally, we can utilize the definition of δ_{rn} and σ_{rn} to test whether the expected log divergence of the residual life trajectories are sufficiently different. The current incarceration is deemed to have had a:

$$\begin{array}{lll} \text{Deterrent Effect} & \text{if} & 0 > \delta_{rn} + 2\times\sigma_{rn} \\ \text{Null Effect} & \text{if} & 0 \in \delta_{rn} \pm 2\times\sigma_{rn} \\ \text{Criminogenic Effect} & \text{if} & 0 < \delta_{rn} - 2\times\sigma_{rn} \end{array} \tag{7}$$

These classifications allow one to model the effects of individual, contextual, and policy options on the likelihood of a releasee's prison experience being one of the three types. This can be done in standard software using multinomial discrete choice models or ordered discrete choice models. Such an analysis could be used, for example, to study what measures can increase the likelihood of the deterrent experience and minimize the likelihood of a criminogenic experience.

In this section, we have developed an information-theoretic framework for modeling the detailed criminal history accumulation process of a group of releasees. Although several other approaches of modeling event histories exist, the method developed here has several benefits over existing strategies. First, unlike fully parametric functional forms, the information-theoretic approach allows an easy incorporation of several constraints that yield flexible functional-form hazard models. Under restrictive assumptions, this approach yields several of the standard hazard models as special cases. As such, the approach can be used to develop models that nest several parametric forms as special cases in order to test (statistically) assumptions about the shape of the evolution of the hazard over time or assumptions about proportionality. Second, given its particular emphasis on minimizing the directed divergence between a prior and posterior trajectory, the approach offers an easy method for assessing whether the evolution of the hazard over the residual life (defined at any appropriate point, e.g., the date of release) is different from a counterfactual. The average log divergence between the two trajectories provides a convenient summary statistic δ for this purpose. Finally, this average divergence measure can then be converted into a classification. Large negative values on this statistic imply large deterrent effects whereas large positive values on this statistic imply large criminogenic effects. Studying how this measure correlates with various attributes as well as policy options can be of immense use to practitioners and policy-makers in understanding what factors may maximize deterrent benefits of incarceration, minimize its criminogenic harm, or both. Finally, the method developed here takes full advantage of dated criminal history records when such information *is* available in developing offending trajectories.[58] Bhati has offered a more detailed overview of the technical aspects of the model.[59]

[58] To be sure, the method described here is not the only way one can study trajectories of offending patterns over time. There exists a large literature in criminology that aims to model the trajectories of offending patterns over the life course of individuals using group-based modeling techniques. *See, e.g.*, DANIEL S. NAGIN, GROUP BASED MODELS OF DEVELOPMENT (2005); Alex R. Piquero, *Taking Stock of Developmental Trajectories of Criminal Activity over the Life Course*, *in* THE LONG VIEW OF CRIME: A SYNTHESIS OF LONGITUDINAL RESEARCH (Akiva Liberman ed., 2008). Responding to concerns raised by Hagan and Palloni, see John Hagan & Alberto Palloni, *Crimes as Social Events in the Life Course: Reconceiving a Criminological Controversy*, 26 CRIMINOLOGY 87 (1988), Nagin and Land demonstrated that group-based trajectory models are well suited to take into account the order of arrest events. Daniel S. Nagin & Kenneth C. Land, *Age, Criminal Careers, and Population Heterogeneity: Specification and Estimation on a Nonparametric,*

VII. RESULTS

This section begins by summarizing estimates of the pre-prison-based criminal history accumulation process. These models are then used to make projections of criminal offending for individuals at the time of their release. These projected counterfactual trajectories are next used as a backdrop against which to develop the post-release offending trajectories. Finally, using the methods developed above, we compute the delta statistic and use it to classify individuals' incarceration experiences. The section closes with some estimates of models explaining variation in individuals' experiences. A discussion of the results and implications for theory and policy are provided in the next section.

A. MODELS OF THE CRIMINAL HISTORY ACCUMULATION PROCESS

First, we present the model estimates of the pre-release criminal history accumulation process. In order to keep the estimation manageable and to afford the model full flexibility, we have estimated separate models for each of the fifteen states. The form of the model, however, is held fixed across all state samples.

Mixed Poisson Model, 31 CRIMINOLOGY 327 (1993). Similarly, the approach developed here is not incompatible with approximating unobserved heterogeneity via finite mixture modeling strategies, at least in theory. Therefore, it would be a profitable extension of the current work to include distinct group-based heterogeneity in the models as well. For example, it is reasonable to expect that the Lagrange Multiplier should vary randomly across individuals. As such, using a finite mixture model to obtain a finite set of Lagrange Multipliers as well as group membership probabilities could add further clarity to the classification of individuals' incarceration as having had a deterrent, a criminogenic, or a null effect on their future offending patterns. For the approach to have practical utility, however, the emphasis should remain on attempting to construct counterfactual trajectories for each and every individual in the sample (not just for groups). In this Article, we have relied solely on available attributes to model the heterogeneity in the evolution of the hazards.

