Title
Explaining, Measuring, and Predicting the Criminal Behavior of High Rate Offenders

Author
Laqueur, Hannah Sybil

Publication Date
2016

Peer reviewed|Thesis/dissertation

Explaining, Measuring and Predicting the Criminal Behavior of High Rate Offenders

by

Hannah Sybil Laqueur

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Jurisprudence and Social Policy

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Franklin Zimring, Chair
Professor Rob MacCoun
Professor Justin McCrary
Professor Steve Raphael

Fall 2016

Explaining, Measuring and Predicting the Criminal Behavior of High Rate Offenders

Abstract

Explaining, Measuring and Predicting the Criminal Behavior of High Rate Offenders

by

Hannah Sybil Laqueur

Doctor of Philosophy in Jurisprudence and Social Policy

University of California, Berkeley

Professor Franklin Zimring, Chair

This dissertation offers three studies on criminal behavior and criminal risk forecasting. The first two chapters present theoretical models and empirical evidence on the nature and motives of criminal behavior among high risk and high rate offenders and the implications these models have for criminal justice policy. The third chapter is a study of judicial and administrative decision-making with regard to assessments of crime and violence risk.

Chapter 1 gives an account of the 1970s and 80s rise and dominance of the policy of incapacitation through incarceration. The chapter describes the deterministic model of criminal behavior underpinning the theory and policy of incapacitation, and the policy implications of recent re-conceptualizations that view criminal behavior much more like other human choices - a question of contingencies and opportunities. The chapter focuses on Franklin Zimring's (2011) account of the New York City crime decline as evidence against the notion that criminal propensities are fixed and predictable over periods of years. Rather, it appears, relatively modest and superficial changes in circumstances and environmental features can lead to vastly different rates of criminal engagement.

The second chapter turns to a particular aspect of the New York City crime decline and the question of future criminal risk prediction. Specifically, the chapter examines the more than two decade drop in the rate of prison return for a new felony among New York City offenders. The chapter assesses whether the declining prison return rate is indeed an indicator of significant behavior change, or is a reflection of changes in criminal justice system actor practices. Further, to the extent that the statistics are an indicator of behavior change, the chapter evaluates whether this can interpreted as the result of the changing New York

City crime environment over the last two and a half decades, or is better understood as a reflection of changes in the individual criminal propensities of those leaving prison over this period. To tease apart these competing accounts, the chapter analyzes a unique dataset involving individual records of four cohorts of prisoners from New York City released in the years 1990, 1995, 2000, and 2008. The analysis suggests a mixed picture - all three accounts are at work.

Finally, the third chapter of the dissertation turns from models of criminal behavior and criminal decision-making, to judges and administrator decisions regarding criminal risk. The chapter uses machine-learning procedures for prediction and causal estimation to analyze release decisions in California Parole hearings for inmates serving life sentences with the possibility of parole. Using an original dataset generated from all parole suitability hearings conducted since 2011 (over 8,000 transcripts), the chapter offers an empirical analysis of the current system, evaluating the rationality, uniformity, and defensibility of the criteria and decision-making applied to each claim for release. Finally, using the parole analysis as proof of concept, the chapter considers the promises and pitfalls of algorithmic assisted decision-making in the criminal justice system.

Contents

List of Figures

Introduction

This dissertation examines decision-making theory – as it applies to understandings of criminal behavior, and as it applies to criminal justice policy actor judgments about criminal behavior. The first two chapters present theoretical models and empirical evidence on the nature and motives of criminal behavior and the implications these models have for criminal justice policy. The third chapter is a study of judicial and administrative decision-making with regard to assessments of crime and violence risk.

Chapter 1 gives an account of the 1970s and 80s rise and dominance of the policy of incapacitation through incarceration. The chapter describes the deterministic model of criminal behavior that underpinned incapacitation theory, and the policy implications of recent reconceptualizations of criminal behavior, which view criminal behavior to be much more like other human choices - a question of contingencies and opportunities. The chapter focuses on the New York City crime decline as a case study that challenges the notion that criminal propensities are fixed and predictable over periods of years, an assumption upon which incapacitation efficacy estimates relied. The dramatic crime drop in New York City crime, and to some extent the nationwide crime decline more generally, suggest relatively modest and superficial changes in circumstances and environmental features can lead to vastly different rates of criminal engagement. The chapter concludes by pointing to open questions that follow from the recognition that the (crime) environment can have a large impact on individual and community crime rates. In particular, the chapter discusses questions relating to how place and period operate on offenders and offending rates, and concerns that circumstantial or ecological evidence may overestimate the magnitude of environmental effects.

The second chapter turns to a particular aspect of the New York City crime decline as an examination of individual criminal propensities and criminal risk prediction: the more than two decade fall in the rate of new felony prison returns among former prisoners from New York City.[1] The chapter examines whether the declining prison return rate represents behavior change among former prisoners over the last two and half decades, or is instead an artifact of changes in prosecutorical and court practices over this time. Additionally, to the extent that the statistics are a reflection of changed criminal behavior, the chapter

[1] A drop from 28% returned within three years for a new felony among those released in 1990 to 8% among those released in 2012.

assesses whether this should be viewed evidence of the impact of the New York City crime environment, which changed dramatically over these two decades, or reflects changes in the criminal propensities of the individuals being released from prison. To tease apart these competing accounts, the chapter analyzes a unique dataset involving individual records of four cohorts of prisoners from New York City released in the years 1990, 1995, 2000, and 2008. The analysis suggests a mixed picture - all three accounts are at work. We cannot simply interpret the 70% drop in the rate of new felony return over the last two and half decades as a 70% drop in personal crime rates among former prisoners. At the same time, the likelihood of rearrest for a major crime among former prisoners released today, an era in which there is 80% less crime in New York City, is indeed lower than for those prisoners released in 1990, at the height of crime in the city. Additionally, the average and median age of New York City offenders *entering* prison increased over the course of the crime decline, which suggests the crime participation rates of "at-risk" youth dropped more than the individual crime rates of "repeat offenders." This is evidence consistent with a theory of peer and environmental effects.

Chapter 2 concludes with a discussion of the well-known challenge of identifying and estimating environmental and peer effects, in particular the problem of selection bias, which may exaggerate peer and neighborhood effects (see e.g. Angrist 2014; Manski 2000). Given the difficulty of inference, many different approaches and methods of inquiry are relevant and necessary: quasi-experimental research designs when available, qualitative study, and the sort observational and circumstantial evidence presented in chapter two.

The third chapter turns from models of criminal behavior and criminal decision-making, to judges and administrator decisions regarding criminal risk. The chapter uses machine-learning procedures for prediction and causal estimation to analyze release decisions in California Parole hearings for inmates serving life sentences with the possibility of parole. The chapter tells the story of the recent dramatic change in the rate of parole release - from under 5% during the 1990s and early 2000s to the current 30% and, using an original dataset generated from all suitability hearings conducted since 2011 (over 8,000 transcripts), offers an empirical analysis of the current system, evaluating the rationality, uniformity, and defensibility of the criteria and decision-making applied to each claim for release. The parole of inmates serving life sentences now represents an important release valve in the California criminal justice system, yet it has received relatively little empirical attention.

The chapter suggests the California "life" parole system represents a process that is both highly predictable – the outcome of a hearing can be predicted with almost 80% accuracy – and at the same time, is a system that contains a real element of chance –who an inmate happens to get as an evaluating psychologist or commissioner can alter whether they are released or remain in prison for many more years. Further, the analysis of variables suggests that, at least to some degree, factors that by law should not matter in the parole decision, such as the presence of victims at the hearing, may well have a substantial impact on how the Board decides. On the other hand, there is no evidence in this dataset that the parole board commissioners exhibit the psychological biases that researchers have documented in other adjudicators. Specifically, neither the gamblers fallacy nor decision fatigue appears to play a meaningful role in commissioners decision-making.

Finally, the chapter considers broader questions regarding the promises and pitfalls of algorithmic assisted decision-making in the criminal justice system using the California parole analysis as proof of concept. This discussion points to often-overlooked problems with current risk assessment instruments including the problem of selection bias, poor proxy measures of future dangerousness, and the inability to resolve concerns regarding embedded discrimination. The chapter suggests predictive models of past judicial or administrator decisions can act as a kind of "synthetic crowdsourcing" and be used as a tool to help judges and administrators make better and more consistent future decisions. Additionally, the chapter proposes systematic biases in criminal justice actor decision-making such as racial bias may be addressed in an algorithm by making direct changes to algorithmic output based on explicit estimates of bias. Most commentators concerned with racial bias in criminal risk assessment instruments have focused on constructing algorithms without the use of the bias-inducing variable. The problem with this method is that other variables in the model may simply act as proxies, soaking up and storing the bias. The approach presented in this chapter offers a means for removing bias with minimal sacrifice of predictive performance.

.

Chapter 1

Incapacitation: Penal Policy and the Lessons of Recent Experience

Introduction

The measurable correlates of crime and delinquency have long been known and have remained essentially unchanged: delinquent behavior is primarily exhibited by males, it peaks in late adolescence, and it is concentrated in socially and economically disadvantaged communities. At the same time, rates of crime fluctuate considerably between place and over time. Since the early 1990s, both violent and property crime rates have fallen, most significantly in large cities but throughout the developed world more generally. In the United States, the most dramatic and prolonged drop was in New York City, closely followed by Los Angeles. These trends cannot be fully explained by criminal justice policy, demographic changes, or macro-social and economic patterns. Crime has fallen in places in which incarceration rates did not increase; populations have not uniformly aged; economies have improved and worsened without obvious traces on recorded crime. The widespread and unexpected drop in crime in the 1990s and 2000s reanimated the sense that crime is preventable, and made it seem less likely that only intervention grounded in the root causes, whether biological, psychological, macro-sociological or economic, offer the means for doing so. As a way forward, scholars have begun to look to more contingent or seemingly superficial ecological features to account for recent trends: more and better policing, broad cyclical influences and social change (i.e. the abatement of the crack epidemic and its associated violence); fewer opportunities because of increased private security and technological innovations (i.e. it is harder to steal cars, break into houses, etc) (Blumstein and Wallman 2006). The power of the immediate situation or context in determining human behavior, relative to the influence of individual intentions or traits, is thought to be an important lesson from modern psychology (Kahneman 2011); yet, much of the thinking about criminal behavior has, until only recently, vastly underestimated this dimension.

The subject of this paper is the revised understanding of the etiology of crime, which views criminal activity like other human choices - a question of contingencies and opportunities - and the discrediting of the exclusive emphasis on crime control policy of incapacitation through incarceration that follows from this reorientation. The paper gives an account of the rise and dominance of incapacitation theory and policy in the U.S. in the 1970s and 1980s and considers what mixed theory and policy should follow when crime is no longer understood to be a consequence of some set number of criminals as early incapacitation studies and criminological dogma implied. The paper focuses on Franklin Zimring's account of the New York City crime decline as a particularly stark challenge to the criminological assumptions underlying incapacitation efficacy (F. E. Zimring 2011). Specifically, the assumption that criminal propensities are relatively fixed and predictable over periods of years. New York City's roughly 85% drop in major crime over the last twenty-five years suggests observably similar populations in similar structural conditions can engage in significantly different rates of criminal activity; modest and superficial changes in circumstances and environmental features can lead to vastly different rates of criminal engagement.

The paper is organized as follows. Section 1.1 describes the rise of incapacitation theory in the late 1970s as a justification for expanding imprisonment. This section includes a review of the criminological literature on criminal careers, which supported the incapacitation policy of increasing sentences for serious and repeat offenders, and a review of research efforts to empirically estimate incapacitation effects. Section 1.2 details the circumstantial evidence from the New York City crime decline against the notion that long prison sentences to incapacitate career criminals is the only available strategy to successfully reduce crime rates. This NYC evidence includes the drop in the city's prison and jail population that accompanied the dramatic drop in crime, data on the declining rate of new felony prison returns among New York City inmates, and the declining rearrest rate among New York City probationers (F. E. Zimring 2011). Section 1.3 considers the theoretical and policy implications of the dismantling of the "supply-side" accounts of crime, describing alternative conceptions of criminal behavior and behavioral change that takes such behavior to be deeply social, situational, and contingent. The section describes the evidence on micro-environmental influences on crime, in particular social influence, and the challenge of empirically documenting such phenomenon. Section 1.4 concludes.

1.1 Incapacitation Theory, Policy, and & Effects

1.1.1 The Rise of Incapacitation

Incapacitation refers to the effect of physically removing an offender from the community and thereby preventing whatever crimes the offender would commit were he or she still on the streets rather than in prison or jail (P. W. Greenwood 1982; Moore et al. 1984). For at least two hundred years incapacitation has been recognized as a legitimate objective of criminal punishment - deterrence, retribution, and, to some degree, rehabilitation, the others. But beginning in the mid-1970s, incapacitation came to be the primary justification for imprisonment and the principle motive and justification for what would be decades of exponential prison grown (F. Zimring and Hawkins 1995).

The mid-1970s was a turning point in criminological thinking and criminal justice policy-making. It moment of great pessimism about the prospects of preventing criminal behavior. Robert Martinson's review of prison rehabilitaton programs, "What Works? - Questions and Answers About Prison Reform," is often cited the embodiment of the "nothing works" sentiment of the time (Martinson 1974). Martinson's concluded rehabilitation strategies "cannot overcome, or even appreciably reduce, the powerful tendencies of offenders to continue in criminal behavior"(p.)."With few and isolated exceptions the rehabilitative efforts that have been reported so far have had no appreciable effect on recidivism"(p. 25). The demise of the "rehabilitation ideal" coincided with rising crime and more general skepticism about the prospects of crime prevention generally; faith in police patrol tactics, for example.[1]If nothing preventative or rehabilitative could work, by corollary logic, stopping crime required physically removing offenders from society for the duration of their criminal careers."The lack of evidence on the effects of either rehabilitation or deterrence leaves incapacitation as the only utilitarian basis for rationalizing differences in sentence severity for different types of offenders," wrote Peter Greenwood in a 1982 essay on selective incapacitation (P. W. Greenwood 1982). James Q. Wilson's *Thinking About Crime* offers the most forceful articulation of the incapacitation argument: "Wicked people exist," he wrote, "[n]othing avails except to set them apart from innocent people" (p. 209) (Wilson 1975). The belief that incapacitation was essentially the only method to reduce crime is what largely motivated and justified the unprecedented expansion in incarceration in the U.S., which began in the late 1970s and continued into the twenty-first century (F. Zimring and Hawkins 1995). The result has been a sevenfold increase in the prison population between the mid 1970s and the present (a quadrupling of the rate of imprisonment), and a tripling of the rate of incarceration in local jails.

Incapacitation through incarceration became the dominant criminal justice policy in the 1980s and a central focus of criminological scholarship. The early incapacitation framework was a simple one: portions of predetermined criminal careers could not be acted out due to incapacitation. The benefits derived from incapacitation thus depend on the magnitude and duration of what would be the incapacitated individual's crime rate if he staying in the community; the higher an individual's crime rate and longer its duration, the more crimes that can be averted through his incapacitation. The paper now turns to a review of the criminological scholarship on this patterning of criminal careers, known as the "criminal career approach." The study of incapacitation and its role in preventing criminal activity is the central policy question underlying the criminal career framework. The criminal career ap-

[1]The null results of the 1974 Kansas City Preventative Patrol Experiment, for example, called into question the routine police patrol as a preventative strategy (F. E. Zimring 2007).

proach has been at the heart of assumptions of incapacitation efficacy and efforts to estimate crime savings generated by incapacitation (Ludwig and Miles 2007; Piquero, Farrington, and Blumstein 2007).

1.1.2 Theoretical Underpinnings: Criminal Career Approach

The criminal career approach is usually traced to the mid-twentieth century work of Eleanor and Sheldon Glueck ((S. Glueck and E. T. Glueck 1930; S. Glueck and E. T. Glueck 1934; S. Glueck 1945; S. Glueck and E. Glueck 1950)), which comprised the first systematic quantitative investigation into individual trajectories of criminal participation (Lauritsen, Sampson, and Laub 1991).[2] The Gluecks' study followed for twenty-five years a group of 500 male delinquents and a group of non-delinquents matched on age, race/ethnicity, IQ, and place of residence. They collected data on key social, psychological, and biological factors, changes in salient life events, and criminal activity measured by personal interviews and official criminal justice statistics. This longitudinal cohort model developed by the Gluecks came to dominate the criminological study of individual offending, a subject that would gain renewed attention in the 1970s and 1980s.

The Gluecks' approach to the study of criminal participation was not the only one at the time, and the debates it sparked represent foundational disagreements and approaches to the study of crime and criminality that would again become center stage when the criminal career approach gained prominence in the late 1970s ((Sampson and Laub 2003)). For example, Chicago sociologist Edward Sutherland was critical of the Glueck's research arguing criminality was dependent on changing social influences such as neighborhoods and educational opportunities. The Gluecks' work instead focused on the individual determinants of criminal behavior assuming relative stability of between individual differences and consistency in individual offending over time. The Gluecks' research was also part of the first efforts to generate predictive instruments of future offending, efforts which have been criticized on a variety of grounds including their inability to accurately predict future offending partly because of the assumed stability of deviance (Harcourt and Ludwig 2006; Sampson and Laub 2003).

The modern study of cohorts and criminal careers begins with Wolfgang, Sellin, and Figlios 1972 study "Delinquency in a Birth Cohort" (Figlio, Sellin, and Wolfgang 1972). The study followed a group of 9,945 ten-year old boys in Philadelphia from 1945 until their eighteenth birthdays in 1963. The most crucial and enduring result, replicated in numerous

[2] The criminological tradition of studying individual "criminal careers" as a means of understanding the etiology of crime dates back to at least 19th century (Piquero, Farrington, and Blumstein 2003). As Piquero cites in his review of the criminal career approach, German scholar Von Scheel (p. 191) suggested: "(i)deal criminal statistic.. would follow carefully the evolution of criminal tendencies in a given population" (Scheel 1890). Kobner (p. 670) argued, Correct statistics of offenders can be developed only by a study of the total life history of individuals (Köbner 1893). In the United States, Clifford Shaw's The Jack-Roller (1930) and Sutherland's The Professional Thief (1937) are among the original life history accounts of criminal careers.

subsequent cohort studies, was that a small group of chronic offenders commit a disproportionate amount of the total crime.[3] Specifically, they found those with five or more police contacts, accounted for only six percent of the total cohort but they were responsible for over half the police contacts (5,305 offense).

Research on the patterning of criminal careers proliferated in the late 1970s and 1980s. In 1983, the National Academy of Sciences appointed a panel to synthesize and summarize what was by then known as the criminal career approach. The panel sought to evaluate the feasibility of predicting criminal careers and assess the potential of risk assessment instruments to identify high-risk offenders and reduce crime through incapacitation (Piquero, Farrington, and Blumstein 2003). The panel's report, "Criminal Careers and Career Criminals" ((Blumstein et al. 1986)) remains the foundational modern articulation of the criminal career paradigm. The report outlined the parameters and patterning of crime over an individuals life: why and when delinquency begins (onset); the extent to which delinquency continues (persistence); if and how an individuals engagement in crime becomes more serious or frequent (escalation); and, finally, why and when a person ceases criminal involvement (desistance) (p.13).

The "Delinquency in a Birth Cohort" finding that a small fraction of individuals commit a large proportion of the total offenses was reiterated in "Criminal Careers and Career Criminals" and would again be re-articulated in the 1990s with Developmental Criminology's concept of the "life-course persistent offender." The developmental approach, grounded in psychology, was focused on identifying distinctive etiologies of criminal behavior trajectories and the psychological factors explaining developmental processes (see e.g. (Loeber and Stouthamer-Loeber 1998; Moffit 1993; Moffitt 1993)). Terrie Moffitt's (1993, 1994) dual taxonomy serves as the lead example of the developmental approach. The taxonomy decomposes the aggregate age crime curve into two classes of offenders each with distinct criminal trajectory - members of the majority "adolescence-limited" group, who engage in delinquent activity only during adolescence, and "life-course persistent" offenders who continue to engage in antisocial and criminal activities throughout much of their life (Moffit 1993; Moffitt 1993). Moffitt traces this persistent offending to early childhood neuropsychological traits (e.g. cognitive deficits, difficult temperament and lack of self-control).[4]

The consistent finding that a small proportion of individuals are responsible for a vastly disproportionate number of total crimes offered support for incapacitation, in particular,

[3] This pattern that has been found in many contexts besides criminal offending; the use of the medical system, for example.

[4] Unlike the adolescent-limited group, the delinquency of the life-course persistent begins earlier (before the height of peer influence which explains the behavior of the adolescent-limited group), tends to offend more frequently and more violently, and continues offending into adulthood. Although the taxonomy recognizes persistent antisocial behavior to be the product of the cumulative interaction between these early childhood neuropsychological problems and a disadvantaged or criminogenic environment, Moffits explanations for the origins of chronic offending are primarily bio-psychological.

"selective incapacitation." The strategy, articulated in the early eighties (see e.g. (Petersilia 1980; P. W. Greenwood 1982)), described the potential for actuarially identifying and selectively confining those individuals who represented the most serious risk to the community. As such, selective incapacitation offered the possibility of both reducing crime and reducing the number of incarcerated individuals.

By the mid 1980s researchers, including Greenwood himself, had shown the estimated crime savings generated by selective incapacitation had been greatly overstated ((Cohen 1983), (Cohen 1984); Spelman 1984; (Von Hirsch 1984); (Visher 1987)) and the prospects of actually prospectively identifying future offenders to selectively incarcerate was much more difficult than the early work had suggested ((P. Greenwood and Turner 1987)). But political processes can become immune to counter-evidence. The criminal career logic and principle of selective incapacitation was reflected in a number of "get tough" policies passed in the late 1980s and early 1990s aimed at removing the most prolific or habitual offenders from society. Three-strikes laws, for example, which required a minimum term, usually twenty-five-years to life, for anyone convicted of three felony offenses (typically violent). In fact, the effect of three strikes and various forms of habitual offender laws was not the incapacitation of only the most serious offenders but rather the incarceration of increasingly less dangerous and less criminally prone offenders. The implications for estimates of incapacitation crime savings of these laws and the prison expansion more generally are detailed in Section 1.1.4. But first the paper turns to a discussion of the theoretical shortcomings of the criminal career approach and the criminological literature and research developed in response to these shortcomings.