[59] AVINASH S. BHATI, URBAN INSTITUTE, STUDYING THE EFFECTS OF INCARCERATION ON OFFENDING TRAJECTORIES: AN INFORMATION THEORETIC APPROACH (2006), *available at* http://www.urban.org/publications/411427.html.

Table 5

Pre-Prison-Based Hazard Models of the Criminal History Accumulation Process of Prisoners Released in 1994 in Arizona

	Lagrange Multipliers	Asymptotic Standard Errors	Wald- χ^2	p-values
	α_k			
INTERCEPT	-0.5762	0.0846	46	0.0000
EVENTNUM	-0.0323	0.0045	51	0.0000
AGE1ST	-0.0056	0.0018	9	0.0022
CARAGE	0.0163	0.0016	97	0.0000
CONFLAST	0.0887	0.0175	26	0.0000
	β_k			
INTERCEPT	0.1539	0.0280	30	0.0000
EVENTNUM	0.0086	0.0013	46	0.0000
AGE1ST	0.0011	0.0005	4	0.0421
CARAGE	-0.0043	0.0005	66	0.0000
CONFLAST	-0.0264	0.0050	27	0.0000

Table 5 shows estimates of the information-theoretic-model Lagrange Multipliers and presents modified sandwich estimates of the asymptotic standard errors and associated Wald- χ^2 statistics for the sample from Arizona. Since the models are formulated in terms of hazards, a negative Lagrange Multiplier implies that the variable in question decreases the hazard's path or, put another way, the variable in question increases the expected duration to the next event. As such, the negative values of the parameters for EVENTNUM are consistent with expectation. That is, increases in arrest numbers are associated with higher age (duration from birth to event). Moreover, the *positive* sign on the corresponding β multipliers suggests that the decreasing hazard associated with increasing event numbers is at a decreasing rate. This simply means that the relationship between the arrest number and the hazard trajectory is non-linear. Note that all β parameters have the reverse sign when compared with the corresponding α parameters.

Similarly, increases in age at first arrest are associated (as expected) with increasing age at subsequent arrest (i.e., decreasing hazard paths for subsequent events). Moreover, this relationship is non-linear. CARAGE, also as expected, has a positive coefficient in the hazard model. Recall that CARAGE measures the closeness to past clusters of arrests. As such, a positive coefficient in the hazard model suggests that being close to a prior cluster decreases the duration and increases the hazard of the next event.

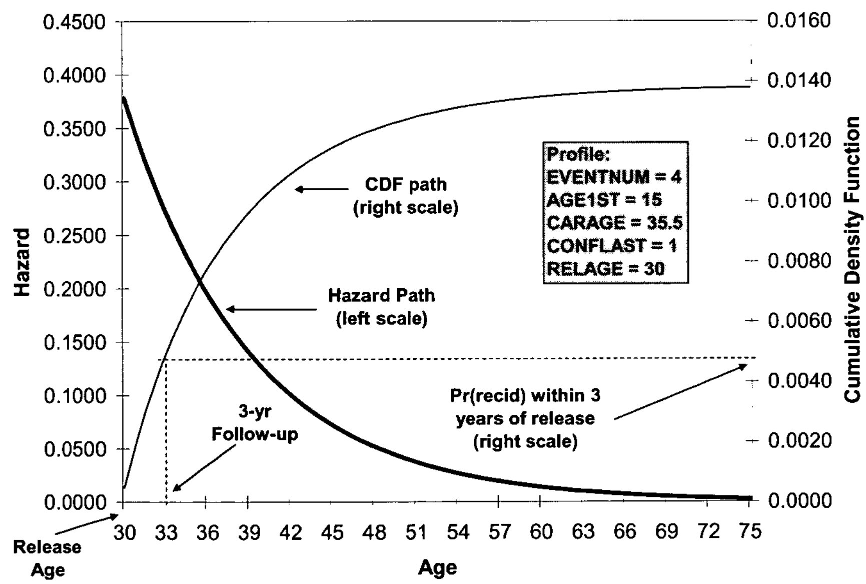
As with the other parameters, this too has a non-linear link with the outcome of interest.

CONFLAST has a positive effect on the hazard path. This result seems surprising at first glance. Being confined should take one off the street for some time, thus the age for the next event should be pushed out (increase) and the hazard should decrease. However, it is also possible that being confined after the arrest implies a higher level of severity of behavior than someone not confined. As such, it should decrease the age at the next arrest (i.e., increase hazard).

In order to see what the projections from this model look like, in Figure 5 we have simulated the predicted post-release offending trajectory for a particular individual profile. This individual was arrested for the first time at age fifteen, and then subsequently was re-arrested at ages twenty-two and twenty-five after which he was incarcerated. He was released from prison at the age of thirty. He is, therefore, at risk of his fourth re-arrest. Figure 5 shows the counterfactual hazard trajectory (left scale) predicted by the model for this individual from his release age (thirty) to age seventy-five (effectively, his entire residual life). Based on this counterfactual hazard, the cumulative density function (right scale) traces the predicted probability of being re-arrested within a certain number of years. For example, within three years of release, at age thirty-three, the cumulative density function ("CDF") is only about half a percent. In other words, this individual is *not* predicted to be re-arrested within the three-year follow-up period using knowledge only about the way he was accumulating his criminal record.

Figure 5

The Counterfactual Micro-Trajectory for a Particular Individual Profile



Similar individual trajectories can be plotted for *each* individual in the sample. Different criminal history accumulation processes will result in very different predictions about the future. In what follows, we present more comprehensive findings by computing predictions from these counterfactual trajectories for each individual. We also present a comparison of these counterfactual predictions with actual offending observed within three years of release. Since the actual values of the parameters are less important than their signs, we summarize all the parameter estimates in Table 6 using the following conventions. Parameters that are positive and significant at the 95% confidence level (using the modified sandwich estimator for the asymptotic standard errors) are indicated with a ++, parameters that are negative and deemed statistically significant using the same criteria are indicated with a --, and parameters that are insignificant are denoted 0. Significance at the 90% level is indicated by a single + or -.[60]

Table 6

Summary of State-Specific Hazard Models of the Pre-Prison Criminal History Accumulation Process and Their Projections for the Three-Year Post-Release Period

	AZ	CA	DE	FL	IL	MD	MI	MN
α_k								
INTERCEPT	--	--	--	--	--	--	--	--
EVENTNUM	--	--	--	--	--	--	--	--
AGE1ST	--	--	--	--	--	--	--	--
CARAGE	++	++	++	++	++	++	++	++
CONFLAST	++	++	0	++	0	++	+	++
β_k								
INTERCEPT	++	++	++	++	++	++	++	++
EVENTNUM	++	++	++	++	++	++	++	++
AGE1ST	++	++	++	++	++	++	++	++
CARAGE	--	--	--	--	--	--	--	--
CONFLAST	--	--	0	--	-	--	-	--
Pseudo R^2 measure (within sample)	0.25	0.35	0.76	0.41	0.27	0.42	0.33	0.54
Three-year re-arrest rate projections from each individual's criminal history-based (counterfactual) trajectories[a]								
Projected	88.3	82.1	95.1	87.9	86.7	90.2	80.3	86.1
Actual	62.1	54.1	86.5	65.4	69.8	66.6	39.3	60.4
False Positives	34.3	39.4	11.5	30.5	25.0	30.6	56.6	35.0
False Negatives	34.9	24.3	46.5	35.1	36.3	40.4	22.5	32.4

[60] Detailed state-specific estimates of the hazard models are available upon request.

Table 6 (continued)

Summary of State-Specific Hazard Models of the Pre-Prison Criminal History Accumulation Process and Their Projections for the Three-Year Post-Release Period

	NJ	NY	NC	OH	OR	TX	VA
α_k							
INTERCEPT	--	--	--	--	--	--	--
EVENTNUM	--	0	--	--	--	--	--
AGE1ST	--	--	--	--	--	--	--
CARAGE	++	++	++	++	++	++	++
CONFLAST	+	++	++	++	++	++	++
β_k							
INTERCEPT	++	++	++	++	++	++	++
EVENTNUM	++	0	++	++	++	++	++
AGE1ST	+	++	++	0	++	++	++
CARAGE	--	--	--	--	--	--	--
CONFLAST	-	--	--	--	--	--	--
Pseudo R^2 measure (within sample)	0.48	0.26	0.50	0.60	0.68	0.44	0.68
Three-year re-arrest rate projections from each individual's criminal history-based (counterfactual) trajectories[a]							
Projected	86.7	90.8	86.0	73.1	90.0	82.4	90.0
Actual	58.1	58.3	54.4	27.2	66.6	45.0	58.8
False Positives	37.4	38.9	42.0	68.3	28.5	50.4	41.2
False Negatives	29.2	30.6	31.3	14.9	22.6	23.4	32.8

Note: ++ = positive coefficient with 95% confidence; + = positive coefficient with 90% confidence; -- = negative coefficient with 95% confidence; - = negative coefficient with 90% confidence; 0 = coefficient statistically insignificant.

[a] Projections are based on converting each individual's predicted hazard trajectories into cumulative densities using equation (14). The criterion for an individual to be projected to fail within three years of release is if (her) his CDF had reached 0.50 within that period after release.