1.1.3 The Place of the 'Environment' in Cohort Research

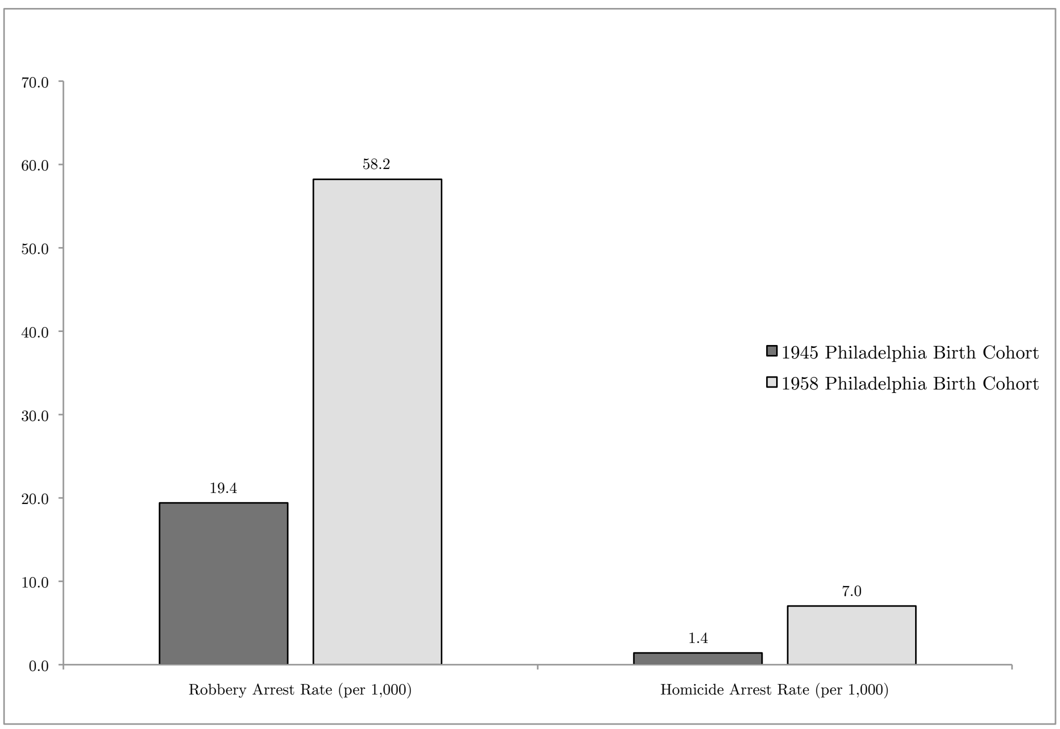
The structure of the longitudinal cohort model, following groups of individuals over time, has generated research centered on individual traits and behaviors, often at the expense of place and time determinants. The criminal careers research literature has not engaged with broader trends in crime rates and has given little attention to the significance of crime opportunities for criminal careers (DeLisi and Piquero 2011).[5] Cohort studies have focused on questions regarding the concentration of offending and the determinants of individual

[5]This absence is revealed in the more general logic of cohort explanations for crime trends over time which attribute crime trends to underlying changes in the size and nature or character of a population. Cohort explanations offered for the nationwide decline in violent crime that began in the mid-nineties include the legalization of abortion in 1973 ((Donohue III and Levitt 2001)) and a decrease in the levels of lead in paint in the 1970s ((Nevin 2000)), both of which it is suggested worked to produce a generation of youth with lowered propensities to engage in criminal behavior. A cohort account also underlies the claim that the decline was the result of higher rates of incarceration (Blumstein and Beck 1999). The initial spike in crime in the late eighties has also been explained by a change in the cohort. Period theories on the other hand emphasize the social, economic, and policy environment that may be more or less conducive to crime. Period explanations offered for the rise in crime in the late 1980s include emergence of crack-cocaine drug markets, the corresponding increasing in the demand and prevalence of guns, and related cultural explanations such as the development of gangs and a subculture of violence (Blumstein and Wallman 2006). The decline is explained by the subsiding of these factors. Cohort theories include the legalization of abortion, the decline

offending persistence, but place and time are of course manifest in these studies even if not the central subject. For example, the roughly six percent of chronic offenders found in a 1942 Racine, Wisconsin birth cohort study engaged in fewer and less serious criminal activities than the boys in the 1945 Philadelphia birth cohort (Shannon et al. 1988). Wolfgang et al's study of a second Philadelphia birth cohort, born in 1958, found the cohort exhibited the same concentration of offending as had the 1945 birth cohort, but the 1958 cohort committed a much higher volume of serious offenses compared to the 1945 cohort (Figlio, Tracy, and Wolfgang 1990).

Figure 1.1 presents the rate of robbery and homicide arrests per 1,000 individuals for the 1945 and 1958 birth cohort. The dramatic difference in the magnitude of crime commission volume shown in the figure illustrates the importance of period on crime volume. This was often lost in cohort research which was focused on the patterning of behavior, and the correlates and causes of crime, particularly among serious offenders, rather than on accounting for variations in the quantity and type of crime across cohorts.

Figure 1.1: Rate of Robbery and Homicide Arrests per 1,000 boys, 1945 vs 1958 Birth Philadelphia Birth Cohorts



The discounting of environmental and social determinants of crime contributed to what

in lead poisoning, and the rise in imprisonment. Of course, age, period, and cohort are not mutually exclusive explanations for crime trends. Rather, most age-period-cohort analyses recognize all three to be at work to some degree.

Zimring terms "supply side criminology". This view, in broad strokes, predicts and explains crime volume based on the "supply" of offenders drawn from high risk populations. A supply side view presumes chronic or high rate offenders will continue to offend at relatively fixed rates unless they are removed by incarceration or age out of crime. And so demographics translate to crime volume.

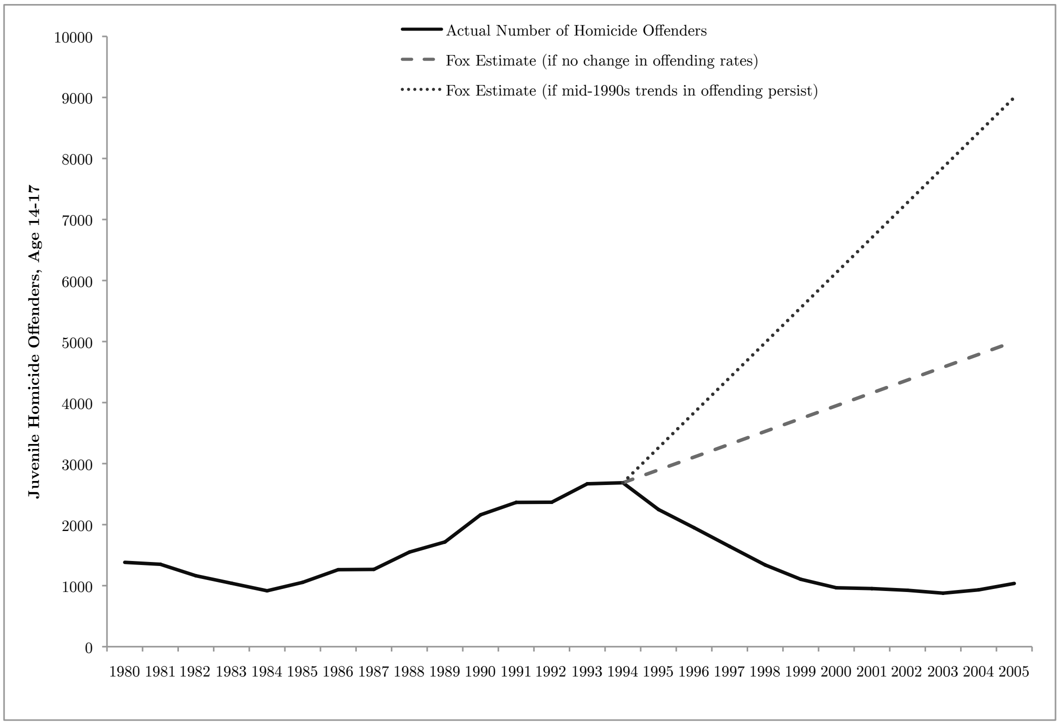
In fact, demographic-based predictions of crime volume have been shown to be wildly inaccurate. This failure of crime forecasting based on cohort characteristics is typified by the mistaken predictions of a several prominent scholars in the mid-1990s - John J. DiIulio (1997), James A. Fox (1996), and James Q. Wilson (1993)- who warned that rising violent crime trends, particularly among youth, would only worsen as the so-called echo boomers aged into their crime-prone years (Samson 1997; Fox 1996; Wilson 1993). John DiIulio, credited with coining the term "super predator," warned, along with his co-authors: "America is now home to thickening ranks of juvenile super-predators radically impulsive, brutally remorseless youngsters" (Bennett, Dilulio Jr, and Walters 1996) (p. 27). The trend was the result of "'moral poverty' children growing up without love, care, and guidance from responsible adults" (p. 59). DiIulio cautioned that by 2010 there would be "approximately 270,000 more juvenile super-predators on the streets than there were in 1990" (Samson 1997). James Q. Wilson likewise warned of looming disaster based on an assumption of a constant age-specific offending rate among high-risk populations: by the year 2000 there would be "30,000 more young muggers, killers, and thieves than we have now." The estimate was based on a projection of an additional million teenagers, half male, and the Philadelphia studys six-percent chronic offender rate. James A. Fox, in a Bureau of Justice Statistics report, predicted that by the year 2005, "even if the per-capita rate of teen homicide remains the same, the number of 14-17 year-olds who will commit murder should increase to nearly 5,000 annually because of changing demographics." But, Fox warned, given recent crime trends, there could be nearly 9,000 homicide offenders age 14-17. [6]. For this coming wave of super predators Fox saw no way out but incapacitative incarceration. "No one in academia is a bigger fan of incarceration than I am... By my estimate, we will probably need to incarcerate at least 150,000 juvenile criminals in the years just ahead."

To illustrate the magnitude of the failed predictions of the 1990s, figure 1.2 presents Fox's upper and lower bound predictions, alongside the actual trends in the number of homicide offenders age 14-17. Even Fox's conservative estimate turned out to be a five-fold overstatement; there were in fact just over 1,000 known juvenile homicide offenders in 2005. The predictions of coming super predators and rising violence turned out to have been made at what would be the *peak* of violent crime and juvenile arrests; crime and arrests fell substantially in the second half of the nineties and into the 2000s.

The failed predictions from 1990s of rising youth crime underscore a more fundamental

[6] between 1985-1992 the rate at which males ages 14 to 17 committed murder increased by about 50% for whites and more than 300% for blacks

Figure 1.2: Forecast of Juvenile Homicide Offender Trends vs. Actual Juvenile Homicide Trends



point: the predictions, and the incapacitation framework, assumed a simplistic model of offending in which individuals were characterized by their personal crime rates (λ), insensitive to costs and benefits, opportunities, policies, and the general environment in which they operate.[7] But evidence suggests, contrary to this model, there is no "supply" of criminals; potential criminals are adaptable and malleable.

While much of the cohort research has neglected social and ecological context and thereby encouraged a "supply-side" view of crime, there have been some efforts to explicitly incorporate these important dimensions within the study of criminal behavior trajectories. Specifically, life-course criminology, which developed in the 1990s, was, like the criminal career approach, concerned with the patterning of individual offending, but it focused on the importance of social structures and community context in understanding dynamic processes of criminal involvement. The work of Robert Sampson and John Laub provides the leading example of the life course perspective ((Laub and Sampson 1993; Sampson and Laub 2003; Sampson and Laub 2005)). The framework is critical of the implicit rigidity of the categories developed under the criminal career and developmental models and instead suggests

[7]This point was made by some in the 1980s at the height of incapacitation scholarship and policy. Philip Cook (1986) makes the argument the mechanical model of incapacitation will not be reliable because criminals in fact exhibit adaptive behavior (Cook 1986).

the causes of crime are more dynamic and will vary across an individuals lifespan as the result of shifting social bonds and pivotal moments. Criminal behavior trajectories are "socially emergent" and "contextually shaped" - the product of a constant interaction between individual propensities, their environment, human agency, and "random developmental noise" (Sampson and Laub 2005).

Laub and Sampson in an analysis of reconstructed and augmented data from Gluecks' classic longitudinal study, show the difficulties of actually identifying the high risk "career criminals" or "persisters" using the usual correlates. They were not able to find distinguish between the persisters at the beginning of their delinquent careers and the majority who desisted by their early twenties. Instead, major turning points such as getting a job, enlisting in the military, or marrying was what predicted criminal career termination. They argue such turning points can play an important role in enhancing the probability of desistance and changing criminal trajectories by influencing both immediate routines, supervisions, and other situational factors that induce or discourage crime, as well providing a broader platform on which an individual can recreate their identity and distinguish the present from the past.[8] The findings underscore the challenge of prospectively identifying the high-risk inmates to be incapacitated. Further, the study suggests imprisonment may cause real harm on criminal behavior trajectories by precluding the possibility of turning points.[9]

Despite the theoretical import of the life course recognition of environmental context, the individual-level unit of analysis in cohort studies makes it inherently difficult to examine or empirical test for. The most notable effort to combine longitudinal analysis with the study of social and environmental determinants was the Project on Human Development in Chicago Neighborhoods (PHDCN), conceived in the 1990s. The project involved data collection on eighty Chicago neighborhoods in 1995-1996, along with a longitudinal study of youth from these targeted neighborhoods ((Buka et al. 2001)). It was designed to advance the understanding of the developmental pathways of both positive and negative human social behaviors. In particular, the Project examined the pathways to juvenile delinquency, adult crime, substance abuse, and violence. Much of the literature produced from PHDCN has been from the neighborhood perspective. That is, unpacking and providing theoretical accounts of neighborhood-level variations in problem behaviors including violence and delinquency. Studies from PHDCN have suggested social and organizational characteristics of a neighborhood to be important predictors of violence, beyond the aggregated demographic characteristics of the individuals in the community. An early and important finding from the project, for example, was the idea that collective efficacy defined as neighborhood social

[8]Important social bonds can include childhood attachments to parents, school and peers, as well as social ties embedded in adult transitional moments such as marriage, employment, military service, and residential change (Laub and Sampson 1993).

[9]Recent advances in data collection and data-adaptive estimation techniques have generated great advances in predictive exercises. At the same time, the turning points pointed to by Laub and Sampson are not ones a researcher could even today imagine having access to prospectively.

cohesion and a willingness to intervene on behalf of the common good- can help to mitigate violence in the community (Samson 1997).

Data from PHDCN has also been used to disentangle the age-crime curve from cohort and period effects, confirming the importance of the environmental context on individual crime trajectories. Studies using PHDCN data have shown violent behavior peaks for all cohorts in the late teens, but the curve for youth reaching their late teens during a period of lower crime and violence is lower and peaks somewhat earlier than cohorts coming of age in a higher crime environment ((C. Johnson and Raudenbush 2006)). The influence of period on the shape of the age-crime curve has also been confirmed internationally: high-crime periods may extend the age-crime curve by leading to earlier initiation of violence and/or later desistance (Fabio et al. 2006). And the finding of period effect strength has been supported more generally by researchers. For example, Cook and Laub compared national homicide commission and victimization rates over a ten-year span for different age cohorts, relative to the average same-age rates for a baseline period (Cook and Laub 1998; Cook and Laub 2002). Each cohort had an elevated rate during the violent crime epidemic, and each groups criminal activity dropped as national crime rates fell.

The fact that place and time profoundly affect both the volume and types of criminal behavior is on some level obvious and unsurprising. But coming of age in a higher crime environment was implicitly discounted in supply-side accounts of crime and the cohort research focused on measuring the causes, correlates, and patterning of criminal behavior, rather than the variations in the quantity and type of crime across cohort.[10] This discounting contributed to the faulty assumptions about the estimated crime savings generated by incapacitation. The paper now turns to a discussion of the conceptual and practical problems with estimates of incapacitation generated crime savings.

1.1.4 The Search for Lambda: Estimates of Incapacitation Crime Savings

This basic "steady-state" model for estimating incapacitation effects was developed by Avi-Itzhak and Shinnar and Shinnar and Shinnar (Avi-Itzhak and R. Shinnar 1973; S. Shinnar, Maciewicz, and Shofer 1975). It assumes a finite population of offenders who, if free in the community, would commit crimes at a given rate for a given time (i.e., the duration of their criminal careers). The amount of crime prevented by incapacitation depends on two behavioral components - the rate at which offenders commit crime when free and the duration of the criminal career. It will also depend on the criminal justice system responses

[10]The developmental and life course theories speak to the development of offenders, but do not provide an account of the occurrence of offenses, or situational and environmental factors such as opportunities and victims. Studies have looked at the social factors that impact criminal activity, such as marriage, but these factors have been examined for the individual in isolation rather than in connection with cultural and social trends broadly.

to criminal behavior: the likelihood of apprehension, conviction, prison sentence, and the length of the prison term.

Much of the scholarship attempting to estimate incapacitation effects has been grounded in the criminal career approach with estimates derived from measures of individual offending rates (referred to in the literature as λ) and assumptions regarding the expected length and trajectory of a criminal career. Much of this research was conducted in the late 1970s and 1980s with estimates of offending rates derived from retrospective inmate surveys or records of inmates prior arrests (e.g., (Blumstein and Cohen 1979)). The average offending rate for the prison population surveyed then annualized and translated into the number of crimes prevented per-prison year.

These early estimates of the crime savings generated by incapacitation have ranged widely. Zedlewski in a report on the cost benefits of expanding prisons reported an average of 187 non-drug crimes prevented per prisoner-year (Zedlewski and Justice (USA) 1987).[11] Greenberg (1975), using arrest data, estimated as few as three index crimes (murder and non-negligent manslaughter, forcible rape, robbery, aggravated assault, burglary, larceny (theft), and motor vehicle theft) prevented per prisoner-year (Greenberg 1975), while Cohen (pp. 20-21) suggested an upper limit of 12 index crimes averted (Cohen 1983). Marvell and Moody's review of the arrest-rate and self-report lambda estimate research present an uncertain estimate of the effects of incapacitation ranging from 16 to 25 index crimes per prisoner per year (Marvell and Moody 1996). Ultimately, however, they advocate for a panel regression approach to provide a better estimate of the total impact of imprisonment (incapacitation and deterrence) on crime.

The wide range of estimates reflect the range of data collection instruments, jurisdiction of study, crimes counted, and methods of translating lambda estimates to crime savings. This enormous variation in the estimates reveals both practical and conceptual problems with estimates of "lambda" and its translation into crime savings estimates. These concerns are detailed below.

Problems with Incapacitation Estimates

The first problem with estimates of individual crime rates is that of measurement and reporting. Both self-reporting and official arrest records will likely generate under-counts of actual offending rates. On the other hand, extrapolating annual rates from the window period in which the data was collected will likely overestimate annual offending rates because the period just before an offender is caught is likely one in which they were engaging more heavily in criminal activity (F. Zimring and Hawkins 1995). The point is made clear when

[11] Zedlewski uses the estimates from the Rand Corporation National Institute sponsored survey of 2,190 inmates confined in jails and prisons in California, Michigan, and Texas that found inmates averaged between 187 and 287 crimes per year exclusive of drug deals. But they suggest an upper limit of 12 index crimes per year (1983, pp. 2021)

taken to the extreme: if the "window" is simply be the day the offender was caught, this would translate to an estimate of at least 365 crimes per year.

More fundamentally, even if prior offending records could be accurately constructed, it does not follow that these individual offending rates can be used to calculate imprisonment crime savings (F. E. Zimring, Hawkins, and Ibser 1995; Marvell and Moody 1996). To begin, assumptions about the crime reducing effects of incapacitation are undermined insofar as there is offender replacement or group criminality (Cook 1986; Ehrlich 1981; F. E. Zimring, Hawkins, and Ibser 1995). Putting a drug dealer or gang leader in prison, for example, may simply open up a position for someone else. To the extent that offenses are committed in groups, the assumptions regarding crime savings from incarcerating one individual will inevitably overestimate the amount of crime prevented unless all those who would engage in the group activity are incarcerated.