With few exceptions, models from all states largely mirror the findings from Arizona discussed above. The exceptions typically involve the Lagrange Multiplier corresponding to the CONFLAST flag. Qualitatively, the rest of the predictors are very consistent across states with the exception of New York, where increasing arrest numbers seem not to be associated with decreased hazard (increased age) for the next arrest event. To assess the overall accuracy of the model, we compute a within-sample Pseudo-R^2 measure.[61] This measure, although based on a model-wide Chi-square

[61] PAUL D. ALLISON, SURVIVAL ANALYSIS USING THE SAS SYSTEM: A PRACTICAL GUIDE (1996).

statistic, can be approximated by summing the Chi-square tests for each of the individual Lagrange Multipliers. In our models, this approximation ranged from a low of 25% (Arizona) to a high of 75% (Delaware). In Table 6, we also provide estimates of the projections from these models. These projections are constructed as follows. Since estimated hazards, probability density functions, and cumulative density functions are different ways of characterizing the same underlying process, we can convert one into the other fairly easily.[62] For example, the cumulative density function may be estimated as

$$\mathrm{CDF}_n = 1 - \exp\left(- \sum_{j=1}^{m} d_{rjn} \hat{\lambda}_{rjn} \right) \quad \forall r, m, n, \tag{14}$$

where $d_{rmn} = 0$ for all points before the age of release, $d_{rmn} = 1$ for all points after release, and $\hat{\lambda}_{rmn}$ is the projected hazard for all ages based on the estimated Lagrange Multipliers. This allows us to compute the cumulative probability of re-arrest for the next arrest assuming the individual survives to some point after release. Here, we present summary statistics for the three-year window. In the lower panel of Table 6 we present the proportion of state-specific sample members that are predicted to be re-arrested within three years of release based purely on knowledge about their prior criminal history accumulation process. Note that we should not expect these predictions to be very good unless the model has captured some salient underlying feature of the process under study. This is because the current prediction problem is very different from predicting in-sample or predicting out-of-sample using a randomly selected validation sub-sample. Here, the predictions are being done for a period beyond the estimation sample—i.e., off the sample support for each individual.

In the lower panel of the table, we present the proportion predicted to be re-arrested within the three-year follow-up period using the following rule. If the CDF is larger than 0.50 by three years of release, the individual is projected to be re-arrested; otherwise not. In addition to the predictions, we also present the proportion of the sample that actually failed within the follow-up period as a way to assess the accuracy of the projections. Lastly, we present the false positive and false negative rates resulting from the criterion described above.

The findings in this part of the table are quite remarkable. Although the counterfactuals consistently over-predict the three-year re-arrest rates, the overall rate seems to follow the trend of actual arrests across states.

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[62] *Id.* at 16.

That is, states that experience high levels of actual re-arrest rates are those that are predicted to have higher levels of re-arrest rates, relative to others.

More remarkable, however, are the false positive and false negative rates. With the exception of Michigan, Ohio, and Texas, where the false positive rates exceed 50%, the false positive rates in all other states are well below this amount. In fact, averaged across all fifteen states (including Michigan, Ohio, and Texas), the false positive rate is 38% and the false negative rate is 27%. This means roughly two-thirds of those individuals projected to be re-arrested within a three-year window, based purely on knowing how they were accumulating crimes in their past, did actually get re-arrested. Similarly, roughly three-quarters of those predicted to not be re-arrested within the three-year follow-up period actually did not fail. These findings, although remarkable, should not be very surprising given the persistence in offending that is well documented in the literature.[63] We next present results of the models that use these projected counterfactuals as the trajectory towards which each post-release trajectory is shrunk while ensuring that the evidence in the sample (in the form of constraints) is still satisfied.

B. MODELS OF POST-RELEASE TRAJECTORIES AS DEVIATIONS FROM COUNTERFACTUALS

As discussed in the previous section, the sole purpose of developing the counterfactual was to assess the post-release actual re-arrest patterns in an attempt to understand how, if at all, the current incarceration has deflected the trajectory a particular individual was on. In order to do so, we first projected the re-arrest hazard for each of the individuals in the sample utilizing knowledge about the event number they were at risk of when they came out of prison in 1994 (i.e., how far along on their arrest sequence they were), their age at release (i.e., how far along in their life they were), and all other variables used in the pre-prison-based models. Note that even though the post-release sample includes censored observations (i.e., not everyone is re-arrested within the follow-up period), we have a counterfactual trajectory for each and every individual in the sample.

Although the statistical significance of the Lagrange Multipliers can still be tested using the sandwich and modified sandwich estimates of the asymptotic standard errors, the interpretation of the Lagrange Multipliers is now different. Recall that a + value on α_k now symbolizes an upward pressure on the trajectory relative to the counterfactual while a - value implies a downward pressure on the trajectory relative to the counterfactual. Consider, for example, a situation where all parameters are found to be

[63] *See* Piquero et al., *supra* note 16.

insignificant. That would mean that the post-release trajectory is statistically indistinguishable from the prior (i.e., the counterfactual). Hence, if one or more of the parameters are found to be significant, this would indicate that, in the sample as a whole, there has been a deviation of at least some of the post-release trajectories from their counterfactuals. It should not be taken to mean that every trajectory has deviated from its counterfactual.

We present the results of the post-release sample in Table 7 in a manner analogous to the presentation in Table 6. The pattern of coefficients is different from those in Table 6, which is to be expected. However, unlike the pre-release models, the post-release model parameters vary somewhat across states, with some parameters taking the opposite signs. For example, the value of α_k for AGE1ST is positive and significant for Delaware but is negative and significant for Illinois. In a similar manner, the signs of the significant values of β_k for AGE1ST vary considerably across states. This suggests that the way trajectories are deflected between the pre- and post-release periods varies somewhat across states and that the effects of AGE1ST in particular can even be reversed across different states.

Table 7

Summary of State-Specific Hazard Models of the First Post-Release Re-Arrest Event and Their Predictions for the Three-Year Post-Release Period

	AZ	CA	DE	FL	IL	MD	MI	MN
α_k								
INTERCEPT	++	++	++	++	++	++	++	++
EVENTNUM	++	++	++	++	++	++	++	++
AGE1ST	0	0	++	0	--	-	0	0
CARAGE	--	--	--	--	--	--	--	--
CONFLAST	-	--	-	--	-	--	0	--
β_k								
INTERCEPT	--	--	--	--	--	--	--	--
EVENTNUM	--	--	--	--	--	--	--	--
AGE1ST	0	0	--	+	++	++	+	0
CARAGE	++	++	++	++	++	++	++	++
CONFLAST	++	++	+	++	++	++	0	++
Pseudo R^2 measure (within sample)	0.46	0.41	0.32	0.64	0.67	0.46	0.46	0.56
Three-year re-arrest rate projections from each individual's criminal history-based (counterfactual) trajectories[a]								
Projected	77.9	61.7	97.0	77.2	81.1	80.0	26.6	73.2
Actual	62.1	54.1	86.5	65.4	69.8	66.6	39.3	60.4
False Positives	29.2	29.5	12.1	24.3	21.3	25.6	41.9	27.8
False Negatives	31.5	27.7	40.0	30.4	31.7	35.0	32.5	28.3

Table 7 (continued)

Summary of State-Specific Hazard Models of the First Post-Release Re-Arrest Event and Their Predictions for the Three-Year Post-Release Period

	NJ	NY	NC	OH	OR	TX	VA
α_k							
INTERCEPT	++	++	++	++	++	++	++
EVENTNUM	++	++	++	++	++	++	++
AGE1ST	0	0	0	--	--	0	--
CARAGE	--	--	--	--	--	--	--
CONFLAST	0	--	--	--	--	0	--
β_k							
INTERCEPT	--	--	--	--	--	--	--
EVENTNUM	--	--	--	--	--	--	--
AGE1ST	+	0	++	++	++	0	++
CARAGE	++	++	++	++	++	++	++
CONFLAST	0	++	++	++	+	+	++
Pseudo R^2 measure (within sample)	0.45	0.26	0.50	0.33	0.40	0.21	0.61
Three-year re-arrest rate projections from each individual's criminal history-based (counterfactual) trajectories[a]							
Projected	69.2	69.5	62.0	12.3	77.0	41.7	72.7
Actual	58.1	58.3	54.4	27.2	66.6	45.0	58.8
False Positives	28.3	28.9	32.3	40.7	22.4	39.1	32.8
False Negatives	27.7	29.2	32.6	22.7	30.0	33.6	36.5

Note: ++ = positive coefficient with 95% confidence; + = positive coefficient with 90% confidence; -- = negative coefficient with 95% confidence; - = negative coefficient with 90% confidence; 0 = coefficient statistically insignificant.

[a] Projections are based on converting each individual's predicted hazard trajectories into cumulative densities using equation (14). The criterion for an individual to be projected to fail within three years of release is if (her) his CDF had reached 0.50 within that period after release.

Still, in general, there are many commonalities across states in key covariates as some factors exert unambiguous pressure on offending trajectories. Being later in the criminal career exerts an upward pressure on the offending trajectory relative to the counterfactual. That is, large values of EVENTNUM are associated with an upward pressure on the offending trajectory. Similarly, being closer to past cluster exerts a downward pressure on the trajectory relative to the counterfactual. As noted above, these are aggregate statements about the sample as a whole. The actual deflection for each and every releasee will be computed and discussed in the following section.

Pseudo-R^2 measures for the models showed considerable improvement compared to the pre-incarceration part of the sample. However, signs of the deflection of the trajectories can best be seen in the projected re-arrest rates as well as the false positive and false negative rates. Although the prediction problem is no longer an out-of-sample one, simple comparisons between these projected re-arrest rates and the counterfactual projections of the last section show that the post-release projections are far superior to those of the counterfactuals. With the exception of Michigan and Ohio, where the false positive rates are about 40%, we see that the false positive rate typically is between 25-30%.