Further, using the average offending rate from the surveys is deeply problematic given the highly skewed distribution of offending, well-recognized in the criminal career literature, but nonetheless neglected in its application to incapacitation generated crime savings estimates. If a small percentage commit many crimes annually, estimated incapacitation effects derived from the average offending rate will be highly skewed; the average much higher than the median. Moreover, neither the average nor the median offending rate of incarcerated inmates is the right metric to use when considering a change in incarceration policies. Instead, what matters is the crime commission rate of offenders on the margin of being admitted or released from prison, depending on the imprisonment policy in question. The crime savings derived from an expansion in prison admissions, for example, will depend on the offending rates of the marginal convicted criminals – those who would now be incarcerated under the more expansive regime; and the expected effect from a policy involving the release of inmates depends on the offending rates of the marginal releasees (E. Owens 2009; Ludwig and Miles 2007). The policy changes in the 1980s and 1990s that generated the massive growth in prison populations involved both a broadening of the pool of offenders admitted to prison (i.e. offenders admitted for less serious crimes), as well as increases in the length of sentences, which meant increasingly older inmates. Both factors resulted in a substantially lower risk marginal, and in fact lower risk average and median, imprisoned offender.[12]

Recent Estimates of the Effect of Incapacitation through Incarceration

Recent empirical research on incapacitation, exploiting the randomization in changes in prison sentencing and release policies to derive estimates, are more reliable and have found much smaller incapacitation effects than the earlier survey estimates suggested. Owens, for example, analyzed the criminal activity among convicted felons who ended up serving shorter sentences as a result of a 2001 change in sentencing guidelines in Maryland and found the

[12] The tendency of criminal offending to decline precipitously with age means individuals will age-out of their peak offending years while in prison.

implied incapacitation effect for this population was only 1.4-1.6 index crimes per person per year (E. Owens 2009).[13] Similarly, Raphael and Johnson and Raphael and Stoll, using an instrumental variables approach, estimate the net effectiveness of incarceration on crime, plainly demonstrating the declining effects of incarceration on crime rates as incarceration rates rose (R. Johnson and Raphael 2012; Raphael and Stoll 2013).[14] Raphael and Stoll estimate that between 1977 and 1988 the average effect of a one-person increase in incarceration was between 1.3 and 2.1 violent crimes and between 9 and 19 property index crimes. Between 1989 and 1999 and 2000 and 2010 they found no statistically significant effect of incarceration on either violent or property crime (Raphael and Stoll 2013). In short, the increased rates of incarceration during these latter time periods had little or no measurable effect on the rates of serious crimes. Both of these studies estimate average net incarceration effects generally rather than isolating incapacitation specifically, and so the estimates will include the effect of deterrence as well as incapacitation. But the finding of diminishing returns supports the claim that, insofar as incarceration affects crime, the primary channel is through incapacitation. Consistent with an incapacitation interpretation, as the scale of imprisonment increases, the risk profile of the marginal offender decreases. That is, lower-rate offenders are brought into the system and older offenders remain in the system both groups that will on average commit fewer crimes were they in the community. There is, on the other hand, no easy account for why there would be a declining general deterrent effect.

In summary, while it is undisputed that incapacitation through incarceration reduces crime by some amount, it is relatively small and often difficult to quantify. And recent studies have produced academic agreement on a general point: there are diminishing marginal returns – the effectiveness of prison in reducing crime rates diminishes as the incarceration rates increase (e.g. (Levitt 1998; F. Zimring and Hawkins 1995; R. C. Johnson and Raphael 2009). Again, these findings are consistent with the consensus that the incarceration-crime effect operates chiefly through incapacitation rather than deterrence. With no more crime today than there was in 1970, but five times as many individuals in prison, the marginal and average prisoner will be lower risk, making the marginal crime affects small or non-existent. Finally, in addition to the diminishing marginal returns of incarceration effects on crime, many scholars have also pointed to the need to consider the broader set of negative effects of incarceration with respect to crime. For example, Sampson argues mass incarceration has reduced the ratio of males to females leading to family disruption and higher rates of violence (Sampson 2011). Western et. al. has shown imprisonment has negative effects on employment, which may also lead to more crime (Geller, Garfinkel, Western, et al. 2006).

[13]Estimates derived from changes in sentencing policy or selective prisoner releases, such as Realignment in California, measure the incapacitation effect of incarcerating or releasing the offender on the margin which may be the most relevant estimate for policy purposes, but is not the same as the average or medians derived in the inmate and arrest record survey work and therefore will be smaller for that reason alone.

[14]The authors use exit and entrance probabilities to identify the variations in incarceration that are not due to contemporaneous criminal offending.

1.2 New York City Evidence Against The Dominant Role of Incapacitation in Crime Reduction

The paper now turns to the New York City crime decline a case study demonstrating the variations possible in crime volume that cannot be understood as a function of changes in criminal supply so to speak. "Where have all the New York criminals gone?" Zimring asks in his account of the city's crime decline. "No where," is the answer. There was little out-migration and incarceration rates declined for much of the period of the crime drop. Zimring argues the crime decline must then have included substantial reductions in crimes committed by the "career criminals" incapacitation theory would have assumed must be locked up. The following sections detail the New York City evidence suggesting the malleability of criminal careers.

1.2.1 New York City Crime & Incarceration Trends

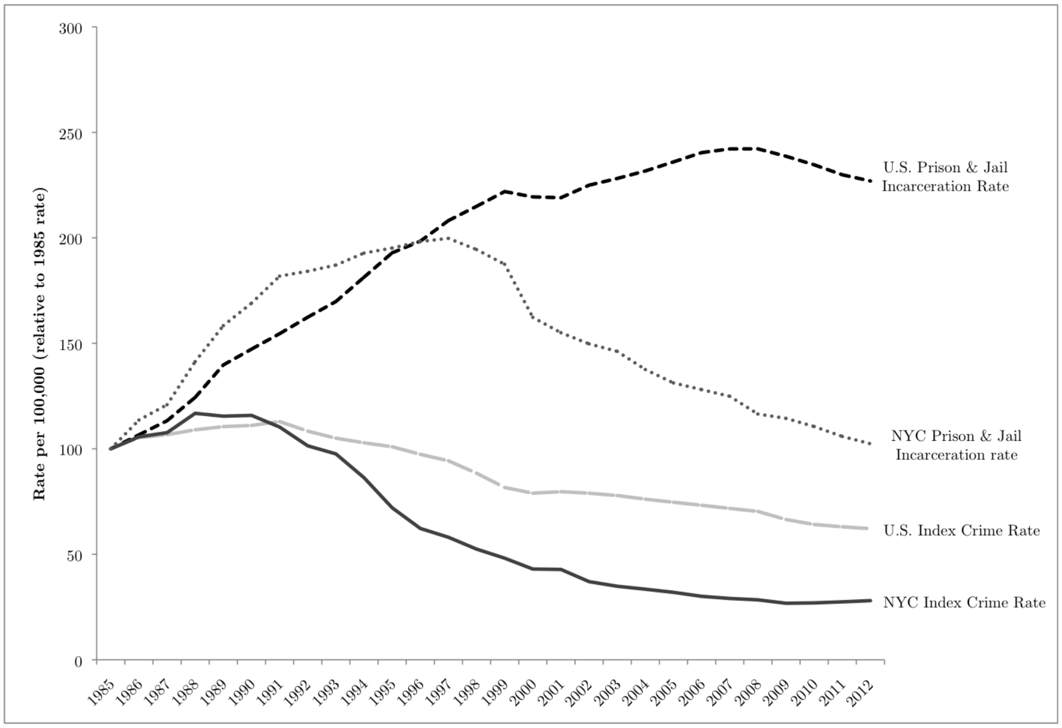
The most general evidence offered in *The City that Became Safe* against the reign of incapacitation through incarceration policy are the city's trends in crime and incarceration rates. Whatever combination of police policy, local social and economic forces, and national and global trends, contributed to the city's decline in crime, incarceration is not a part of the story. Counter to the national trend of relentless incarceration growth, for almost two-thirds of the past twenty-five years of declining crime in New York City, the population in prison and jails (as well as on probation and parole) has fallen.[15] Figure 1.3 presents New York City and U.S. prison and jail confinement rates alongside trends in the rate of crime. To isolate the comparative decline and growth in rates, each rate is translated to a 1985 base of 100 and subsequent years are expressed relative to the 1985 value. The figure shows New York City's incarceration rate dropping substantially after 1997, while the rate of prison and jail confinement in U.S as a whole grows until 2009.[16]

Empirical scholarship on New York City's crime drop has paid relatively little attention to the contribution of incarceration, likely because, unlike the changes in policing since the early 1990s, imprisonment trends in the city have not lined up with trends in crime. Measures of imprisonment have been included in a handful of studies. Corman and Mocan (2005) analyze the effect of sanctions and economic factors on crime in New York City using monthly time-series data from 1974-1999 (Corman and Mocan 2005). They find increases in the number of inmates from the city in state correctional facilities are associated with decreases in homicide, robbery, burglary, rape and Motor Vehicle Theft. But the magnitudes of their estimated

[15] Between 1990 and 2013, the citys rate of incarceration in prison and jail has fallen 43%.

[16] President Obama in his 2015 state of the union address made note of many states recent reductions in incarceration coinciding with crime continuing to fall: "Surely we can agree that it's a good thing that for the first time in 40 years, crime and incarceration have come down together, and use that as a starting point for Democrats and Republicans, community leaders and law enforcement, to reform Americas criminal justice system so that it protects and serves all of us."

Figure 1.3: Prison, Jail & Crime Trends NYC vs. U.S.: Relative Change Since 1985



elasticities are quite low, ranging from .02 to .08. Moreover, the negative correlation they find might well disappear were the analysis extended to the present, a fifteen-year period in which the citys prison admissions and incarceration rates consistently declined alongside declining crime.

Several other studies have examined trends at the precinct level and found that neither prison admissions nor the ratio of imprisonment to felony arrests are significantly related to rates of homicide or robbery ((Cerdá et al. 2009; Rosenfeld and Messner 2009)). Cerda et al. in fact find incarceration rates are associated with increases in gun-related homicides among certain age groups. This finding is consistent with an emerging body of work that points to the deleterious community effects of imprisonment; U.S. incarceration policy is not only racially and socially inequitable, but counter-productive in its crime prevention aim (e.g. (Clear 2007; Fagan, West, and Holland 2003)).

Zimring does not offer regression estimates of incarceration effects, or lack therefore. Instead, the argument is a broader and intuitive one: the New York City experience makes stark that expanding prisons and jails is by no means a necessary condition for lowering crime. What for over a generation had been taken to be an important if not the determinative influence on crime appears almost inoperative in New York. As such, the New York City crime drop experience undercuts the ascendancy of imprisonment as the go-to response to street crime, and much of the theory of crime prevention upon which imprisonment policy gained its dominance. Specifically, as detailed in section 1.1, the incapacitation research program of the 1970s and 1980s, which helped motivate sentencing policy changes leading to the massive expansion in imprisonment, promoted a simplistic model of crime that assumed individuals had predetermined criminal careers, insensitive to the environmental context. Such a framework yields misleading predictions. The changes in the volume of major violent and property crime in New York City between 1990 and 2015, presented in table 1.1 reveals the fallacy of any easy translation between the number of people incarcerated and the number of crimes on the street. Focusing on the opportunity reduction role of the police is a version of

Table 1.1: Part I Crime Volume: 1990 vs. 2015

Crime	**1990**	**2015**	**% Change**
Homicide	2,262	352	-84%
Rape	3,126	1,438	-54%
Robbery	44,122	20,271	-54%
Burglary	100,280	16,931	-83%
Auto Theft	146,925	7,332	-95%
Larceny	108,487	44,007	-54%

a routine activities theory account - a theory which holds that a criminal event will take place when a motivated offender finds a suitable target, absent a guardian to prevent the crime from happening (e.g. (Clarke and Felson 1993)). The police function as formal guardians and, by reducing the number of suitable targets, change the environmental context in which crimes can occur and thereby reduce crime.

The trends in incarceration and crime rates in New York City make penal confinement look so unimportant that it appears nearly irrelevant.[17] At the same time, our ability to make conclusive causal claims with respect to the effects of incarceration (or incapacitation specifically) is limited. None of the studies testing New York City incarceration impacts em-

[17]The loose relationship between trends in crime and trends in incarceration is present at the national, state, and local level. In the United States, from the 1920s through the mid 1970s, the number of people incarcerated in American state and federal prisons hovered around 110 per 100,000 in the population (with a high of 131.5 and low of 95.5 in 1972 (F. E. Zimring 2010). Since 1972, state and federal imprisonment rates grew every year; by 2007 it had increased more than fivefold, reaching 503 per 100,000 in 2007. Likewise, the nations jail population expanded considerably, albeit at a slightly slower rate, from 80 per 100,000 in 1980, the first year data are available, to 247 per 100,000 in 2009. Meanwhile, over these decades of unabated prison and jail expansion, serious crime cycled up and down several times. Today, despite the dramatic increase in the rates of incarceration, the national crime rate in the U.S. is roughly what it was in 1970. Cross-sectional state comparisons similarly bare no consistent association between incarceration and crime levels. The rate of imprisonment in Texas, for example, increased by 144% during the 1990s while crime dropped by 35%; in New York State, on the other hand, the incarceration rate increased by only 24% during the decade while crime across the state fell by 43% (King, 2005). Since 2000, the New York State incarceration rate has fallen by 20%, and crime has fallen another 25%.

ploy experimental designs or natural experiments to account for the problem of endogeneity between crime and incarceration rates. That is, the problem that crime and incarceration are, in part, simultaneously determined and the effects pull in opposite directions: more incarceration should, in theory, reduce crime; but changes in crime that are unrelated to incarceration policy will push incarceration in the same direction ((Nagin 2012). This endogeneity problem is now widely recognized as a fundamental identification problem likely to bias estimates of the prison-crime effects toward zero. A failure to account for the simultaneous relationship was an inherent flaw in early panel regression studies of the crime-incarceration relationship and is similarly present in the studies estimating incarceration effects on crime in New York.

More generally, seeking any causal explanation (such as incarceration) for the New York City crime difference, or the 1990s nationwide crime drop more broadly, is a form of "backward looking causality" - the study of the causes of an effect rather than the effect of a cause - and this limits strong causal conclusions (Holland 1989). The causal turn and rise of the counterfactual paradigm in the social sciences, including in criminology, has moved research towards a focus on identifying the specific effect of an identified cause (e.g. the effect of police on crime) as compared to seeking causes (e.g. the causes of falling crime) (Sampson, Winship, and Knight 2013). With this causal turn, correlational evidence is more readily dismissed.

At the same time, causal stringency may lead us to miss the forest for the trees. A simple time-series association, or lack thereof, between crime and incarceration does not offer an estimate of a well-identified effect. But the lack of correlation between incarceration and crime highlights the relatively weak place that incarceration (at least at the level seen in the U.S. in the last decades) has in explaining changes in crime. All else equal, more imprisonment may have some crime-suppressing effect, and higher (or lower) crime should result in higher (or lower) imprisonment. But the impact in either direction is quite small. Whatever the precise magnitude of incarceration effects, expanding prisons and jails does not provide a plausible account for New York City's steeper and longer crime drop relative to other American cities.

A final point on the interpretation of the New York City incarceration and crime trends: even if there is agreement that incarceration played little role in the crime decline, Zimring's account and the recent quasi-experimental research on the diminishing returns of incarceration offer potentially different, albeit not incompatible, interpretations. As discussed in section 1.1.4, recent empirical work has presented evidence for the diminishing returns of incarceration and the near non-existent crime reducing effects present at current incarceration rates in the U.S.[18] This is consistent with a story that New York was imprisoning far too many individuals - relatively low risk offenders - for incarceration to generate meaningful incapacitation effects on crime. Zimring interprets the data as demonstrating the flaws in the

[18] This work suggests diminishing returns set in with levels of incarceration at less than 200 per 100,000 (Raphael 2014).

simplistic and mechanical model of incapacitation, showing offenders are in fact malleable and subject to contingencies and their environmental context. The diminishing returns interpretation does not necessarily demand a revision of the notion of fixed proclivities for high risk career criminals; it could be argued the career criminals simply make up a very small proportion of offenders in prisons.[19] On the other hand, accurately identifying the few "bad apples" has turned out to be at best deeply imprecise. And this imprecision comes from the high variance found in criminal behavior and crime rates across place and time, variance that can't be explained by individual or structural "fundamentals." This variance, at the very least, demonstrates the flaws in the simplistic model of incapacitation that viewed incarceration as taking "a slice out of criminal career."

1.2.2 Declining Return to Prison & Probationer Rearrest Trends

In addition to New York's general trends in crime and incarceration Zimring offers additional evidence that speaks more directly to individual behavior trajectories: declines in re-offending between two high-risk groups - former prisoners and probationers. These time series offer some more direct evidence of the malleability of so-called criminal careers. 28% of New York City offenders released from prison in 1990 were returned to prison within three years for a new felony offense; only 8% of those released from prison in 2012 were returned within three years for a new felony.[20] Data on probationer rearrests is only available dating back to 1995, but the same pattern of decline is present: between 1998 and 2011 the rate of re-arrest within three years for any felony fell from 42% to 31% and from 18% to 12% for violent re-arrests. These smaller drops over the shorter time frame are consistent with the larger decline over the longer time period in the rate of prison return.

These trends, Zimring argues, illustrate the significant effect the general crime environment can have on criminal behavior and the criminal trajectories of already experienced offenders. Offenders returning from prison to a city in which their friends are doing less crime will be less likely themselves to engage in crime. The New York City crime decline was not just a matter of a new generation of youth committing crimes at lower rates, but also included the participation of already active and serious offenders. If this is the case, criminal behavior, even among high-risk groups, is much more situational and contingent than the theories underlying incapacitation have assumed.

While the data are suggestive, there are assumptions required to interpret them as evidence against the notion of fixed criminal proclivities. It must be assumed the decline in the prison return rate is not an artifact of prosecutorial and court practices but rather represents changes in criminal behavior; and we must assume the risk profile of the offenders did not change in significant ways. If it did, this would be evidence of the practical problems of

[19]This would be an account consistent with the theory of selective incapacitation.

[20]Zimring's data is from 1990-2005; 10% of the 2005 release cohort were returned for a new felony within three years.

estimating incapacitation effects, but not evidence against the foundational assumption of within-person counter-factual estimates of incapacitation generated crime savings. A more detailed analysis of the New York City prison return data is offered in a second paper.

The probationer rearrest data offers an advantage over the prison return data in that it is a less mediated measure of criminal behavior. There is not the same concern about changes in prosecutorial charging or court sentencing. But there are alternative account for changing rearrest patterns that are not a story of behavior change: it is possible at least that the profile of probationers changed or the nature of supervision changed over the period of study.

Whatever the data deficiencies, the circumstantial evidence from New York City presented by Zimring is at the very least suggestive of the malleability of criminal careers. The paper now turns to alternative models of criminal behavior that recognize this malleability.

1.3 Alternative Models of Criminal Behavior

Early incapacitation studies assumed a simplistic framework that took offenders to have largely predetermined criminal careers only to be interrupted with incarceration. As the paper has discussed, these assumptions have been shown to be deeply flawed. If this model of criminal behavior is now defunct, what has replaced it? The following sections discuss alternative models of behavior that recognize potential criminals as sensitive to their economic, social and policy environments. Specifically, the paper reviews the rational choice theory of deterrence and social influence and social contagion models of crime.[21]

1.3.1 Deterrence & The Economic Model of Crime

The economic literature on crime has long recognized a model of offending behavior that assumes offenders are sensitive to costs and benefits. Economist studying crime and incarceration have long given more attention to deterrence, rooted in a rational-choice expected utility model of decision-making, then to incapacitation, the focus in criminology (F. E. Zimring 2007). And a deterrence model is also what underpins the study of the police effect on crime. The principle assumptions at the heart of deterrence theory are that individuals

[21]The paper does not discuss Routine Activities Theory, a theory in criminology focused on how criminal events are produced rather than explaining the motivation to commit crime. But both deterrence and social influence effects on criminal behavior are compatible with Routine Activities theory, which describes a criminal event as the product of the interaction between an individual with criminal tendencies and environmental opportunities an available target and the absence of a guardian to prevent the crime from happening (Clarke and Felson 1993). Felson (1998, ch. 9) has offered a routine activities explanation for the national drop in crime in 1990s, at least the drop in property crime: electronic equipment became more widespread and easy to take; prices and the value of stealing equipment dropped commensurately. Likewise, the explosive growth in ATM and credit card use reduced the value of robbery targets.

respond to changes in the certainty, severity, and that celerity (immediacy) of punishment, and the decision to engage in crime involves a calculation of net utility gains and losses. These foundational principles were first articulated by the Enlightenment legal philosophers Beccaria (1764) and Bentham (1789) who both advocated for a rationalization of the criminal law with an aim to prevent rather than punish crime. Beccaria argued the problem with the laws of the *ancien regime* was not just that they were cruel but also that they were applied so disparately and irrationally they were ineffective in reducing crime (Beccaria 2009). Instead, punishment should be certain, severe enough to sufficiently offset the anticipated gains of crime (proportionate), and swift. Bentham further and more explicitly articulated a model of criminal behavior decision-making in which a potential offender weighed the potential pains of punishment against the pleasures of the offense.

The modern writings on criminal deterrence and the empirical attempts to verify and quantify its magnitude are rooted in Gary Becker's seminal article "Crime and Punishment: An Economic Approach" ((Becker 1968)). Becker plainly described his efforts as a resurrection and modernization of the pioneering studies of Beccaria and Bentham, which at the time of his writing had fallen out of favor (p. 45). From the mid nineteenth century through much of the twentieth, the study of crime had been concerned primarily with establishing the root causes of law breaking, be it through an individual-centered psychological or biological model of criminal behavior. These conceptions viewed criminal behavior as the result of a pathological mind, or, on the other hand, a sociological model of crime focused on ecological and social conditions (e.g. (Shaw and McKay 1942)). And indeed, the individual focused cohort studies in criminology followed this model with a focus on individual traits. Becker argued that crime should instead be seen as an activity like any other economic activity: the product of rational self-interest. "Some persons become 'criminals,' not because their basic motivation differs from that of other persons, but because their benefits and costs differ" (p. 9). The economic theory of crime, takes a distribution of individual preferences, or "characters," as a given and then asks how incentives influence crime-related choices.

Becker offered a simple expected utility model of criminal decision-making. An individual is assumed to be a rational actor who will engage in criminal activity when the benefits of committing a crime, discounted by the expected cost of punishment, is greater than the utility associated with the risk-free choice of abstaining from crime. The expected cost calculus is comprised of two components: the probability of sanctioning, p, and the magnitude or severity of the punishment imposed on those caught. In short, an individual will engage in crime when the utility associated with committing a crime and getting away with it, U(Reward), and the (dis)utility associated with committing a crime and getting apprehended and punished, U(Punishment) is greater than the utility of not committing crime U(Legal Activity).

$$(1-p) * U(Reward) + p * U(Punishment) > U(LegalActivity)$$

According to the model, whether potential criminals will be more deterred by increases in the probability of sanction or by the severity of the sanctions will depend on whether individuals are risk preferring or risk adverse. An increase in the probability of punishment will be more effective only if individuals are risk preferring; if individuals are risk averse, increasing the severity of punishment will be a more effective deterrent.[22] The optimal enforcement policy will thus depend on potential offenders responsiveness to changes in enforcement or sanctioning (and the cost to the state of apprehending, convicting and punishing offenders). Becker advocated the use fines whenever feasible (p. 28) because doing so will allow the state to achieve the same expected punishment with lower apprehension probabilities, which are costly, and high sanction severity, which, in the form of monetary fines, are costless. In practice, of course, sanctions in the United States have not been monetary fines but have been very costly sentences to prison.

There are a number of intervening steps required for deterrence to operate as the Beckarian expected utility model predicts and scholars have pointed to failures at each stage. First, potential offenders must accurately perceive the objective probabilities that they will be apprehended and sanctioned. An extensive literature has emerged in an attempt to measure the correspondence between risk perceptions and actual sanction realities. By and large, this perceptual deterrence research has found potential offenders do not accurately perceive, and often substantially underestimate, the risks of apprehension and the severity of the punishments.

Second, even if a potential offender had perfect information, for deterrence to operate, the perceived threats must induce a behavioral response. Evidence suggests that in practice, the underlying behavioral parameters of those generally inclined towards criminal behavior are such that large increases in sanctioning will not imply meaningful behavior change. To some extent, behavioral modifications can and have been integrated into the rational actor expected utility framework (e.g. (Polinsky and Shavell 1999; Nagin and Pogarsky 2001; Nagin and Pogarsky 2004)). For example, if offenders are extremely present-oriented, that is they tend to be focused on factors in the immediate present but ignore those related to future contexts, distant and severe penal punishments will have minimal impact. A very high discount rate (or low discount factor) can capture a potential offenders failure to take future punishment into full account ((Nagin and Pogarsky 2001; Nagin and Pogarsky 2004)). However, present-orientation may not reflect an individual devaluing of the future, but rather may be the result of poor impulse control - a failure to consider or fully recognize the consequences of ones actions (Nagin and Pogarsky 2004).

A lack of self-control is one among many of the deviations from pure utility- maximizing rationality that scholars have pointed to in challenging the descriptive and predictive validity of the expected utility model of criminal decision-making. A growing body of research in cognitive psychology and behavioral economics, traced to work of Kahneman and Tversky,

[22] Although Brown and Reynolds (1973) note that this result in Beckers model requires the assumption that the baseline utility is that of getting away with crime.

has documented a variety of ways in which individuals predictably and systematically deviate from the rational actor model, with a number of findings particularly relevant to criminal decision-making (Kahneman and Tversky 1973; Kahneman and Tversky 1979). For example, experiments have demonstrated that, contrary to expected utility theory, individuals tend to consider outcomes relative to a reference point, and exhibit inconsistent preferences when assessing possible gains and losses. This is, individuals tend to exhibit loss aversion: losses feel worse than gains feel good. Further, very small probabilities are often either greatly overweighted or neglected altogether.[23] The importance of the availability heuristic ((Kahneman and Tversky 1982; Akerlof 1991; Slovic et al. 2004), the tendency of people to judge the likelihood of uncertain events depending on how salient they are rather than on factors related to the actual probability of an event, will also affect criminal decision-making. The perceptual deterrence literature has experimentally documented the disjunction between the actual risk of sanctions and the perceived risks of incurring a sanction.

Deterrence: Empirical Estimates

The evidence in support of the deterrent effect of the certainty of punishment, specifically, the certainty of apprehension, is far more consistent than evidence for the severity of punishment. Recent reviews of the literature on the threat of incarceration as a deterrent have concluded that the effect is modest at best (e.g. (Donohue III 2009; Nagin 2012; Durlauf and Nagin 2011; Raphael 2014).[24] There has been growing consensus in academic and policy communities that the nation's crime control dollars should be shifted from prisons towards spending on law enforcement and other forms of crime prevention.

A variety of strategies have been used to try to estimate the deterrent effect of the threat of imprisonment, independent of incapacitation. One approach has been to study the effects of sentence enhancements, which extend prison terms for certain offenders or certain offenses. Because sentence enhancements generally do not increase the size of the incarcerated population (in the short term), any declines in crime shown to result from the enhancement may be attributed to deterrence rather than incapacitation. Findings from a handful of particularly credible studies along this vein have reached varied conclusions, often depending on whether the researchers analysis considers the overall effects or is isolated among the specific targeted populations. On the other hand, Helland and Tabarroks analysis of the three strikes law in California did find some deterrent effects among the sub- population of targeted two-strikers (Hellend and Tabarrok 2007). The authors compared the criminal behavior of individuals convicted of a second strikeable offense to those who were tried for a second strikeable offense but ultimately convicted of a lesser offense, and found individuals

[23] MacCoun and Caulkins, for example, apply these findings to a discussion of a drug dealers initial decision to engage in the behavior, and subsequent decisions to continue once their reference point has changed so that not dealing becomes framed as a loss and thus probabilities are assessed differently (R. J. MacCoun 2005).

[24] As Beccaria argued 250 years ago, swift and certain punishment provides a more effective and less costly way to achieve law obedience than does severity.

with two strikes on their record had approximately 20 percent fewer felony arrests than was the case for a comparable group with only one strike. Despite these findings, the authors still conclude three-strikes can not be justified on cost-benefit grounds given the costs of incarcerating third strikers and the amount of crime prevented the three strikes policy likely prevents. Zimring, Hawkins and Kamins earlier analysis of the California three-strikes law similarly found individual offenders with two strikes were less likely to be arrested, but found little evidence for an effect of the law on overall rates of crime (F. E. Zimring, Hawkins, and Kamin 2001).

Other scholars have tried to estimate the deterrent effects of incarceration as a sanction by exploiting the discontinuity in the severity of sentencing at the age of majority. For example, Lee and McCrary analyze Florida arrest data for individuals immediately before and after their eighteenth birthdays (Lee, McCrary, et al. 2009). For any given criminal conviction the expected sanction jumps by roughly 230%. Despite this large increase, they find the rate of offending decreases by only 2%. The authors hypothesize the minimal impact of the change in sanction may be because young offenders are uninformed or underestimate the consequences of being tried as an adult, or they may have extremely myopic or present-oriented time preferences.

While evidence for sanction deterrence suggests the effect is minimal, there is much stronger empirical support for apprehension deterrence. Much of this is documented in the study of the effect of the police on crime. The most recent and statistically sophisticated estimates of a policing effect, using quasi-experimental designs to account for the problems of simultaneity and measurement error bias, have found increased levels of police have a significant negative effect on rates of crime. McCrary and Chaflin for example, examine changes in police staffing and crime in large U.S. cities between 1960-2010, and find an elasticity of -.67 for murder, -0.56 for robbery, and -.23 for burglary. A 10% increase in police will, on average, reduce crime by between roughly 2% and 7%, depending on the crime type (Chalfin and McCrary 2013).

These elasticities provide an estimate of the average effect of the police on crime measured as a function of resources or manpower, but much of the literature on the police suggests what matters most is not the number of police, but the particular form policing takes (e.g. (Telep and Weisburd 2012; Weisburd and Eck 2004).[25] Recent innovations of the last two decades are thought to have been particularly effective. The computerized collection and analysis of crime statistics has allowed police departments to track, analyze, and pro-actively and preemptively respond to crime by saturating high crime areas. Information systems have

[25] When the McCrary and Chaflin restrict their analysis to the 1990s the estimates effects of police on crime are larger, supporting the hypothesis of the efficacy of recent police innovations. Evidence from New York City indicates the key variable may not be police number but rather what matters are the policing strategies. NYCs police force declined in number, most significantly between 1999 and 2003, yet crime continued to drop.

also provided a boon for police department management by increasing officer accountability. Place-based strategies - the concentration on crime hot spots and the destruction of street-level drug markets - were employed in New York City and are thought to have played an important role in the decline (F. E. Zimring 2011). Findings from randomized experiments in several smaller cities support the idea that hot spots deployments produce significant reductions in crime (Braga 2005).[26]

The finding that these targeted interventions do not merely displace crime to other parts of a city but actually reduce rates of crime underscores the importance of criminal opportunities in determining not only how crime is distributed, but also its volume.[27] Individuals do not move to a non-patrolled street corner, but instead seem to engage in different non-criminal activities altogether.[28] The absence of displacement suggests a situational and opportunistic model of criminal behavior that is somewhat distinct from the classic rational actor interpretation at the heart of deterrence theory. This is discussed in the following section, which describes the conceptual distinction between police deterring crime and police serving to reduce criminal opportunities.

Distinguishing Deterrence from Opportunity Reduction

The literature on the responsiveness of crime to changes in police manpower has noted incapacitation as a second mechanism, besides deterrence, by which police might reduce crime (e.g. (Levitt 1998; E. G. Owens 2013)), but police-oriented deterrence theory has missed an important and conceptually distinct third mechanism: the sheer presence of the police on the street removes entirely criminal opportunities for those in the immediate vicinity of the police.[29] If there is a police officer standing within eyesight of an individual, there

[26]The recent emergence of hot spots policing has been traced to the advance of computerized mapping and database technologies, as well as an emerging focus in criminological theory and research on the distribution of crime in the context of place (Weisburd and Braga 2006). Studies have consistently confirmed that crime is highly concentrated in certain micro places. In fact, the skewed distribution in place is greater than the well-known disproportion found among chronic offenders. It is estimated that 10% of the victims of crime in the U.S. are involved in 40% of the cases of victimization; 10% of offenders are involved in over half of the reported crimes; and 10% of the locations in which crimes occur account for close to 60% of crimes (Spelman and Eck 1989). Given these concentrations, researchers and practitioners have recognized the possibility of efficiently and effectively reducing total crime by focusing limited police resources on these high-activity crime persons and places.

[27]If there were complete crime displacement, this would suggest opportunity plays no part in crime determination.

[28]Until the relatively recent implementation and evaluation of place-based policing efforts, it was assumed that targeted crime reduction interventions could not produce overall crime prevention benefits because crime would just move to another place or time (Reppetto 1976)

[29]The police effect through incapacitation is the effect of offenders being apprehended by the police and eventually incarcerated; the deployment of more police on the street may affect crime rates by mechanically removing active offenders from the community. The econometric literature on the responsiveness of crime to changes in police resources has grappled with the problem of teasing apart deterrence from incapacitation as well as with the statistical identification problem of finding random variation that would allow for causal

is no decision-making or expected utility calculation on the part of the potential offender. The price of the act, the crux of deterrence theory, is irrelevant because there is no potential benefit to be had. In this case,the police have not changed the demand for crime by raising the price, but have altered the supply of criminal opportunities.[30]

Distinguishing between police deterrence and a more mechanical opportunity reduction police function may not be possible with observational data, nonetheless, the discrete mechanisms set out different frameworks for understanding criminal behavior and police effects. The later represents a version of a routine activities theory account - the police function as formal guardians and, by reducing the number of suitable targets, change the environmental context in which crimes can occur. Again, the finding from recent studies that there is relatively little temporal and spatial crime displacement, suggests some amount of crime is opportunistic - if prevented today, or stymied on this corner, it does not inevitably occur tomorrow or somewhere else.

There are a host of theoretical and empirical gaps in our understanding of how police reduce crime, and scholars continue to debate the size and nature of the police effect –the relative importance of police volume versus police strategies, the relative value-added of any given strategy, the degree to which there might be a heterogeneous police effects. But there is nonetheless increasing consensus, and mounting empirical evidence, that policing can make a difference.

Returning to the New York City case, by process of elimination, offers policing as a partial explanation for the city's crime decline difference - the 85% drop in major crime as compared to the close to 40% drop in most American cities ((F. E. Zimring 2011)). "The circumstantial evidence that some combination of policing variables accounts for much of the New York difference is overwhelming. There was simply nothing else" (p. 101) Zimrimg concludes. But the book goes on to argue that the police are only part of the New York City crime decline story. The fact that small changes in the environments of high-risk individuals could produce such big changes in the number of serious crimes they commit implies models of criminal behavior that take crime to be social, situational, and contingent. Zimring does not directly measure peer effects or social influence, but does suggests a social phenomena likely contributed to the decline and may help to explain the gap between the scale of demographic and policy changes in the city and the scale of the crime decline. "If all your friends are doing less crime and youre hanging out with them, so are you."[31] The paper now turns to the theory and estimation of social determinants of criminal behavior, in particular

interpretation of effects. These efforts present the same statistical challenges encountered by the attempts to estimate incarceration effects using state or city level panel data. Insofar as there is empirical evidence, the results suggest that unlike the findings from the literature on incarceration, deterrence rather than incapacitation is the principal mechanism by which police reduce crime (Nagin 2013).

[30] A potential exception to the absolute prevention of a crime when the police are present may be in the case of rioting or looting where the police greatly outnumbered.

[31] http://www.thecrimereport.org/news/inside-criminal-justice/2011-10-the-new-york-miracle

the literature on "social interactions" or "peer effects."

1.3.2 Social Interaction Models

The concept of an endogenous and self-generating social process that will produce a non-linear affect has been articulated in a scattered set of disciplines and literatures. Models of this nature include: tipping points, contagion effects ((Crane 1991; Loftin 1986; Wallace 1991)), epidemic theories ((Crane 1991; Fagan 2006)), threshold models ((Granovetter 1978; Wallace 1991)), diffusion models ((Burt 1987; Granovetter and Soong 1983)), and bandwagon effects ((Granovetter 1978). MacCoun (2012) showed that many of these models are just special cases of a more general soft logistic threshold model. These "threshold" models carry several important implications relevant to how we study and think about crime trends and criminal behavior. First, these models highlight the idea that individual predispositions to engage in criminal behavior will be affected by social context and the extent to which this behavior is already occurring. Second, the models point to the possibility of seeing rapid and non-linear changes in crime following a tipping point or threshold.

Fagan, Wilkinson and Davies explicitly examine the possibility of social contagion in New York City (Fagan, Wilkinson, and Davies 2007). Specifically, they test for and find some evidence that gun contagion can explain the non-linear increase and decline in homicides in the city between 1986-1996. More generally, versions of social contagion models have been used to understand the spread of violence within and across communities ((Cook and Laub 1998; Loftin 1986; Sah 1991; Hemenway et al. 1996)) and social interactions have been offered as an account for the high variance in rates of crime across time and space - the large differences in community crime rates that aren't explained by standard demographic variables (e.g. (Glaeser, Sacerdote, and Scheinkman 2003)) Notably, while the group nature of delinquency and the idea that peers influence criminal behavior has long been recognized in the sociological and criminological literature on crime (e.g., (**shaw1942**; Arbuthnot and Sutherland 1947; Sarnecki 2001; Warr 2002)), the sociological literature has not focused empirically on group criminality as a way to understand crime fluctuations and variability across place and over time.

Empirical Estimates of Social Interactions

The central difficulty in estimating social interaction effects is distinguishing between three possible group behavior phenomenon: correlation of individual characteristics (correlated effects), the influence of group characteristics on individuals (contextual effects), and the influence of group behavior on individual behavior (endogenous effects) (Manski 1993). Correlated effects (institutional models), focus on variation across neighborhoods in structural differences and the quality of local institutions such as schools, public transportation, and police ((Jencks and Mayer 1990; Levitt 1997; Levitt 2002; Sherman 2002; Lochner and Moretti 2004)). Here the attention is on exogenous structural features rather than on the characteristics or behavior of neighborhood residents. Contextual effects (collective socialization), points to the characteristics of neighborhood social factors and the attributes of fellow residents to explain variation across place. This logic underlies social disorganization, sub-culture and labeling theory. The concept animates William Julius Wilson's account of the effects of social isolation and the absence of role models in communities of the underclass, as well as the Sampson et al concept of collective efficacy, which refers to the shared values and levels of trust in a neighborhood that can produce greater levels of social control and correspondingly lower levels of crime (Sampson, Raudenbush, and Earls 1997). An endogenous model takes the prevalence of a behavior itself to affect an individuals propensity to engage in that behavior. Thus, while peer effects are often theorized to affect crime, the challenge of separating these three phenomenon has meant there's limited robust empirical evidence of peer effects.

The Moving to Opportunities randomized housing mobility experiment sponsored by the U.S. Department of Housing and Urban Development was motivated by the assumption that there are causal neighborhood and peer effects and the need for experimental evidence on the subject.[32] Over 4,500 families living in high-poverty public housing projects in five cities were randomized into a control group, a group receiving geographically-unrestricted Section 8 vouchers, and a full treatment group that received vouchers to move to subsidized private-market rental units in neighborhoods with lower levels of poverty (Comey, Popkin, and Franks 2012).[33] The effects of the move for the families were mixed depending on the sub-group and outcome: only short-term crime-reduction effects were found for boys but longer term decreases in delinquency only for girls ((Holzer et al. 2008; Sampson 2008). More generally, researchers found improvements in adult physical and mental health, but no improvement in educational employment outcomes.

MTO was an unusual opportunity in which to estimate the importance of neighborhood on short and long-term individual outcomes without the usual concern of spurious correlations.[34] But even with a randomized design, it is not possible to separate contextual from endogenous effects. That is, to the extent that there were neighborhood effects, whether these effects were driven by changes in incentives or by social interactions. Criminal behavior could be affected by changes in social expectations associated with the act, the perceived pay-off of engaging in crime, or a non-social phenomena in which the actual probability of

[32] Although Sampson, for example, has argued sorting should not simply be seen as an empirical nuisance that biases estimates, but rather is important in its own right as part of the phenomena of social reproduction (Sampson 2008).

[33] The demonstration project sought to test the hypothesis that families residing in less poor environments would see long-term improvements in their employment, income, education, health, and social well-being. The experiment was launched in the mid-1990s and included fifteen years of follow-up study.

[34] Some have suggested the effects were not larger because MTO represented a weak treatment the neighborhoods to which families relocated were only moderately wealthier than the neighborhoods from which they moved, the schools little better, and many families ended up moving back to their original pre-treatment neighborhoods over time ((Souza Briggs, Popkin, and Goering 2010; Sampson 2008)).

arrest varies by neighborhood context ((Ludwig, Duncan, Hirschfield, et al. 2001; Kling, Ludwig, and Katz 2005; Sah 1991; Glaeser, Sacerdote, and Scheinkman 2003)).

In addition to the experimental evidence generate by the MTO project, there is some quasi-experimental research that speaks to peer effects and criminal behavior. For example, MacCoun, Cook, Muschkin, and Vigdor exploit a rare natural experiment provided by the randomized grade configuration in North Carolina middle schools (Cook, R. MacCoun, et al. 2008). They find sixth graders exposed to older peers have higher rates of delinquent behavior. Jacob and Lefgren use the exogenous variation generated by teacher in-service days to estimate the short-term effect of school on juvenile crime (Jacob and Lefgren 2003). They find the level of property crime committed by juveniles decreases by 14% on days in which school is in session, suggesting school serves an incapacitation function, but find that levels of violent crime increase by 28% on such days, suggesting a concentration influence on juvenile crime. Unsupervised, juveniles are more likely to engage in property crime, but social interactions appear to play an important role in explaining violent crimes.

1.3.3 Program & Policy Alternatives to Incarceration

The models of criminal behavior described in the preceding section all share the assumption that criminal behavior is malleable and susceptible to modest changes in environmental and social circumstances. Again, this is in contrast to the early incapacitation framework that assumed some significant number of "life course persistent" offenders with fixed proclivities will engage in criminal behavior. A number of crime prevention strategies, including various forms of policing, follow from the insight that criminal activity is much like any other human behavior - social, subject to incentives, opportunities and contingencies. Below is a brief discussion of a few specific examples of strategies and programs that self-consciously incorporate a social and environmental understanding of criminal behavior.

Epidemiologist Gary Slutkin's CeaseFire Chicago model, for example, applies public health principles to treat and prevent gun violence, recognizing the importance of environmental and social factors on determining criminal and violent behavior. The CeaseFire model treats violence like a disease, and asks how it can be stopped by examining how, when, and by whom it is spread. The intervention specifies immediate causes of violence and potential change agents: norms regarding violence, "in the moment" triggers, and the perceived risks and costs of involvement among the targeted population (Skogan 2008). The principle of the CeaseFire program is to break the "cycle of violence" by identifying high-risk people and places, interrupting violence through mediation and de-escalation, and simultaneously attempting to change behaviors and norms. The theoretical assumptions behind this kind of model draw attention to the malleability of criminal behavior and the influence of circumstances, social interactions and norms. Empirical evaluations of Chicago CeaseFire and its various replications in Baltimore, MD, Newark, NJ, and Pittsburgh, PA have been mixed, indicating positive results in some of the programs targeted areas (Kirk and Papachristos 2011).

A second example of a crime control strategy that recognizes the group dimension and dynamics central to the perpetuation of violent crime is the focused deterrence framework, or pulling-levers policing (D. Kennedy n.d.; D. Kennedy 2008). The framework and strategy was developed in Boston in the 1990s to address serious gang violence (D. M. Kennedy, Piehl, and Braga 1996) and has since been applied in a number of U.S. cities through federally sponsored violence prevention programs such as the Strategic Alternatives to Community Safety Initiative and Project Safe Neighborhoods (Dalton 2002). David Kennedy, one of the architects of the approach, describes his major innovation as turning from the usual model of deterrence focused on individual threats, to instead focusing on increasing the legitimacy of law enforcement in the eyes of the group. The "focused deterrence" strategy relies on core deterrence ideas - increasing risks - but also attempts to enlist the communitys "moral voice." Members of gangs and drug crews are brought into meetings with fellow community members, social services representatives, and law enforcement who are there to offer support and make clear there will be rapid and enhanced enforcement of criminal behavior.