C. CLASSIFYING AND UNDERSTANDING THE DETERMINANTS OF THE INCARCERATION EXPERIENCE

The last set of results includes models used to study the effects of various predictors on the incarceration experience as predicted by the models. The averaged divergence measure δ that was defined in the previous section is used to study this aspect of the model. Using (13) as a way to classify individuals as having had a deterrent, a criminogenic, or a null effect, the data reveal that only a small part of the sample (4.3%) actually were classified as having had a criminogenic experience. The largest share was classified as having had a null effect (56.2%) and the remaining (39.5%) experienced some deterrent effects. In other words, roughly 4% of the released cohort returned to trajectories higher than, and 40% of them returned to a trajectory lower than, what was anticipated of them. Most, however, returned to a trajectory that was anticipated of them based on their pre-prison arrest patterns—they were merely incapacitated while in prison. Note that these classifications are based on the entire residual life of the releasee (up to age 100 in this analysis). They are not based on just the follow-up period.

Next, we present the results of several logistic regression models that are aimed at assisting practitioners and policy-makers in investigating what factors may be helpful in maximizing any deterrent benefits, and minimizing any criminogenic harm, resulting from incarceration. Since the proportion of releasees that were deemed to have had a criminogenic experience is fairly small, we combined those classified as having had a criminogenic and null effect into one category. Hence, the estimates in Table 8 are from models that attempt to link various available attributes to the likelihood of being deterred versus not. Once again, the Table only summarizes the signs of the various predictors in affecting the likelihood a deterrent effect.

Table 8

Effects of Predictors on the Probability of a Releasee Being Deterred from Incarceration

	Group I[a]	Group II[a]	Group III[a]	Group IV[a]
# PRIOR ARRESTS	--	--	--	--
CARAGE	++	++	++	++
AGE1ST	--	--	--	--
RELAGE	++	++	++	++
BLACK	+	0	0	--
MALE	--	--	0	-
VIOLENT	0	-	--	--
PROPERTY	0	--	-	--
DRUG	0	--	0	0
PAROLE[b]	0	++	...	...
MANDATORY	0	...	...	...
CONDITIONAL	...	...	0	...

Note: All models include an intercept term and fixed state effects. ++ = Positive coefficient with 95% confidence; + = positive coefficient with 90% confidence; -- = negative coefficient with 95% confidence; - = negative coefficient with 90% confidence; 0 = coefficient statistically insignificant; . . . = Variable not part of this model.

[a] Group I: MD, NY, NC, TX, & VA; Group II: MN & OR; Group III: AZ, FL, NJ, & OH; Group IV: CA, DE, IL & MI.

[b] Reference category is UNCONDITIONAL for Group I and MANDATORY for Group II models.

Four sets of parameter estimates are presented. One of the key policy variables to be investigated—the type of release from prison—was not consistently available in all states. The variable was re-coded into discretionary release to supervision (PAROLE), mandatory release to supervision (MANDATORY), and unconditional release (UNCONDITIONAL). Based on this variable, we collapsed states into four groups. Group I included all states that had sufficient detail to model the effects of various types of release mechanisms (Maryland, New York, North Carolina, Texas, and Virginia); Group II included states that only allowed a comparison of discretionary release to mandatory release (Minnesota and Oregon); Group III included states that only allowed a comparison of CONDITIONAL (including mandatory and parole releases) versus UNCONDITIONAL releases (Arizona, Florida, New Jersey, and Ohio); and Group IV included states that did not contain enough variation to permit estimating the effects of this policy variable on the effects of incarceration (California, Delaware, Illinois, and Michigan).

Since the logistic regression models were predicting the probability of deterrent experience, positive and significant coefficients can be expected to increase the likelihood of a releasee having been deterred as a result of this incarceration. Similarly, negative coefficients imply increased likelihood that the releasee was merely incapacitated or even exhibited a criminogenic experience.

As should be expected, releasees who have higher numbers of prior arrests are *less* likely to experience deterrent effects. Those closer to their prior arrest clusters and those released later in life were more likely to experience deterrent effects. Surprisingly, those with later ages of first arrest were consistently less likely to experience deterrent effects. Among the Group I states, blacks were more likely to experience deterrent effects while among Group IV states they were less like to be deterred. Males were less likely to be deterred by incarceration (among the states in Groups I, II, and IV) and, typically, prisoners released from Violent, Property, or Drug-Related crimes were less likely to experience deterrent effects (relative to Public Order crimes). Surprisingly, the prison release mechanism seemed unrelated to the probability of an individual being deterred. The only model in which the type of release played a significant role was among Group II states. Among these states, and as was found by Rosenfeld et al.,[64] being released via discretionary release was more likely to result in a releasee being deterred than being released mandatorily.[65]

VIII. DISCUSSION AND CONCLUSION

A key theoretical and policy question in criminology is whether incarceration serves a deterrent, criminogenic, or null effect on subsequent criminal activity. Motivated by a general lack of research in this area, we used data for a large sample of prisoner releasees from fifteen states in order to provide some evidence on this question by developing counterfactual micro-trajectories utilizing detailed information about past arrest patterns and tested whether the post-release trajectory of several

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[64] *See* Rosenfeld et al., *supra* note 36.