Finally, judge Alm's Hawaii Opportunity with Probation Enforcement (HOPE) intervention - a community supervision program aimed at substance-abusing probationers - offers another example of an intervention model that recognizes the dynamics of criminal behavior and law enforcement, the value of directly communicating punishment threats to potential violators, and the importance of swift and certain rather than severe sanctions. The HOPE program aims to efficiently and effectively allocate scarce resources by setting out clear conditions of probation, closely monitoring compliance, and meting out quick and predictable sanctions for rule violations- two days in jail for a first violation, for example, a week for a second.[35] The results of a randomized experiment found the HOPE program dramatically improved probationer behavior at lower cost.[36] 21% of HOPE probationers experienced new arrests as compared to 47% of probationers in the control group (Hawken and Kleiman 2009). HOPE probationers were also found to be less likely to miss probation appointments (9% of the treatment group compared to 23% of the control group) or have positive urine drug test results (13% in the treatment group, 46% in the control).

CeaseFire, focused deterrence strategies, and Project HOPE are just a few examples of a strategies and programs that rely on the recognition that much of the population at risk is

[35]Kleiman describes the problem of rule enforcement with a tipping model to help explain geographic and temporal crime concentration and the frequency of self-sustaining high (or low) violation states because high violation rates generate small risks of punishment and low violation rates generate large risks. Kleiman's enforcement model aims to move from a high violation low punishment risk equilibrium to a low violation and high punishment risk equilibrium.

[36]Some of the savings come from the principle of targeting resources – unlike the drug court model, not every probationer in HOPE is mandated formal drug treatment, nor does the program require frequent meetings with a judge. It is only when a probationer has violated the terms of probation that he or she must appear before a judge.

malleable in their behavior. Criminal propensities are changeable with modest adjustments in circumstances. Offenders don't simply have predetermined criminal careers only to be interrupted with incarceration.

1.4 Conclusion

This paper has focused on the New York City crime decline as a case study that challenges the once dominant crime control policy of incapacitation through incarceration. Californias recent realignment policy offers collaborative large-scale circumstantial evidence. In New York City there was a dramatic decline in crime without increases in imprisonment; in California, there was substantial decarceration did not result in substantive increases in crime. Between 2012 and 2014 the California's prison incarceration rate had dropped from 622 inmates per 100,000 residents to 570 inmates per 100,000 with only about a third offset by increases in the jail population. This amounted to roughly 20,000 more formerly incarcerated individuals on the street. Yet researchers have found no evidence that realignment had an impact on violent crime or property crime, except for motor vehicle theft (Lofstrom and Raphael 2015). California, like the New York City case, points to the fallibility of early incapacitation theory, which assumed a straightforward translation between the number of incarcerated offenders and the amount of crime.

However, even if we now accept the importance of contingencies and opportunities in determining criminal behavior, we are still left with many open questions as to how place and period operate on offenders and offending rates. There is substantial circumstantial evidence that changes in the environment have a high impact on personal crime rates and community crime rates, but there is no direct or observational evidence to confirm this inference. And circumstantial evidence may overestimate the magnitude of the effect - it is because there was such a large drop in crime in New York City in the first place that we even begin to search for the cause of the effect. Moreover, even if we had credible evidence for an environmental effect, this still tells us nothing about *how* environments influence individuals and groups. The critical next step is to seek evidence and generate research strategies to make visible whatever processes are operating on individuals and groups.

References

Akerlof, George A (1991). "Procrastination and obedience". In: *The American Economic Review* 81.2, pp. 1–19.

Arbuthnot, May Hill and Zena Sutherland (1947). "Children and books". In:

Avi-Itzhak, Benjamin and Reuel Shinnar (1973). "Quantitative models in crime control". In: *Journal of Criminal Justice* 1.3, pp. 185–217.

Beccaria, Cesare (2009). *On crimes and punishments and other writings.* University of Toronto Press.

Becker, Gary S (1968). "Crime and Punishment: An Economic Approach". In: *Journal of Political Economy*, pp. 169–217.

Bennett, William J, John J Dilulio Jr, and John P Walters (1996). *Body count*.

Blumstein, Alfred et al. (1986). *Criminal Careers and" Career Criminals,"* vol. 2. National Academies.

Blumstein, Alfred and Allen J Beck (1999). "Population growth in US prisons, 1980-1996". In: *Crime. & Just.* 26, p. 17.

Blumstein, Alfred and Jacqueline Cohen (1979). "Estimation of individual crime rates from arrest records". In: *The Journal of Criminal Law and Criminology (1973-)* 70.4, pp. 561–585.

Blumstein, Alfred and Joel Wallman (2006). *The crime drop in America*. Cambridge University Press.

Braga, Anthony A (2005). "Hot spots policing and crime prevention: A systematic review of randomized controlled trials". In: *Journal of experimental criminology* 1.3, pp. 317–342.

Buka, Stephen L et al. (2001). "Youth exposure to violence: prevalence, risks, and consequences." In: *American Journal of Orthopsychiatry* 71.3, p. 298.

Burt, Ronald S (1987). "Social contagion and innovation: Cohesion versus structural equivalence". In: *American journal of Sociology*, pp. 1287–1335.

Cerdá, Magdalena et al. (2009). "Misdemeanor policing, physical disorder, and gun-related homicide: a spatial analytic test of" broken-windows" theory". In: *Epidemiology*, pp. 533–541.

Chalfin, Aaron and Justin McCrary (2013). "Are U.S. Cities Underpolices? Theory and Evidence". In: *National Bureau of Economic Research*.

Clarke, Ronald Victor Gemuseus and Marcus Felson (1993). *Routine activity and rational choice*. Vol. 5. Transaction Publishers.

Clear, Todd R (2007). "The impacts of incarceration on public safety". In: *social research*, pp. 613–630.

Cohen, Jacqueline (1983). "Incapacitation as a strategy for crime control: Possibilities and pitfalls". In: *Crime and justice*, pp. 1–84.

— (1984). "Selective incapacitation: An assessment". In: *U. Ill. L. Rev.* P. 253.

Comey, Jennifer, Susan J Popkin, and Kaitlin Franks (2012). "MTO: A successful housing intervention". In: *Cityscape*, pp. 87–107.

Cook, Philip J (1986). "Criminal incapacitation effects considered in an adaptive choice framework". In: *The Reasoning Criminal. Rational Choice Perspectives on Offending*.

Cook, Philip J and John H Laub (1998). "Unprecedented Epidemic in Youth Violence, The". In: *Crime & Just.* 24, p. 27.

— (2002). "After the epidemic: Recent trends in youth violence in the United States". In: *Crime and justice*, pp. 1–37.

Cook, Philip J, Robert MacCoun, et al. (2008). "The negative impacts of starting middle school in sixth grade". In: *Journal of Policy Analysis and Management* 27.1, pp. 104–121.

Corman, Hope and Naci Mocan (2005). "Carrots, sticks, and broken windows". In: *Journal of Law and Economics* 48.1, pp. 235–266.

Crane, Jonathan (1991). "The epidemic theory of ghettos and neighborhood effects on dropping out and teenage childbearing". In: *American journal of Sociology*, pp. 1226–1259.

Dalton, Erin (2002). "Targeted crime reduction efforts in ten communities: Lessons for the Project Safe Neighborhoods initiative". In: *US Attorney's Bulletin* 50, pp. 16–25.

DeLisi, Matt and Alex R Piquero (2011). "New frontiers in criminal careers research, 2000–2011: A state-of-the-art review". In: *Journal of Criminal Justice* 39.4, pp. 289–301.

Donohue III, John J (2009). "Assessing the relative benefits of incarceration: Overall changes and the benefits on the margin". In: *Do prisons make us safer? The benefits and costs of the prison boom*, pp. 269–342.

Donohue III, John J and Steven D Levitt (2001). "The impact of race on policing and arrests". In: *Journal of Law and Economics* 44.2, pp. 367–394.

Durlauf, Steven N and Daniel S Nagin (2011). "Imprisonment and crime". In: *Criminology & Public Policy* 10.1, pp. 13–54.

Ehrlich, Isaac (1981). "On the usefulness of controlling individuals: an economic analysis of rehabilitation, incapacitation and deterrence". In: *The American Economic Review* 71.3, pp. 307–322.

Fabio, Anthony et al. (2006). "Why some generations are more violent than others: assessment of age, period, and cohort effects". In: *American Journal of Epidemiology* 164.2, pp. 151–160.

Fagan, Jeffrey (2006). "Death and Deterrence Redux: Science, Law and Casual Reasoning on Capital Punishment". In: *Ohio St. J. Crim. L.* 4, p. 255.

Fagan, Jeffrey, Valerie West, and Jan Holland (2003). "Reciprocal effects of crime and incarceration in New York City neighborhoods". In: *Fordham Urban Law Journal*.

Fagan, Jeffrey, Deanna L Wilkinson, and Garth Davies (2007). "Social contagion of violence". In:

Figlio, Robert M, Thorsten Sellin, and Marvin E Wolfgang (1972). *Delinquency in a birth cohort*.

Figlio, Robert M, Paul E Tracy, and Marvin E Wolfgang (1990). *Delinquency in a Birth Cohort II: Philadelphia, 1958-1986*. Inter-university Consortium for Political and Social Research.

Fox, James Alan (1996). *Trends in juvenile violence: A report to the United States Attorney General on current and future rates of juvenile offending*. US Department of Justice, Bureau of Justice Statistics Washington, DC.

Geller, Amanda, Irwin Garfinkel, Bruce Western, et al. (2006). "The effects of incarceration on employment and wages: An analysis of the Fragile Families Survey". In: *Center for Research on Child Wellbeing, Working Paper* 2006-01.

Glaeser, Edward L, Bruce I Sacerdote, and Jose A Scheinkman (2003). "The social multiplier". In: *Journal of the European Economic Association* 1.2-3, pp. 345–353.

Glueck, Sheldon (1945). *Crime and justice*. Harvard university press.

Glueck, Sheldon and Eleanor Glueck (1950). "Unraveling juvenile delinquency". In: *Juv. Ct. Judges J.* 2, p. 32.

Glueck, Sheldon and Eleanor Touroff Glueck (1930). *500 criminal careers*. AA Knopf.

Glueck, Sheldon and Eleanor Touroff Glueck (1934). "One thousand juvenile delinquents." In:

Granovetter, Mark (1978). "Threshold models of collective behavior". In: *American journal of sociology*, pp. 1420–1443.

Granovetter, Mark and Roland Soong (1983). "Threshold models of diffusion and collective behavior". In: *Journal of Mathematical sociology* 9.3, pp. 165–179.

Greenberg, David F (1975). "The incapacitative effect of imprisonment: Some estimates". In: *Law & Society Review* 9.4, pp. 541–580.

Greenwood, P W (1982). "Selective Incapacitation". In:

Greenwood, Peter and Susan Turner (1987). "Selective incapacitation revisited". In: *Why High-Rate Offenders Are Hard to Predict. Santa Monica.*

Harcourt, Bernard E and Jens Ludwig (2006). "Broken windows: New evidence from New York City and a five-city social experiment". In: *The University of Chicago Law Review*, pp. 271–320.

Hawken, Angela and Mark A.R Kleiman (2009). *Managing Drug Involved Probationers with Swift and Certain Sanctions: Evaluating Hawaiis HOPE.* Tech. rep.

Hellend, Eric and Alexander Tabarrok (2007). "Does three strikes deter? A nonparametric estimation". In: *Journal of Human Resources.*

Hemenway, David et al. (1996). "Gun carrying among adolescents". In: *Law and Contemporary Problems* 59.1, pp. 39–53.

Holzer, Harry J et al. (2008). "The economic costs of childhood poverty in the United States". In: *Journal of Children and Poverty* 14.1, pp. 41–61.

Jacob, Brian A and Lars Lefgren (2003). *Are idle hands the devil's workshop? Incapacitation, concentration, and juvenile crime.* Tech. rep.

Jencks, Christopher and Susan E Mayer (1990). "The social consequences of growing up in a poor neighborhood". In: *Inner-city poverty in the United States* 111, p. 186.

Johnson, Christopher and Stephen W Raudenbush (2006). "A repeated measures, multilevel Rasch model with application to self-reported criminal behavior". In: *Methodological issues in aging research* 1, p. 131.

Johnson, Rucker C and Steven Raphael (2009). "The effects of male incarceration dynamics on acquired immune deficiency syndrome infection rates among African American women and men". In: *Journal of Law and Economics* 52.2, pp. 251–293.

Johnson, Rucker and Steven Raphael (2012). "How much crime reduction does the marginal prisoner buy?" In: *Journal of Law and Economics* 55.2, pp. 275–310.

Kahneman, Daniel (2011). *Thinking, fast and slow.* Macmillan.

Kahneman, Daniel and Amos Tversky (1973). "On the psychology of prediction." In: *Psychological review* 80.4, p. 237.

— (1979). "Prospect theory: An analysis of decision under risk". In: *Econometrica: Journal of the econometric society*, pp. 263–291.

— (1982). "Variants of uncertainty". In: *Cognition* 11.2, pp. 143–157.

Kennedy, David. "Pulling Levers: Chronic Offenders, High-Crime Settings, and a Theory of Prevention". In: 31, pp. 449–484.

Kennedy, David (2008). *Deterrence and Crime Prevention: Reconsidering the Prospect of Sanction*. Routledge Press.

Kennedy, David M, Anne M Piehl, and Anthony A Braga (1996). "Youth violence in Boston: Gun markets, serious youth offenders, and a use-reduction strategy". In: *Law and Contemporary Problems* 59.1, pp. 147–196.

Kirk, David S and Andrew V Papachristos (2011). "Cultural Mechanisms and the Persistence of Neighborhood Violence1". In: *American Journal of Sociology* 116.4, pp. 1190–1233.

Kling, Jeffrey R, Jens Ludwig, and Lawrence F Katz (2005). "Neighborhood effects on crime for female and male youth: Evidence from a randomized housing voucher experiment". In: *The Quarterly Journal of Economics*, pp. 87–130.

Köbner, Otto (1893). "17. Die Methode einer wissenschaftlichen Rückfallsstatistik als Grundlage einer Reform der Kriminalpolitik." In: *Zeitschrift für die gesamte Strafrechtswissenschaft* 13.1, pp. 615–740.

Laub, John H and Robert J Sampson (1993). "Turning points in the life course: Why change matters to the study of crime". In: *Criminology* 31.3, pp. 301–325.

Lauritsen, Janet L, Robert J Sampson, and John H Laub (1991). "The link between offending and victimization among adolescents". In: *Criminology* 29.2, pp. 265–292.

Lee, David S, Justin McCrary, et al. (2009). *The deterrence effect of prison: Dynamic theory and evidence*. Citeseer.

Levitt, Steven D (1997). *Juvenile crime and punishment*. Tech. rep. National Bureau of Economic Research.

— (1998). "Why do increased arrest rates appear to reduce crime: deterrence, incapacitation, or measurement error?" In: *Economic inquiry* 36.3, pp. 353–372.

— (2002). "Using electoral cycles in police hiring to estimate the effects of police on crime: Reply". In: *The American Economic Review* 92.4, pp. 1244–1250.

Lochner, Lance and Enrico Moretti (2004). "The effect of education on crime: Evidence from prison inmates, arrests, and self-reports". In: *The American Economic Review* 94.1, pp. 155–189.

Loeber, Rolf and Magda Stouthamer-Loeber (1998). "Development of juvenile aggression and violence: Some common misconceptions and controversies." In: *American Psychologist* 53.2, p. 242.

Lofstrom, Magnus and Steven Raphael (2015). "Realignment, incarceration, and crime trends in California". In: *San Francisco: Public Policy Institute of California*.

Loftin, Colin (1986). "Assaultive violence as a contagious social process." In: *Bulletin of the New York Academy of Medicine* 62.5, p. 550.

Ludwig, Jens and Thomas J Miles (2007). "The Silence of the Lambdas: Deterring Incapacitation Research". In: *Journal of Quantitative Criminology*.

Ludwig, Jens, Greg J Duncan, Paul Hirschfield, et al. (2001). "Urban poverty and juvenile crime: Evidence from a randomized housing-mobility experiment". In: *QUARTERLY JOURNAL OF ECONOMICS-CAMBRIDGE MASSACHUSETTS-* 116.2, pp. 655–680.

MacCoun, Robert J. (2005). "Voice, control, and belonging: The double-edged sword of procedural fairness". In: *Annu. Rev. Law Soc. Sci.* 1, pp. 171–201. URL: `http://www.`

annualreviews.org/doi/abs/10.1146/annurev.lawsocsci.1.041604.115958 (visited on 10/05/2015).
Manski, Charles F (1993). "Identification of endogenous social effects: The reflection problem". In: *The review of economic studies* 60.3, pp. 531–542.
Martinson, Robert (1974). "What Works? - questions and answers about prison reform". In: *The Public Interest*, pp. 22–54.
Marvell, T B and C E Moody (1996). "Specification problems, police levels, and crime rates". In: *Criminology* 34, pp. 609–646.
Moffit, Terrie E (1993). "Adolescence-limited and life-course-persistent antisocial behavior: A developmental taxonomy". In: *Psychological Review* 100.
Moffitt, Terrie E (1993). "Adolescence-limited and life-course-persistent antisocial behavior: a developmental taxonomy." In: *Psychological review* 100.4, p. 674.
Moore, Mark H et al. (1984). *Dangerous offenders: the elusive target of justice*. Harvard University Press Cambridge, MA.
Nagin, Daniel S (2012). "Deterrence: A Review of the Evidence by a Criminologist for Economists". In: *Annual Review of Economics*.
— (2013). "Deterrence: A Review of the Evidence by a Criminologist for Economists". In: *Annu. Rev. Econ.* 5.1, pp. 83–105.
Nagin, Daniel S and Greg Pogarsky (2001). "Integrating Celerity, Impulsivity and Extralegal Sanction Threats Into a Model of General Deterrence: Theory and Evidence". In: *Criminology* 39(4), p. 865.
— (2004). "Time and punishment: Delayed consequences and criminal behavior". In: *Journal of Quantitative Criminology* 20.4, pp. 295–317.
Nevin, Rick (2000). "How lead exposure relates to temporal changes in IQ, violent crime, and unwed pregnancy". In: *Environmental Research* 83.1, pp. 1–22.
Owens, Emily (2009). "More Time, Less Crime? Estimating the Incapacitative Effects of Sentence Enhancements". In: *Journal of Law and Economics* 52(3), pp. 551–579.
Owens, Emily G (2013). *COPS and Cuffs, Lessons from the Economics of Crime: What Reduces Offending*. MIT Press.
Petersilia, Joan (1980). "Criminal career research: A review of recent evidence". In: *Crime and justice*, pp. 321–379.
Piquero, Alex R, David P Farrington, and Alfred Blumstein (2003). "The criminal career paradigm". In: *Crime and justice*, pp. 359–506.
— (2007). *Key issues in criminal career research: New analyses of the Cambridge Study in Delinquent Development*. Cambridge University Press.
Polinsky, A Mitchell and Steven Shavell (1999). *The economic theory of public enforcement of law*. Tech. rep. National bureau of economic research.
Raphael, Steven (2014). "How Do We Reduce Incarceration Rates While Maintaining Public Safety?" In: *Criminology & Public Policy* 13.4, pp. 579–597.
Raphael, Steven and Michael A Stoll (2013). *Why are so many Americans in prison?* Russell Sage Foundation.

Reppetto, Thomas A (1976). "Crime prevention and the displacement phenomenon". In: *Crime & Delinquency* 22.2, pp. 166–177.

Rosenfeld, Richard and Steven F Messner (2009). "The crime drop in comparative perspective: the impact of the economy and imprisonment on American and European burglary rates". In: *The British Journal of Sociology* 60.3, pp. 445–471.

Sah, Raaj Kumar (1991). "Social osmosis and patterns of crime: A dynamic economic analysis". In: *Journal of political Economy* 99.6.

Sampson, Robert J (2008). "Rethinking crime and immigration". In: *Contexts* 7.1, pp. 28–33.

— (2011). "11 Neighborhood effects, causal mechanisms and the social structure of the city". In: *Analytical sociology and social mechanisms*, p. 227.

Sampson, Robert J and John H Laub (2003). "Life-course desisters? Trajectories of crime among delinquent boys followed to age 70". In: *Criminology* 41.3, pp. 555–592.

— (2005). "A life-course view of the development of crime". In: *The Annals of the American Academy of Political and Social Science* 602.1, pp. 12–45.

Sampson, Robert J, Stephen W Raudenbush, and Felton Earls (1997). "Neighborhoods and violent crime: A multilevel study of collective efficacy". In: *Science* 277.5328, pp. 918–924.

Sampson, Robert J, Christopher Winship, and Carly Knight (2013). "Translating causal claims". In: *Criminology & Public Policy* 12.4, pp. 587–616.

Samson, Steven Alan (1997). "James Q. Wilson and John DiUlio: American Government: Study Guide". In:

Sarnecki, Jerzy (2001). *Delinquent networks: Youth co-offending in Stockholm*. Cambridge University Press.

Scheel, Hans von (1890). "Zur einfuhrung in die kriminalstatistik insbesondere diegenige des deutschen reichs". In: *Allgemeines Statistisches Archiv* 1, pp. 183–194.

Shannon, Lyle W et al. (1988). *Criminal career continuity: Its social context.* Human Sciences Press.

Shaw, Clifford R and Henry D McKay (1942). "Juvenile delinquency and urban areas". In: *Chicago, Ill*.

Sherman, Lawrence W (2002). "Trust and confidence in criminal justice". In: *National Institute of Justice Journal* 248, pp. 22–31.

Shinnar, Shlomo, Raymond J Maciewicz, and Robert J Shofer (1975). "A raphe projection to cat cerebellar cortex". In: *Brain Research* 97.1, pp. 139–143.

Skogan, Wesley G (2008). "Why reforms fail". In: *Policing & Society* 18.1, pp. 23–34.

Slovic, Paul et al. (2004). "Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality". In: *Risk analysis* 24.2, pp. 311–322.

Souza Briggs, Xavier de, Susan J Popkin, and John Goering (2010). *Moving to opportunity: The story of an American experiment to fight ghetto poverty*. Oxford University Press.

Spelman, William and John E Eck (1989). *Sitting ducks, ravenous wolves and helping hands: new approaches to urban policing*. Lyndon B. Johnson School of Public Affairs, University of Texas at Austin.

Telep, Cody W and David Weisburd (2012). "What is known about the effectiveness of police practices in reducing crime and disorder?" In: *Police Quarterly*, p. 1098611112447611.

Visher, Christy A (1987). "Incapacitation and crime control: Does a "Lock'em up" strategy reduce crime?" In: *Justice Quarterly* 4.4, pp. 513–543.

Von Hirsch, Andrew (1984). "The ethics of selective incapacitation: Observations on the contemporary debate". In: *Crime & Delinquency* 30.2, pp. 175–194.

Wallace, Rodrick (1991). "Expanding coupled shock fronts of urban decay and criminal behavior: how US cities are becoming "hollowed out"". In: *Journal of Quantitative Criminology* 7.4, pp. 333–356.

Warr, Mark (2002). *Companions in crime: The social aspects of criminal conduct*. Cambridge University Press.

Weisburd, David and Anthony A Braga (2006). *Police innovation: Contrasting perspectives*. Cambridge University Press.

Weisburd, David and John E Eck (2004). "What can police do to reduce crime, disorder, and fear?" In: *The Annals of the American Academy of Political and Social Science* 593.1, pp. 42–65.

Wilson, James Q (1975). *Thinking About Crime*. Basic Books.

— (1993). "The moral sense." In: *American Political Science Review* 87.01, pp. 1–11.

Zedlewski, Edwin W and National Institute of Justice (USA) (1987). *Making confinement decisions*. US Department of Justice, National Institute of Justice.

Zimring, Franklin E (2007). *The Great American Crime Decline*. Oxford University Press.

— (2010). "The scale of imprisonment in the United States: twentieth century patterns and twenty-first century prospects". In: *The Journal of Criminal Law and Criminology* 100.3, pp. 1225–1246.

— (2011). *The City that Became Safe*.

Zimring, Franklin E, Gordon Hawkins, and Hank Ibser (1995). "Estimating the Effect of Increased Incarceration on Crime in California". In: California Policy Seminar.

Zimring, Franklin E, Gordon Hawkins, and Sam Kamin (2001). *Punishment and democracy: Three strikes and you're out in California*. Oxford University Press on Demand.

Zimring, Franklin and Gordon Hawkins (1995). *Incapacitation: Penal confinement and the restraint of crime*. Oxford University Press.

Chapter 2

Repeat Offending in the New York City Crime Decline: Exploring Dynamics of Personal Crime Rates

Introduction

Since the beginning of the 1990s, New York City has experienced the largest and longest crime decline on record in the United States - a more than 80% drop in major violent and property crime that was twice the national decline of the 1990s and lasted twice as long (Zimring 2011).[1] Franklin Zimring's *The City that Became Safe* seeks to explain this "New York City difference." The book offers strong circumstantial evidence that it can be accounted for in significant part by some combination of policing interventions. But an equally important conclusion of the book is what *does not* explain New York City's particularly dramatic fall in crime: it cannot be accounted for by incarceration, demographic shifts, or discernible changes in the social and economic fabric of the city. Beyond a story of effective policing, the New York City experience is an important demonstration that serious crime is not hard-wired into populations. Observably similar populations can have substantially different rates of crime commission (Zimring 2011).

This conclusion that observably similar populations can engage in very different rates of crime commission corresponds with broader conclusions that have been drawn from the 1990s nationwide crime decline. In contrast to the rise in crime in the 1960s and 1970s, which

[1]Some scholars have argued that the New York City crime drop was less exceptional relative to other cities. The differences in part arise from the periods of study and the crimes included. Zimring compares New York City to aggregate national trends, and includes all index crimes (i.e., homicide, rape, robbery, aggravated assault, burglary, larceny and auto-theft), whereas other researchers have compared only homicide trends in New York City relative to other cities (e.g. (Fagan 1998; Rosenfeld and Lewis 2005) and found smaller differences between cities.

was almost universally attributed to demographic change, the 1990s decline had almost no demographic dimension. Those scholars who assumed an easy translation from demographics to crime rates (e.g. (**wils**; Fox 1996), predicted crime rises throughout the 1990s and into the 2000s that never came to pass. Given that population changes can't plausibly account for much of the 1990s nationwide crime drop, scholars have turned to alternative and more contextual explanations including more and better policing, broad cyclical influences and social change such as the abatement of the crack epidemic and its associated violence, and fewer criminal opportunities resulting from increased private security and technological innovations (Blumstein and Wallman 2006).

Given the substantial aggregate crime reductions in New York City that occurred without shifts in demographics of the population, "high risk" offenders must have to some degree stopped or substantially curtailed their criminal activity. Yet, with aggregate crime rate statistics we can only make indirect and speculative inferences. As Zimring acknowledges, "the problem with all these statistics is that they are after the fact of the behavioral changes that underlie these remarkable percentage reductions. There is little direct observation of changing patterns of street life in formerly high crime neighborhoods (p)."

The most direct evidence presented in the book for changing individual criminal behavior patterns are administrative statistics on the rate of new felony return to prison among former prisoners from New York City, which fell substantially over the last two and half decades along with the citywide drop in crime. Specifically, 28% of those released from prison in 1990 were returned for a new felony conviction within three years as compared to only 8% of those released in 2012 (DCJS).

Zimring provides the new felony return statistics as potential documentation that experienced felons fully participated in the decline in serious crime in the city. On some level, the common sense view might be that whatever it is that causes crime to drop generally should affect known felony offenders proportionately. On the other hand, much of the criminological literature has long argued that offending among experienced felons is significantly more stable than offending in the general population. High rates of recidivism have been stable and a notoriously intractable problem. But, as Zimring writes, "if the 64% drop in conviction rates reflects a 64% drop in crime commission rates, it would be a record setting documented positive change in crime commission rates for a prison release cohort" (p.). Indeed, if the drop in felony returns represents a drop in crime commission this would suggest criminal trajectories among active offenders are much less fixed and predictable than once thought; the general crime environment (and whatever its causes) can have a major impact on criminal careers.

The question this paper asks is what realities do the administrative prison return statistics in fact represent. That is, can we interpret the declining felony return rate as a reflection of real changes in the rates of criminal behavior across release cohorts, or is the drop an epiphenomena of prosecutorial and court practices? Further, to the extent that the lower felony return rate represents a lower rate of felony activity, can this be understood as circumstantial evidence that the features of the city environment to which offenders returned had an impact on personal crime rates, or is this the result of changes in the risk profile of individuals being released from prison over the last two and half decades? To begin to tease apart these competing accounts for the drop in the new felony prison return rate over the last twenty-five years this paper analyzes a unique dataset involving individual records of four cohorts of prisoners from New York City released in the years 1990, 1995, 2000, and 2008.

The paper proceeds as follows. Section 2.1 reviews the literature on recidivism - measures of the return to criminal behavior - and why the substantial decline in the prison return rate in New York City is potentially so important. Unlike the fluctuations in rates of crime, reported recidivism rates have been remarkably constant. Further, the literature has long focused on individual-level characteristics associated with re-offending (also notably consistent and stable) as compared to social, environmental, and contingent determinants, which scholars have increasingly recognized to be important and which Zimring argues must be important if we are to explain the substantial decline in crime commission rates across cohorts.

Section 2.2 details the aggregate prison return statistics, updated with an additional five years of data. The section points to some of the untested assumptions that Zimring makes in interpreting the data as circumstantial evidence for the environmental influence on personal crime rates and presents evidence that there were changes in the court's treatment of criminal charges and convictions, particularly drug offenses, over the period of study.

Section 2.3 analyzes the underlying individual-level data that make up the aggregate prison return trends to assess the extent to which the data does indeed offer conjectural evidence for environmental influences on criminal behavior among high risk offenders. This analysis entails a unique dataset involving individual records of four cohorts of prisoners from New York City released from prison in the years 1990, 1995, 2000, and 2008. The analysis presents a mixed picture. The individuals leaving prison were observably different in certain respects, most importantly, the average and median age of the release cohorts increased during the 1990s and into the 200s. But there are still differences in the rearrest rates for serious violent and property crime across release cohorts, which leaves open the potential for social and environmental effects on offending and re-offending behavior. Additionally, the aging of the population entering prison has more general implications for interpreting the composition of the crime decline: it suggests the crime participation rates of "at-risk" youth and less experienced offenders dropped more than the personal crime rates of "repeat offenders" represented in the prison release cohorts.

Section 2.4 concludes pointing to some potential avenues for future research.

2.1 Background: The Recidivism Literature

2.1.1 State and National Recidivism Statistics

Unlike the fluctuations in rates of crime, reported recidivism rates have been remarkably constant. As national crime rates have risen and fallen, national recidivism rates have remained essentially unchanged since the first Bureau of Justice Statistics (BJS) study in the 1980s: 40% - 50% of released prisoners are returned to prison within three years ((Beck and Shipley 1989; Langan and Levin 2002; States 2011; Durose, Cooper, and Snyder 2014). Such high rates of recidivism have long generated debate about the need for rehabilitation and reentry programs to combat recidivism. Or, more pessimistically, the impossibility of rehabilitation and thus the need for longer prison sentences to keep known offenders incapacitated.

In fact, the national recidivism statistics mask a great deal of variation across place and time and represent a mix of actual re-offending and technical violations. A 2011 PEW survey of recidivism rates across states among 1999 and 2004 prison release cohorts found return rates ranging from a low of 24% returned to prison within three years in Oklahoma to a high of over 65% returned in Utah (States 2011). These statistics encompass both new felony prison returns and and parole violation returns, substantively two very different types of recidivism. New felony returns are in some degree a measure of re-offending, mediated by criminal justice system practices; rates of parole violation returns are almost entirely dependent on system policies and practices. In California, for example, the states consistently high rate of prison returns has been in large measure an artifact of what was, until recently revised under realignment, an exceptionally long mandatory period of parole. Studies have consistently found individuals who are closely supervised during parole are, not surprisingly, returned to prison at higher rates, often for technical violations (e.g. failing regular drug testing) (Petersilia 2006). Pew reported the rate of prison return for a new felony ranged across states from a high of 42% in North Carolina to a low of 8% in Georgia; returns for technical violations were as high as 51% in Utah and as low as 2% in North Carolina.

Besides the problem of over aggregation across place and the conflation of new felonies with technical violations, interpreting trends in recidivism statistics as trends in re-offending is complicated by the possibility of changes in criminal justice system reporting, response to criminal activity, and the composition of prison releasees. Over the last decades, for example, as the result of longer prison sentences, the population in prison and being released has been getting older. Thus, we should expect a lower rate of re-offending given the well known relationship between age and offending. On the other hand, advances in how the FBI and states create and store criminal history records may, for example, mean BJS can more easily document arrests. If so, this would lead to higher reported re-offending, at least as measured by re-arrests, but the trend would not actually reflect higher rates of re-arrest. And of course arrests themselves are determined in part by policing policy and practice, which can change over time. As sections 2.2 and 2.3 detail, the mediation of criminal justice system policy and a changing risk profile of prison releasees are both relevant to how we are to interpret the decline in the rate of new felony prison returns among former prisoners from New York City.

2.1.2 Individual and Environmental Correlates of Re-offending

Criminological research on recidivism has predominantly focused on the study of individual-level correlates of re-offending. Like the correlates of crime and criminal behavior more generally, predictors of re-offending are well documented and consistent. Essentially every study has found younger offenders, those with more extensive criminal histories, and individuals sentenced to prison for property crimes are more likely to recidivate relative to older offenders, those with less extensive criminal records, and those sentenced for violent crime (Petersilia 2006). Individuals with drug problems and individuals with less education are also more likely to recidivate, controlling for other variables (Kubrin and Stewart 2006).

More recently, scholars have been critical of the recidivism literature's near exclusive focus on individual-level characteristics rather than ecological determinants of re-offending. These later environmental or neighborhood features such as community crime levels, poverty, racial and ethnic heterogeneity, and residential instability have long been important in the study of crime more generally (see e.g. (Sampson, Winship, and Knight 2013; Reisig et al. 2007)), but analysis of contextual effects on re-offending has been rare ((Clear, Waring, and Scully 2005; Kubrin and Stewart 2006)).

Recent research attempting to remedy this deficiency has confirmed that neighborhood features are indeed important in predicting the likelihood that an individual will re-offend. Kubrin and Stewart, for example, using observational data, find individuals returning to more disadvantaged communities recidivated at higher rates even after controlling for individual level variables (Kubrin and Stewart 2006). The authors find "neighborhood context" accounts for roughly 13% of the variance in recidivism. Lin, Grattet, and Petersilia, after controlling for a number of individual-level variables, find the quality of neighborhood social services impacts a former prisoners chances of rearrest and reconviction (Lin, Grattet, and Petersilia 2010). Finally, Kirk, using a quasi-experimental design that exploits the exogenous variation produced by Hurricane Katrinas forced relocation of parolees, finds those who were moved farther from their former geographic location were significantly less likely to be reincarcerated (Kirk and Papachristos 2011). Specifically, Kirk reports the probability of reincarceration was .15 lower for those parolees who did not move back to the parish where they were originally convicted relative to parolees who did return to their original parish. The finding supports the peer and contextual effects hypothesis: residential change removes ex-prisoners from previous criminogenic environments including former criminal peers.

Zimring does not explicitly or empirically test for environmental effects on re-offending rates in New York City, but infers that the micro social environment was likely an important determinant of re-offending (and offending) (Zimring 2011). Individuals returned to a city in which the big change was crime itself. If your friends are not engaging in criminal behavior then you are less likely to, and this may itself then create a kind of virtuous cycle of declining crime. Zimring's emphasis on social and environmental effects on criminal behavior is of course not only relevant to accounting for re-offending trends, but is part of a broader argument made in the book about how we should understand the New York City crime decline. The argument draws on a long tradition of criminological and sociological literature that has recognized the social and group nature of crime and delinquency and the idea that peers influence criminal behavior (e.g. (Sarnecki 2001; Shaw and McKay 1942; Arbuthnot and Sutherland 1947; Warr 2002)), as well as more recent Routine Activities and Situational Crime Prevention theories that treat circumstantial and contingent factors as important determinants of behavior. At the same time, actually identifying and estimating environmental and peer effects is notoriously difficult (see e.g. (Angrist 2014)) and so strong empirical evidence as to whether this well-known association is causal or merely correlational remains much more limited.[2]

If and to what extent social dynamics explain declining re-offending trends in New York City is an open question, but before seeking an account for dropping rates of re-offending, we must first assess the extent to which the fall in the new felony prison return rate actually represents a fall in rates of re-offending. The paper now turns to unpacking the New York prison return statistics demonstrating the challenge of inferring criminal behavior from aggregate criminal justice statistics.

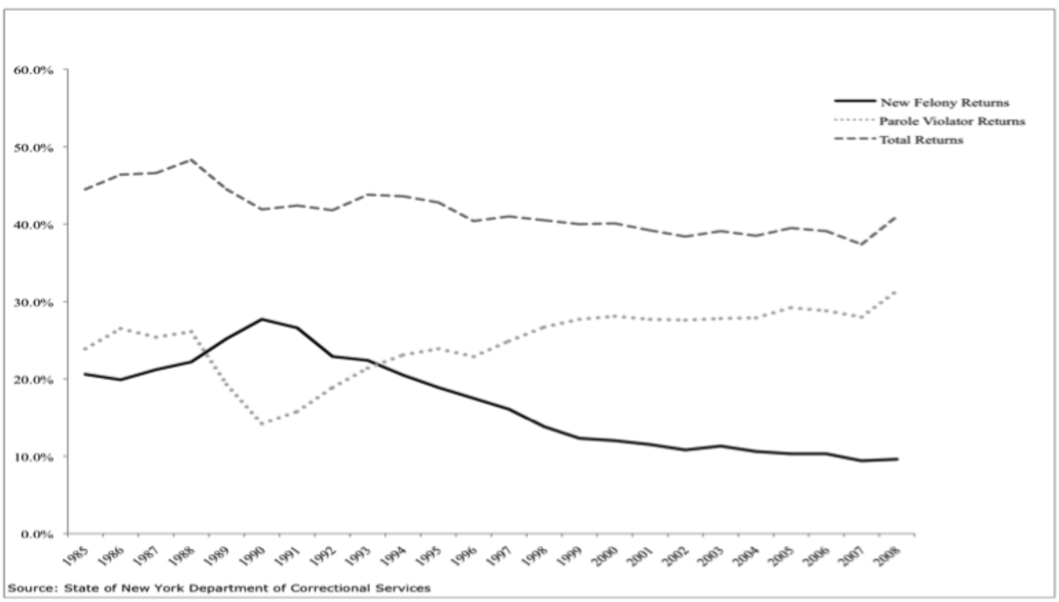
[2]The are, for example, non-social accounts for non-linear changes in crime rates. "Enforcement swamping" describes the fact that a higher prevalence of offending will generally mean a lower risk of sanction for any given offender, which can result in self-sustaining high and low crime rates. Multiple equilibria will mean temporary interventions can have long-term consequences if the system is pushed past the "tipping pint."The positive association between an individuals criminal behavior and the prevalence of crime in a neighborhood or among a peer group might also reflect non-social phenomenon such as common exposure to institutions, social structures and expectations, which will impact the perceived costs and benefits of engaging in criminal activity ((Glaeser, Sacerdote, and Scheinkman 2003)). Disadvantaged neighborhoods might simply provide more physical spaces without guardians, or a lower probability of arrest ((Sah 1991; Cook and Goss 1996)). On the other hand, there are many social accounts. Peers may provide support, disapproval or information relating to criminal activity ((Cook, MacCoun, et al. 2008)). Perceived payoffs of engaging in criminal activity might be driven by social penalties or stigma associated with committing crime ((Sampson, Raudenbush, and Earls 1997; Schrag and Scotchmer 1997)). Or criminal peers may have an effect not through social learning or imitation, but rather in providing opportunity.

2.2 The Decline in New Felony Prison Returns Among New York City Inmates

2.2.1 The Prison Return Data

As described in the introduction, the most direct evidence Zimring presents against a notion of fixed proclivities and in support of the conjecture that the crime environment importantly influenced the personal crime rates of known offenders is the time series showing a declining rate of new felony returns to prison. As shown in figure 2.1, the rate of new felony returns among former New York City residents closely tracks the citys crime trends: the return rate rises in the late 1980s, as did crime rates, reaches a high of 28% returned among the 1990 release cohort, and then declines steadily, falling to 8%-9% returned within three years for the last three release cohorts (2009-2011) for whom data is available.

Figure 2.1: Three-Year Prison Return Rate for NYC Prisoners: 1985 - 2011



There are several problems or potential problems with interpreting the dropping new felony prison return rate as evidence of declining personal crime rates: the return statistics include felony drug conviction returns, a poor proxy for the criminal behavior of other kinds, and shifts in the criminal justice systems treatment of offenses, particularly drug offenses, confound trends in actual re-offending. Further, to the extent that return rates reflect criminal behavior, the assumption that declining personal crime rates was driven by the changed city environment as compared to the risk-profile of individuals leaving prison is untestable with aggregate prison return data. What follows is a discussion of the changes in the New York City criminal justice system environment over the course of the crime decline. Section 2.3 will then turn to the analysis of the underlying individual level data that make up the aggregate prison return trends to assess whether, insofar as there were real changes in criminal activity, these might be interpreted as the result of the environmental context to which former offenders returned rather than differences in the risk profile of the individuals released from prison over the last two decades.

2.2.2 The Problem of Drug Felony Prison Returns

All criminal justice statistics are to some degree mediated measures of criminal behavior, but in the case of the prison return data, there are several particular reasons to worry whether the trends reflect significant criminal justice system changes as compared to behavior change among former prisoners. Most problematic is that the new felony prison returns trends include returns for felony drug convictions. This is problematic for several reasons. First, unlike major felony crimes, there are no official reports of drug crimes independent of drug arrests, and drug arrests (and convictions and sentences for that matter) are largely a reflection of criminal justice system priorities rather than indicators of the prevalence of drug offending. In fact, a version of this point is made in Zimring's demonstration that the New York City Police Department (NYPD) successfully attacked open-air drug markets and the associated street crime without impacting the levels of drug use or drug distribution. The concern of the NYPD was not with reducing the levels of drug offending per se, but with using drug law policing to reduce serious crime connected to the drug markets. Felony drug arrests grew substantially during the late 1980s, continued throughout most of the 1990s and then began a sustained decline. Misdemeanor drug arrests, on the other hand, even more discretionary and widely thought to be pretextual, increased substantially in the later 1990s and 2000s.[3]

Besides significant changes in felony drug arrests since mid-1980s, there have been substantial changes in the city's sentencing policy and practice, with respect to drug offenses. Figure 2.2 shows the number of felony drug dispositions and sentences to prison from 1986 - 2013; figure 2.3 shows the top five dispositions for felony drug arrests. As the number of felony drug arrests grew in the late 1980s and early 1990s, so too did the number of sentences to prison for felony drugs (and the proportion of felony drug arrests resulting in a prison term). The New York City courts imposed 3,183 prison sentences for felony drug convictions in 1986 (15% of total drug felony dispositions) and by 1993 this number had more than tripled to a peak of 10,379 prison sentences (27% of felony drug dispositions). In 2013, the last year for which there is data, the total number of felony drug sentences had dropped to 7,039 (9% of felony drug dispositions). Assuming the courts' general treatment of drug offenders applied to the courts' sentencing of previously incarcerated offenders, this shift in sentencing would account for some of new felony prison return trends.