[65] These findings are not intended to provide any specific policy recommendations. Rather, they are presented as a means of showcasing the utility of the proposed analytical strategy in assisting practitioners in decision-making. For instance, state and local authorities that have sufficiently detailed information about the programs in which releasees participated while in prison or the kinds of assistance being offered to them after release, whether they have employment available upon release, whether they are returning to a family with strong ties, etc., could all be used in the type of model described above in an attempt to study how these variables (many of which are choices available to practitioners and policy-makers) can increase or decrease the likelihood that a releasee will be deterred from future crime.

thousand offenders was, in some sense, better, worse, or about the same as the counterfactual. Several important findings stand out.

First, the key finding was that a comparison of the counterfactual and actual offending patterns suggested that most (96%) releasees were either deterred from future offending or merely incapacitated by their incarceration, while a small percentage (4%) exhibited a criminogenic effect. In other words, roughly 4% of the releasees returned to trajectories of offending higher than, and 40% of them returned to a trajectory lower than, what was expected of them. Second, the substantive findings were largely consistent across fifteen diverse states. Third, states that experienced high levels of actual re-arrest rates were those that were predicted to have higher levels of re-arrest rates, relative to others. Fourth, with a few exceptions (Michigan, Ohio, and Texas), the false positive rates were well below 50% (the average false positive rate was 38%, while the average false negative rate was 27%). In other words, two-thirds of those individuals projected to be re-arrested within a three-year window based solely on knowledge of their past crime accumulations were actually re-arrested, while roughly three-quarters of those predicted to not be re-arrested within the follow-up period actually did not fail. Fifth, unlike the pre-release models, the post-release model parameters varied somewhat across the states and the effect of some parameters reversed across different states. Specifically, in the aggregate, being later in the criminal career exerts an upward pressure on the offending trajectory relative to the counterfactual, while being closer to past cluster exerts a downward pressure on the trajectory relative to the counterfactual. Finally, in an analysis that linked the limited set of attributes available to study the likelihood of being deterred versus not being deterred, results indicated that those with higher numbers of prior arrests were less likely to experience deterrent effects, while those closer to their prior arrest clusters and those released later in life were more likely to experience deterrent effects. Some variation existed with regard to some of the demographic variables across states classified on the basis of the type of release from prison.

With regard to theory, the study's key finding is troubling with respect to a key labeling theory hypothesis which anticipates an aggravating circumstance with regard to an incarceration experience, and much more in favor of deterrence-based theories which argue that incapacitation serves a role in reducing the rate of subsequent criminal activity, and/or with those who argue that incapacitation does little, one way or the other, to influence the subsequent rate of criminal activity. This particular finding must, of course, be tempered by the fact that the study was limited in some respects that preclude any definitive statements with regard to the role of incapacitation in influencing micro-careers.[66] For example, while the data are among the largest and most comprehensive, the use of only fifteen states raises the question of generalizability. Second, the database did not contain many important predictors anticipated to be related to offending patterns over the life course. For example, research has shown that previous criminal justice experiences, i.e., prior community supervision sanctions and failures, jail sentences, and convictions, as well as changes in various life events, i.e., marriage, gang affiliation and peers, and employment, are related to changes in criminal activity. Although the requisite data do not yet exist, considering these and other life events will be an important feature of subsequent research. Similarly, the fact that nothing is measured about the prison commitment that resulted in the 1994 release in terms of time served, programming, and prison adjustment is a limiting factor because these could have been related to future criminal trajectories. Inclusion of these factors will be important going forward. Third, only a three-year follow-up was available, and it is unknown the extent to which the patterns observed here would hold for longer periods of time. Fourth, although we focused on one of the key deterrence propositions (the punishment aspect of incarceration), we acknowledge that a more complete assessment of other aspects of the deterrence framework would be useful. Fifth, to be consistent with the extant recidivism and criminal career research tradition, we employed relatively broad offense categorizations. Subsequent research should examine a more distinguished set of offense types in an effort to determine if the re-offending probabilities (within our methodological approach) vary differently than those used in the current study. Ultimately, it is an empirical question as to the extent to which broad offense groupings (as used herein) represent cohesive offender types (as noted in the extant criminal career research area) relative to their post-release offending trajectories. Finally, the database contained only official records of offending (arrest), and thus likely misses the many experiences of crime that go undetected. Recognizing that there exists a larger debate