Finally, besides the problem that drug arrests, convictions and sentences largely reflect

[3]The rise of misdemeanor drug policing has been widely criticized by scholars and advocates for its disproportionate impact on low-income communities of color

Figure 2.2: Number of Felony Drug Dispositions and Prison Sentences: 1986-2013

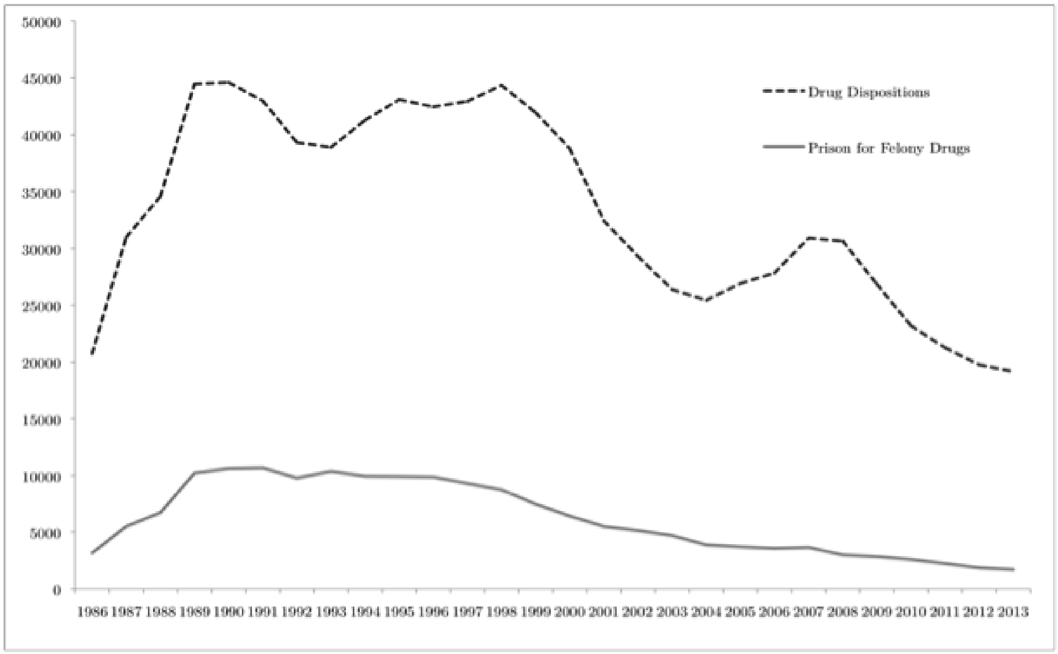
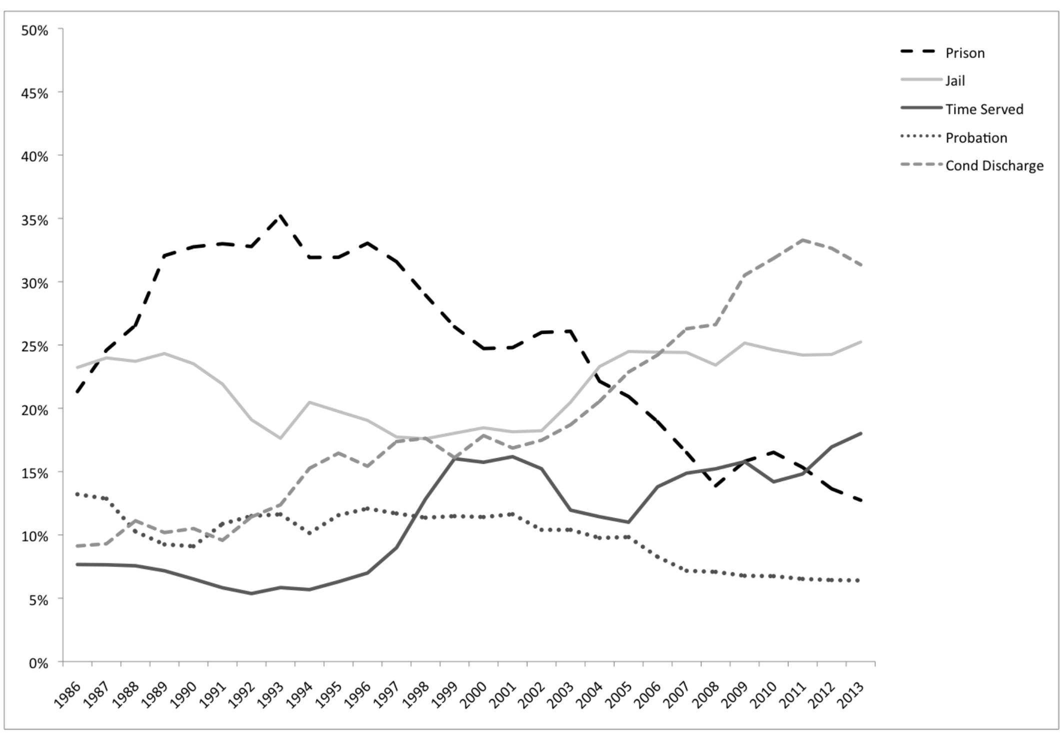


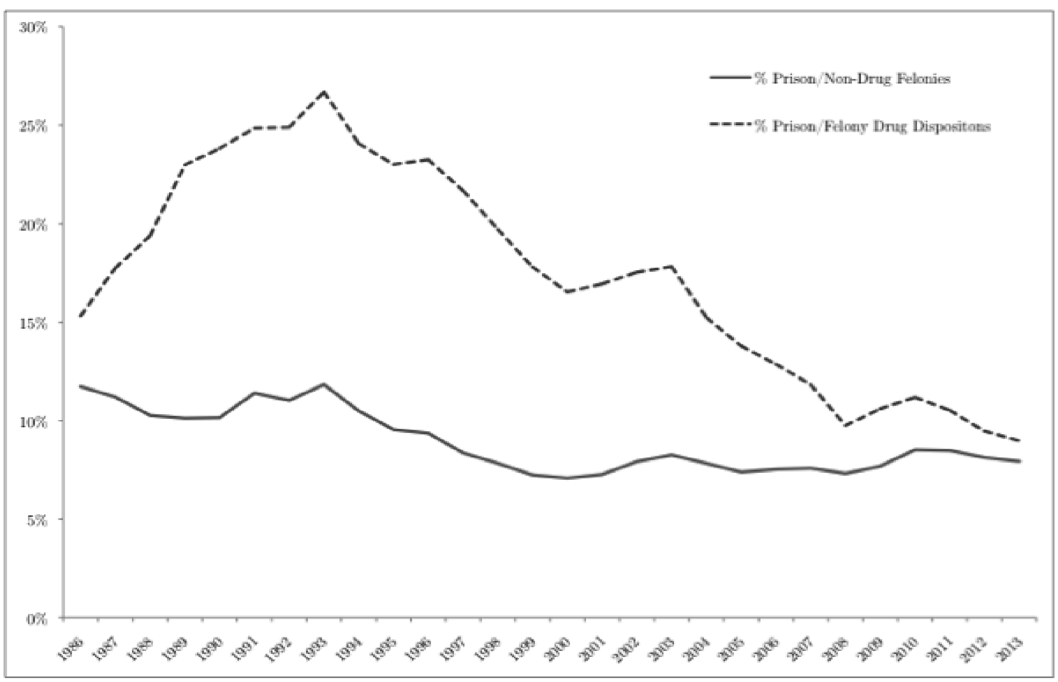
Figure 2.3: Top 5 Drug Dispositions Given Felony Drug Arrest



the behavior of criminal justice system actors as compared to drug related offending activity, drug activity itself is not a measure of the 'street crime' (i.e. violent and property crime) that are the behavioral outcomes of real interest. It is serious crime and violence that is focus of the analysis in Zimring's book and the scholarship on criminal careers with which Zimring engages.

Returns to prison for felony drug convictions do not belong in the prison return time series insofar as the data is used as a proxy for criminal activity. But even if felony drug returns are excluded, there may still be some reason to worry the trends in prison return rates reflect, in part, policy changes as compared to changes in offending behavior. With respect to court sentencing, there were changes, although not dramatic, in the rate of incarceration given an arrest or conviction. Figure 2.4 shows the rate of imprisonment for non-felony drug convictions alongside the rate for felony drug convictions. Again, the large drop is in the rate of imprisonment for felony drugs convictions, but the percentage of non-drug felony dispositions that resulted in a prison sentence did drop: from between 14% and 16% during the first half of the 1990s to between 8%-9% since 2005, a drop of 43% in percentage terms (7% in absolute terms).

Figure 2.4: Percent of Drug and Non-Drug Felony Arrests Resulting in a Prison Sentence



The New York City courts' increasing use of non-prison sanctions for felony convictions is relevant to our interpretation of the new felony prison return trends, but is also noteworthy given its contrast to trends in the rest of the country during the 1990s, where crime rates also fell but imprisonment rates continued to rise.[4] The major decline in felony crime in New York City was clearly an important driver of the reduction in the population under correctional supervision, but changes in sanctioning also played a role. And part of the political and policy importance of the New York City crime decline story is that imprisonment played no part; the city was able to reduce crime dramatically while simultaneously reducing the number of people it sent to prison.

2.2.3 The Problem of Parole Violation Returns

Besides the dramatic change in sentencing for felony drug crimes over the last two and half decades, and smaller change in felony crime sentencing more generally, another potential concern is the rise in parole violation returns that coincided with the decline in new felony returns and might indicate a substitution effect. 14% of the 1990 release cohort was returned within three years for a parole violation versus 34% of the 2011 release cohort. Zimring acknowledges the possibility of a statewide policy favoring re-incarcerating via parole violations rather than new criminal conviction. To assess such a possibility, Zimring compares the trends in the five New York City boroughs with those in other urban jurisdictions in the state. This analysis shows jurisdictions in the rest of the state had no such increase in technical returns, thus suggesting no uniform statewide parole policy change.

Zimring also notes the uniformity of trends across each of New York City's five boroughs, and argues that this consistency, given each borough has an independent District Attorney, supports an interpretation of the return rates as not a mere reflection of changes in system practices. On the other hand, neither the state centralized or District Attorney centralized tests rule out the possibility that the rise in parole violation returns might represent a more informal citywide shift in prosecutorial preference and practice for resolving re-arrests. Even if not due to top-down directions, it is possible that prosecutors came to increasingly negotiate a prison return via technical violation following a criminal rearrest, rather than spending the time to pursue a new conviction in the criminal court. Such a practice has been documented in California, for example, in the pre-realignment era (Petersilia 2002).

In summary, each of these points in the criminal justice system - the decision to arrest, to criminally prosecute, to convict and imprison - are involved in who ends up being returned to prison. Insofar as these practices change, new felony returns to prison will not serve as a consistent proxy for the individuals' returns to crime. But even if we assumed the prison return trends were a good proxy for re-offending trends, the aggregate statistics cannot speak to the question of what explains changes re-offending. Zimring proposes the city environment, specifically the crime environment, impacted personal crime rates, and this impact manifests in the decline in new felony prison returns. But an alternative explanation would be that

[4] New court commitments to prison from New York City began to decline as early as 1992. Reductions in the prison population were not seen for several years, however, because the decline in new admissions was partially offset by longer sentences.

the risk profile of the individuals leaving prison changed over the period of study. This dispositionally oriented account is not testable with the aggregate prison return data. The following section offers some purchase on the question with an analysis of individual-level data that make up the aggregate prison return trends.

2.3 Individual-Level Analysis of The New York City Prison Release Cohorts

2.3.1 The Data

The following analysis entails a unique dataset involving individual records of four cohorts of prisoners from New York City released from New York State prison in the years 1990, 1995, 2000, and 2008. The individual-level data were obtained from the New York Department of Corrections and Community Supervision (DOCCS) and the New York State Division of Criminal Justice Services (NYSDCJS). The compiled dataset contains every finger-printable unsealed arrest along with all associated criminal court outcomes for every individual sentenced in New York City and released from prison for the first time on a new commitment offense in the years 1990, 1995, 2000, or 2008. The original raw data file, containing 435,175 arrest rows, represents a total of 39,862 individuals: 11,674 released in 1990, 10,725 released in 1995, 11,309 released in 2000, and 7,688 released in 2008. The dataset contains all arrests and criminal justice system actions involved in the disposing of each arrest (disposition, conviction, sentence) dating back to 1953 through 2013. This allows for the construction of past criminal histories for each offender and post-release criminal justice system involvement. The demographic variables available in the dataset are age, race, and gender.

2.3.2 Differences in Cohort Rearrest Rates

In an effort to best measure re-offending, and consistent with much of the recidivism literature (e.g (Kubrin and Stewart 2006; Benedict and Huff-Corzine 1997; Lanza-Kaduce, Parker, and Thomas 1999; Shinnar, Maciewicz, and Shofer 1975)),the following analysis focuses on post-release arrests rather than returns to prison. Arrests are an imperfect measure of offending behavior, but may represent the best proxy for a "return to crime" given prison return statistics represent the culmination of decisions made by multiple actors and agencies in the criminal justice system, including the police, prosecutors, and judge. [5]

Table 2.1 presents a simple snapshot of the percentage of each release cohort rearrested after one, two, three, four and five years post release, broken down by crime type - a rearrest for any offense, a major violent offense, a major property offense, and arrests for drug

[5] Arrest data does not capture crimes that were undetected or did not result in an arrest, making arrests likely to be an underestimate of the true amount of recidivism. And of course arrests are not a pure measure of behavior but are partially determined by police manpower, policy and practice.

sales and drug possession. [6] "Cohort 1" represents the 1990 release cohort; "cohort 2" the 1995 release cohort; "cohort 3" those released in 2000, and "cohort 4" those released in 2008. Survival curves are presented in Figure **??**, offering visualizations of the rearrest probabilities over a five year follow up period for each of the four cohorts.[7]

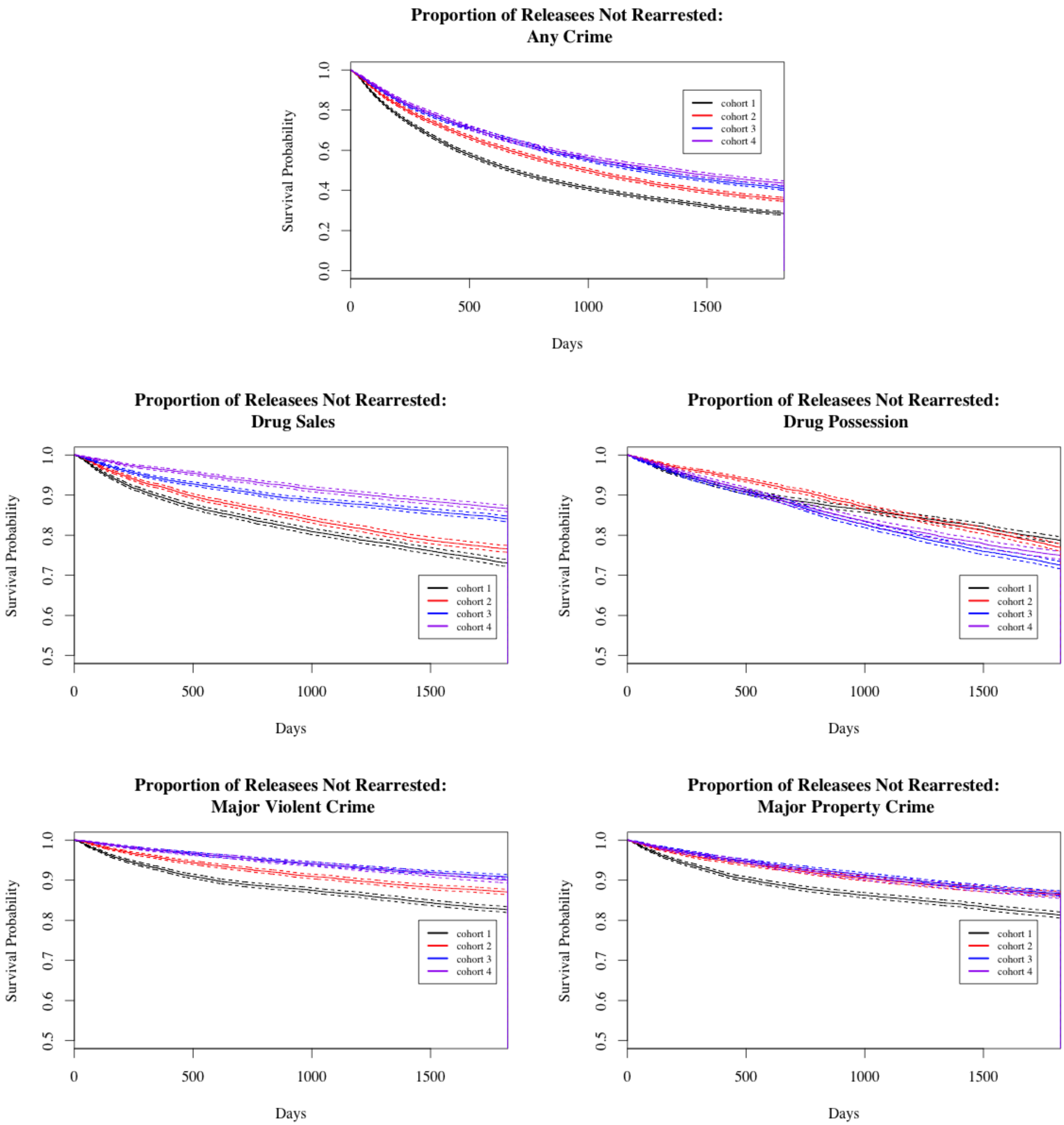
Table 2.1: Re-Arrest Rates after One, Two, Three, Four, and Five Years

	Cohort 1	**Cohort 2**	**Cohort 3**	**Cohort 4**
1 Year Re-Arrests				
Any Arrests	30%	23%	21%	22%
Major Violent	7%	4%	2%	3%
Major Property	7%	4%	4%	4%
Drug Sale	9%	7%	5%	3%
Drug Possession	5%	4%	6%	6%
2 Year Re-Arrests				
All Arrests	45%	36%	32%	35%
Major Violent	10%	7%	4%	4%
Major Property	10%	7%	6%	7%
Drug Sale	14%	12%	8%	6%
Drug Possession	9%	7%	11%	12%
3 Year Re-Arrests				
All Arrests	53%	45%	41%	43%
Major Violent	12%	9%	6%	5%
Major Property	12%	9%	9%	8%
Drug Sale	17%	16%	11%	8%
Drug Possession	11%	11%	16%	17%
4 Year Re-Arrests				
All Arrests	59%	51%	47%	49%
Major Violent	14%	11%	7%	8%
Major Property	14%	11%	11%	12%
Drug Sale	20%	19%	12%	11%
Drug Possession	13%	14%	20%	21%
5 Year Re-Arrests				
All Arrests	63%	55%	51%	53%
Major Violent	16%	12%	9%	10%
Major Property	16%	12%	12%	13%
Drug Sale	23%	21%	14%	13%
Drug Possession	16%	18%	23%	25%

[6] The analysis is limited to a five year follow-up because the arrests data runs through 2013 (and the last cohort was released in 2008). Arrest is measured as a binary variable (1= rearrested, 0= not rearrested).

[7] The curves represent Kaplan-Meier predicted step-function survival curves from cox regression model. The broken lines show a point-wise 95-percent confidence envelope around the survival function.

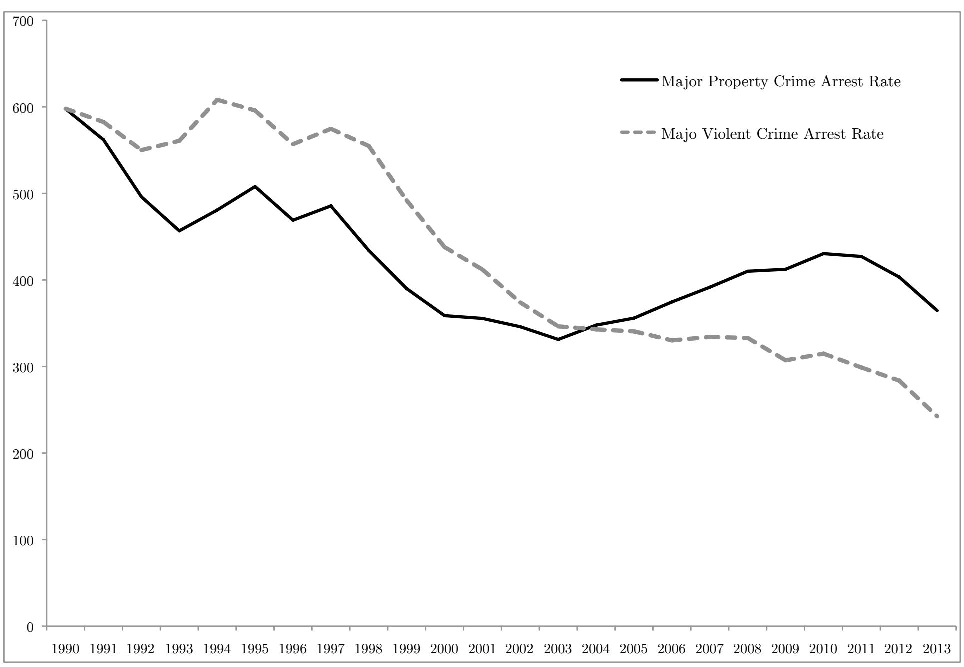
Figure 2.5: Estimated Five Year Survival Curves



Both the percentages rearrested by year, and the survival curves, show the 1990 release cohort to have generally higher rates of rearrest and lower probability of ”survival” relative to the later release cohorts. With respect to the major crime, there is a greater difference between cohorts in rearrests for violent index crimes (murder, rape, robbery, assault) as compared to property index crimes (burglary, larceny, auto-theft). The major violent crime arrest survival curves are all essentially parallel across cohorts, with the 1990 release cohort's chances of remaining arrest free the lowest, followed by the 1995 release cohort. The 2000 and 2008 release cohorts have the highest probability of remaining arrest free, and are indistinguishable from one another.