[66] Further, some caution with respect to the counter-labeling theory result should be noted. Our assessment of the labeling perspective was based on whether offenders released from prison have arrest trajectories that were greater than would be expected from their past arrest history and trajectory. One reviewer noted that it was unusual in the U.S. system of justice and punishment that the first time a damaging label is applied occurs when an offender is sentenced to prison; rather, the vast majority of offenders released from prison have had prior juvenile incarceration and adult prison experiences, been sentenced to local jails, been placed on community supervision one or more times, or been adjudicated as a juvenile delinquent or adult criminal. Thus, although other researchers have recently considered the effect of first-time imprisonment on subsequent offending trajectories, see Nieuwbeerta et al., *supra* note 37, our view that labeling theory holds little weight with respect to the study findings awaits replication, extension, and better measures of the labeling process.

about the merits of official versus self-report records,[67] it is unknown how much the results would hold using alternative measures of criminal activity.

Amidst these limitations, the current effort was one of the few studies to examine, using a counterfactual design, the role of incapacitation in altering the rate of subsequent criminal activity. We envision a healthy research agenda that will serve to continue to supply much-needed empirical information that will provide input for matters related to theory and policy. First, the effect of incarceration on the rate of subsequent criminal activity may matter differently at different periods of the life course. There is some evidence that local life events, such as marriage, serve an inhibitory function at (later) ages,[68] while other life events, such as grade retention, have differential impacts on subsequent aggression depending on when it occurs.[69] Second, properly accounting for career termination during periods of incarceration decreases the estimate of crime reduction through incapacitation because only a portion of incarceration time is served after careers have terminated. Because some careers will terminate while an offender is incarcerated, there is a need to consider dropout and termination rates as they respond to incapacitation. This leads to important questions such as: Are residual careers longer than average time served? Does incarceration delay or lengthen residual career length? If so, this will surely influence the incapacitation effect. Unfortunately, almost no information is known about the extent to which incarceration decreases (or increases) residual career length. Third, the framework outlined in this study can be extended to study the trajectories of multiple types of repeatable events such as offending and drug use over the life course.[70] Such analyses have the potential of shedding light on how incarceration can interrupt the co-evolution of these interrelated behaviors. A related profitable extension of the current work would be to include distinct group-based heterogeneity in the models.[71] Fourth, because we only examined first-arrest post-incarceration, it would be interesting to examine the number of arrests as an outcome instead of duration to first re-arrest. In our analysis, since we modeled our outcome as a duration measure (conditional on event number), the inclusion of durations to subsequent re-arrests (after the first) would have meant that our post-release trajectory and the post-release counterfactual would have utilized different

[67] *See* MICHAEL J. HINDELANG ET AL., MEASURING DELINQUENCY (1981).

[68] *See* Laub et al., *supra* note 22.

[69] Daniel S. Nagin et al., *Life Course Turning Points: The Effect of Grade Retention on Physical Aggression*, 15 DEV. & PSYCHOPATHOLOGY 343 (2003).

[70] Robert Brame et al., *On the Development of Different Kinds of Criminal Activity*, 29 SOC. METHODS & RES. 319 (2001).

[71] *See* Nieuwbeerta et al., *supra* note 37.

sets of information. As such, they would not have been comparable and inferences regarding the deterrent, criminogenic, or null effects of incarceration could have been misleading. Note, however, that the expected number of events (over a period of time) can be computed as the integrated hazard trajectory over that period (if the hazard measures an annual event rate). Hence, despite not explicitly modeling the count outcome, we do utilize information related to it in our analysis. Extensions of the framework developed here to model multiple manifestations of a stochastic process *simultaneously* are possible, at least in theory; they are currently being developed. Fifth and more generally, the framework advanced here could also be extended to study how other interventions, not just incarceration, may deflect the trajectories of offending. For example, the effects of participation in various treatment programs may be quantified in terms of the program's ability to deflect individual's offending trajectories. Sixth, a richer dataset containing predictors of key theoretical constructs and life domains is likely to provide much-needed information on the factors that are associated with these discrepant trajectories.

In the end, a brief comment on the results of this study for the public policy discourse is in order. Let us be clear that we are not suggesting that the use of incarceration be adjusted as a result of the weak criminogenic effect observed; instead, the focus should be on developing mechanisms that facilitate reconnections for offenders as they reenter society.[72] It appears to us that a society that invests in reconnecting individuals to their communities may offer many benefits and speak more generally to what a democratic society is all about.[73]

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[72] *See* LAUB & SAMPSON, *supra* note 21, at 291.

[73] TODD R. CLEAR & ERIC CADORA, COMMUNITY JUSTICE (2003); JEREMY TRAVIS, BUT THEY ALL COME BACK: FACING THE CHALLENGES OF PRISONER REENTRY (2002).