Unlike the major violent crime rearrest curves, the curves for property crime suggest only the rearrest rates for the cohort 1 to be statistically different from the other three cohorts. This larger difference between cohorts in major violent crime rearrests as compared to major property crime is somewhat consistent with the citywide arrests trends. Arrests for major violent and major property crime are presented in figure 2.6. Major property arrests fell faster in the 1990s than did major violent arrests, and by the early 2000s they began to increase. This does not, however, help to account for the comparable rates of rearrests among the 1995 releasees and the 2000 and 2008 releasees.

Figure 2.6: Citywide Major Violent & Property Crime Arrest Rate: 1990 - 2013



Release cohort differences in drug rearrests are largely consistent with citywide trends. With respect to drug sales, releasees from cohort 1 are rearrested at the highest rate, and each subsequent cohort has a lower probability of rearrest from the one prior with the largest gap between the 1995 and 2000 releasees. This likely reflects the citywide trends: drug sales arrests began to fall most precipitously in 2000, the period in which cohort 3 re-entered the community. On the other hand, drug possession arrests have increased substantially in New York City since the mid-1990s and this pattern is revealed in the prison release cohorts' drug possession rearrest trends. The 2000 and 2008 releasees' probabilities of remaining free from a drug possession arrest are the lowest, indistinguishable from one another, and parallel to the 1995 release cohort's curve. Notably, the 1990 release cohort begins with a lower chance of remaining arrest free than the 1995 cohort, but the curve flattens around the third year post-release and matches the 1995 release cohort curve.

The rearrest trends presented in table 2.1 and plots in figure 2.5 offer some support for hypothesis presented in *The City that Became Safe*, and examined in this paper, that re-offending rates among prison release cohorts fell over the course of the crime decline, as former prisoners re-entered a lower crime New York City. The raw data show statistically significant differences in the rate of serious offending, proxied by major violent and major property crime arrests, between those released in 1990 and later release cohorts, particularly with respect to major violent re-offending. And arrests for major violent and property crime offer a much closer proxy for serious criminal behavior than do returns to prison, or rearrests for less serious offenses.[8]

Because serious street crime (as compared to drug crime) is largely the subject of interest in exploring the dynamics of personal crime rates, and given the substantial changes during the last decades in policing and court processing of drug offenses in New York City, it is useful to further separate and compare rearrest patterns for drug and non-drug offenders. Table 2.2 presents the differences in the percentage rearrested for any crime other than drugs within three years for those released from prison after serving a term for a drug offense and those who served a term for any other offense.[9] Among those that served a drug offense prison term there is relatively little difference between prison release cohorts in the rate of rearrest. But, among the non-drug offenders, there is a substantial drop in the rate of rearrest for non-drug crimes that coincides with the citywide crime declined. Thus, when drug offenders and drug offenses are removed from the analysis, the pattern Zimring hypothesized - declining personal crime rates corresponding to the citywide decline - appears even stronger.

At the same time, the rearrest trends presented in these tables and figures do not speak to the question of whether differences in offending behavior, proxied by arrests, can be explained by difference in the city to which offenders returned or differences in the offenders who were being released from prison. The following section begins to address this question.

[8] At the same time, because the overall proportion of each cohort rearrested for a serious crime is relatively low, the differences between cohorts, while statistically significant in some cases, are still fairly small in absolute percentage terms.

[9] The percentage of each cohort released after serving a drug sentence term was roughly half for each cohort: less than half among the 1990 and 2008 releasees and more than half among those released 1995 and 2000. Specifically, 48% in 1990, 52% in 1995, 56% in 2000 and 43% in 2008.

Table 2.2: Percentage Rearrested After Three Years for Any Offense But Drugs

Cohort	Drug Offenders	Non-Drug Offenders
1	16.9%	38.7%
2	14.3%	28.7%
3	12.8%	23.5%
4	16.2%	24.1%

2.3.3 Difference in the Characteristics of Individuals Leaving Prison

Age, gender, and past criminal involvement are well-known predictors of recidivism, with young males who began criminal activities at a younger age at higher risks for future criminal activities.[10] In the following analysis, the paper examines if and to what extent there are cohort differences along these important dimensions that could account for some of the differences in rearrests between cohorts.

Table 2.3 presents criminal history and demographic background variables for the four cohorts. The most dramatic difference between the cohorts, and important difference with respect to correlates of offending, is the increasing age of the prison release cohorts: the average age of those released in 1990 was 30 (the median 29); in 2008 the average age of releasees was 37 (the median 36). While length of stay in prison did increase in the 1990s, particularly for violent crimes, this aging of the release cohorts appears to have be driven in large part by the aging of the population *entering* prison.[11] In 1990, the median age at release was 26; by 2000, the median age was 31. That the average and median age of those entering prison increased during the 1990s crime decline is important not only for interpreting the drop in rearrests and returns to prison, the specific question this paper addresses, but is also important the broader question of the anatomy of the crime decline. The increasing age of the cohorts entering prison suggests that the crime participation rates of less experienced young offenders or at-risk youth likely went down more in the crime decline than did the

[10] Age has been shown to be a consistent gender-invariant risk factor ((Ryan et al. 2010; Kruttschnitt and Gartner 2003; Makarios, Steiner, and Travis 2010; Jones, Lynam, and Piquero 2015; Knaap et al. 2012))

[11] The increase in the average and median age at release, particularly between the 2000 and 2008 cohort, where there was no difference in age at entry, may be in some part be explained by the increase in the average length of stay in prison, which statewide increased from 28 months in 1990 to 48 months in 2013 (DCJS). Data for New York City offenders specifically is not available, but given that over half to two-thirds of the state prison population consists of offenders from New York City the New York state data is informative to understanding the imprisonment of New York City offenders. The largest increase in time served was for violent crime: it grew by roughly 50% between 1990 and 2000, and another 21% between 2000 and 2008. This increase in length of stay for violent crimes was largely due to the passage of the 1995 Sentencing Reform Act and its subsequent extensions, all of which mandated determinate sentences for violent and repeat offenders and required that anyone convicted of a violent crime serve a minimum of six-sevenths of the imposed sentence (Berger 2013) .

rates of experienced repeat offenders. Larger shares of at-risk youth simply never engaged in serious criminal activity. This pattern among the prison release cohorts is also mirrored in citywide data on court commitments to prison from New York City, which dropped by 67% between 1990 and 2009 among those aged 14-24, and only 40% among those over 24.

Besides the change in the age distribution of the prison release cohorts, the later cohorts had on average served more time in prison, had more previous prison admissions, and had more prior convictions. Prior arrests for major violent and major property crime are remarkably similar across the four cohorts.

Table 2.3: Cohort Background Characteristics

	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Demographic Variables				
Black	58%	57%	59%	62%
White	32%	31%	29%	33%
Asian	5%	3%	2%	1%
Hispanic*	49%	52%	52%	52%
Avg Age at Entry	28	30	31	33
Median Age at Entry	26	29	31	31
Avg Age at Release	30	32	34	37
Median Age at Release	29	32	34	36
Sex (% Male)	90%	88%	89%	89%
Criminal History				
Avg # Prior Felonies	1.4	1.2	1.2	1.3
Avg # Prior Convictions	5.8	5.9	6.5	7.8
Avg # Prior Major Property Arrests	1.2	1.1	1.1	1.2
Avg # Prior Major Violent Arrests	1.8	1.5	1.5	1.7
Avg Length of Prison Term (served)	2	2.4	3	3.6
Avg # Prior Prison Admissions	0.31	0.44	0.56	0.67

* Hispanic indicates whether an Hispanic value was ever reported in an inmates criminal history

Tables 2.4 and 2.5 report Ordinary Least Squares coefficient estimates for linear probability models as an initial effort to begin to assess the potential import of the individual-level variables on the differences in rearrest rates between release cohorts. The dependent variable for each model is rearrest within three years for a given crime category. The three year follow-up was chosen to most closely correspond to the three year New York State prison return rate statistics and is also the follow-up period of the BJS nationwide recidivism studies. The same substantive conclusions present when the dependent variable is a rearrest after both a longer (4 or 5 years) or shorter (1-3 years) follow-up period. Logistic regressions, commonly used for dichotomous dependent variable modeling, were also run, the estimates of which, after exponentiating and converting to a probability at the mean, were very similar in magnitude and significance to those of the OLS regression models. Thus, for ease of interpretation, linear model estimates are presented.

Table 2.4: Linear Probability Model: Major Crime Arrests within Three Years Post Release

	Major Violent Rearrest		Major Property Rearrest	
	(1)	(2)	(3)	(4)
Cohort 1 (Relative to Cohort 4)	0.055***	0.027***	0.028***	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Cohort 2 (Relative to Cohort 4)	0.024***	0.012***	−0.006	−0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Cohort 3 (Relative to Cohort 4)	−0.004	−0.008*	−0.011**	−0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Age 26-31 (Relative to under 26)		−0.053***		−0.007*
		(0.004)		(0.004)
Age 32-39 (Relative to under 26)		−0.082***		−0.015***
		(0.004)		(0.004)
39+ (Relative to under 26)		−0.121***		−0.043***
		(0.004)		(0.004)
Prior Convictions		0.001***		0.002***
		(0.0004)		(0.0004)
Prior Drug Sale Arrests		−0.005***		−0.008***
		(0.001)		(0.001)
Prior Drug Possession Arrests		−0.001		−0.0005
		(0.001)		(0.001)
Prior Major Violent Arrests		0.026***		0.005***
		(0.001)		(0.001)
Prior Major Property Arrests		0.001		0.024***
		(0.001)		(0.001)
Prior Prison Length		−0.001*		−0.004***
		(0.001)		(0.001)
Race (white)		−0.009***		0.014***
		(0.003)		(0.003)
Sex (male)		−0.005		−0.004
		(0.004)		(0.004)
Constant	0.063***	0.116***	0.097***	0.084***
	(0.003)	(0.006)	(0.003)	(0.006)
Note:				*p<0.1; **p<0.05; ***p<0.01

These models include only the limited number of background variables available in the dataset. Estimates can by no means be interpreted causally, and of course even with a

Table 2.5: Linear Probability Model: Arrest within Three Years Post-Release

	Any Arrest		Drug Sales		Drug Possession	
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort 1 (Relative to cohort 4)	0.099^{***}	0.043^{***}	0.085^{***}	0.077^{***}	-0.063^{***}	-0.063^{***}
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Cohort 2 (Relative to cohort 4)	0.015^{**}	-0.008	0.068^{***}	0.063^{***}	-0.059^{***}	-0.055^{***}
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Cohort 3 (Relative to cohort 4)	-0.027^{***}	-0.031^{***}	0.017^{***}	0.014^{***}	-0.014^{***}	-0.009^{*}
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Age 26-31 (Relative to under 26)		-0.095^{***}		-0.023^{***}		-0.011^{**}
		(0.007)		(0.005)		(0.005)
Age 32-39 (Relative to under 26)		-0.140^{***}		-0.039^{***}		-0.011^{**}
		(0.007)		(0.005)		(0.005)
39+ (Relative to under 26)		-0.246^{***}		-0.073^{***}		-0.041^{***}
		(0.007)		(0.005)		(0.005)
Prior Convictions		0.007^{***}		0.001		0.003^{***}
		(0.001)		(0.0004)		(0.0004)
Prior Drug Sale Arrests		0.018^{***}		0.032^{***}		0.010^{***}
		(0.002)		(0.001)		(0.001)
Prior Drug Possession Arrests		0.009^{***}		0.009^{***}		0.017^{***}
		(0.002)		(0.001)		(0.001)
Prior Major Violent Arrests		0.032^{***}		0.003^{**}		0.006^{***}
		(0.002)		(0.001)		(0.001)
Prior Major Property Arrests		0.014^{***}		-0.001^{**}		0.001
		(0.001)		(0.001)		(0.001)
Prior Prison Length		-0.015^{***}		-0.003^{***}		-0.007^{***}
		(0.001)		(0.001)		(0.001)
Race (white)		0.037^{***}		0.033^{***}		0.005
		(0.005)		(0.004)		(0.004)
Sex (male)		-0.006		-0.003		-0.004
		(0.007)		(0.005)		(0.005)
Constant	0.434^{***}	0.468^{***}	0.089^{***}	0.073^{***}	0.170^{***}	0.145^{***}
	(0.006)	(0.010)	(0.004)	(0.007)	(0.004)	(0.007)

Note: *p<0.1; **p<0.05; ***p<0.01

fuller set of measurable individual correlates, there is always the possibility of omitted variables. Nonetheless, these simple linear probability estimates do suggest the relevance of the individual-level predictor variables, which, when included, reduce the differences in rearrest probabilities between cohorts.

The difference in major violent and major property crime rearrests between cohort 1 (1990 release cohort) and cohort 4 (2008 release cohort) is cut in half when the individual-level controls are added to the model. The probability of a major property rearrest for cohort 4 is higher than that of cohort 2 (1995 release cohort) and cohort 3 (2000 release cohort). Notably, the inclusion of individual level controls in the models of drug sale and drug possession rearrests does not change the cohort coefficients. This is likely because the "period" effects captured by the cohort coefficients is particularly robust for drug arrests which are largely a reflection of policing rather than individual behavior.

Finally, tables 2.6, 2.7 and 2.8 present linear probability models that describe release cohort differences among those released from prison after serving a sentence for a drug offense and those released after serving a sentence for any other crime. The dependent variables are any arrest within three years, a major violent arrest within three years, and a major property crime arrest within three years. These models reveal several things of note. First, and perhaps not surprisingly, the likelihood of any arrest other than for drugs, a major violent or major property rearrest is substantially higher for those released after serving a non-drug sentence, and this holds for each of the four release cohorts despite the differences in rearrest probabilities between release cohorts and offender types. Second, as was the case in the models on the full dataset, adding the controls reduces the cohort coefficient estimates, but there are still statistically significant differences between cohort 1 and cohort 4 with respect to any non-drug arrest, major violent crime arrests, and major property crime arrests. Third, the controls, age in particular, is predictive in all models - for the drug and non-drug sentenced group. This underlines the point introduced at the outset of the paper: the measurable predictors of offending and re-offending are well-established and consistent, but they can tell us relatively little about the crime volume we can expect to see.

In summary, the analysis of the individual-level data underlying the aggregate prison return trends suggests a mixed picture. Individuals leaving prison were observably different in some relevant manners. Most importantly, the population of former New York City offenders released from New York state prisons have grown older over the last twenty-five years, and it is well-established that older offenders are less likely to return to crime. The aging of the prison release population may explain some of the drop in the rate of new felony prison returns over the course of the crime decline. At the same time, there are still differences between cohorts in rearrest rates, importantly, including rearrests for serious street crime. The cohort differences in rearrests are made stark when only non-drug offenders are examined. What accounts for the drop in the rearrest rates for between cohorts is an open question, but this invites an environmental effects interpretation.

Table 2.6: Differences in Three Year Rearrest Rates for Any Crime but Drugs (Drug vs Non-Drug Offenders)

	Non-Drug Sentence		Drug Sentence	
	(1)	(2)	(3)	(4)
Cohort 1 (Relative to Cohort 4)	0.147***	0.083***	0.007	−0.022***
	(0.009)	(0.009)	(0.008)	(0.008)
Cohort 2 (Relative to Cohort 4)	0.047***	0.007	−0.020**	−0.033***
	(0.009)	(0.009)	(0.008)	(0.008)
Cohort 3 (Relative to Cohort 4)	−0.006	−0.027***	−0.034***	−0.041***
	(0.009)	(0.009)	(0.008)	(0.008)
Age 26-31 (Relative to under 26)		−0.047***		−0.072***
		(0.008)		(0.007)
Age 32-39 (Relative to under 26)		−0.089***		−0.088***
		(0.009)		(0.007)
39+ (Relative to under 26)		−0.145***		−0.139***
		(0.010)		(0.008)
Prior Convictions		0.005***		0.003***
		(0.001)		(0.001)
Prior Drug Sale Arrests		−0.013***		−0.003**
		(0.003)		(0.002)
Prior Drug Possession Arrests		−0.017***		−0.007***
		(0.003)		(0.001)
Prior Major Violent Arrests		0.014***		0.024***
		(0.002)		(0.002)
Prior Major Property Arrests		0.013***		0.010***
		(0.001)		(0.001)
Prior Prison Length		−0.008***		−0.002
		(0.001)		(0.002)
Race (white)		−0.007		0.002
		(0.007)		(0.005)
Sex (male)		0.001		−0.007
		(0.010)		(0.008)
Constant	0.241***	0.298***	0.163***	0.236***
	(0.007)	(0.013)	(0.006)	(0.011)
Observations	20,630	20,628	20,730	20,727

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2.7: Differences in Major Violent Crime Three Year Rearrest Rates (Drug vs Non-Drug Offenders)

	Non-Drug Sentence		Drug Sentence	
	(1)	(2)	(3)	(4)
Cohort 1 (Relative to Cohort 4)	0.089***	0.051***	0.021***	0.002
	(0.006)	(0.007)	(0.005)	(0.005)
Cohort 2 (Relative to Cohort 4)	0.051***	0.026***	0.005	−0.003
	(0.007)	(0.007)	(0.005)	(0.005)
Cohort 3 (Relative to Cohort 4)	0.013*	−0.001	−0.012**	−0.015***
	(0.007)	(0.007)	(0.005)	(0.005)
Age 26-31 (Relative to under 26)		−0.054***		−0.048***
		(0.006)		(0.004)
Age 32-39 (Relative to under 26)		−0.093***		−0.064***
		(0.007)		(0.005)
39+ (Relative to under26)		−0.139***		−0.095***
		(0.007)		(0.005)
Prior Convictions		0.002***		−0.0001
		(0.001)		(0.0004)
Prior Drug Sale Arrests		−0.001		−0.0003
		(0.002)		(0.001)
Prior Drug Possession Arrests		−0.002		0.001
		(0.002)		(0.001)
Prior Major Violent Arrests		0.025***		0.019***
		(0.001)		(0.001)
Prior Major Property Arrests		−0.001		0.002**
		(0.001)		(0.001)
Prior Prison Length		−0.002**		0.001
		(0.001)		(0.001)
Race (white)		−0.014***		−0.004
		(0.005)		(0.003)
Sex (male)		−0.012*		0.004
		(0.007)		(0.005)
Constant	0.075***	0.131***	0.047***	0.091***
	(0.005)	(0.009)	(0.004)	(0.007)
Observations	20,630	20,628	20,730	20,727

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2.8: Differences in Major Property Crime Three Year Rearrest Rates (Drug vs Non-Drug Offenders)

	Non-Drug Sentence		Drug Sentence	
	(1)	(2)	(3)	(4)
Cohort 1 (Relative to Cohort 4)	0.065^{***}	0.033^{***}	-0.009^{*}	-0.015^{***}
	(0.007)	(0.007)	(0.005)	(0.005)
Cohort 2 (Relative to Cohort 4)	0.012^{*}	0.001	-0.016^{***}	-0.018^{***}
	(0.007)	(0.007)	(0.005)	(0.005)
Cohort 3 (Relative to Cohort 4)	0.007	0.004	-0.016^{***}	-0.016^{***}
	(0.007)	(0.007)	(0.005)	(0.005)
Age 26-31 (Relative to under 26)		0.002		-0.014^{***}
		(0.006)		(0.005)
Age 32-39 (Relative to under 26)		-0.003		-0.019^{***}
		(0.007)		(0.005)
39+ (Relative to under 26)		-0.026^{***}		-0.048^{***}
		(0.007)		(0.005)
Prior Convictions		0.001^{**}		0.001^{**}
		(0.001)		(0.0004)
Prior Drug Sale Arrests		-0.006^{**}		-0.0005
		(0.002)		(0.001)
Prior Drug Possession Arrests		0.003		-0.0003
		(0.002)		(0.001)
Prior Major Violent Arrests		-0.001		0.005^{***}
		(0.002)		(0.002)
Prior Major Property Arrests		0.025^{***}		0.019^{***}
		(0.001)		(0.001)
Prior Prison Length		-0.006^{***}		0.001
		(0.001)		(0.001)
Race (white)		0.022^{***}		0.005
		(0.005)		(0.003)
Sex (male)		-0.0002		-0.009^{*}
		(0.007)		(0.005)
Constant	0.115^{***}	0.088^{***}	0.071^{***}	0.070^{***}
	(0.005)	(0.009)	(0.004)	(0.007)
Observations	20,630	20,628	20,730	20,727
Note:				*p<0.1; **p<0.05; ***p<0.01

2.4 Discussion

We know crime rates have fallen substantially in New York City, but we know much less about the patterns of individual behavior that make up these aggregate trends. Zimring offers New York state prison return statistics showing a 64% decline in the rate of new felony prison return amongst New York City offenders as potential documentation of major reductions in the personal crime rates of experienced felons, and conjectural evidence for the importance of the crime environment in determining criminal behavior and behavioral trajectories (Zimring 2011). This paper has examined the hypothesis with a more detailed analysis of the aggregate prison return statistics, updated with five years of additional data, as well as an analysis of individual-level data underlying aggregate prison return rates for four prison release cohorts (from 1990, 1995, 2000, and 2008). This examination revealed that not all of the assumptions required for interpreting the declining new felony prison return trends as declining personal crime rates are in fact justified. In general, prison return statistics are always an imperfect proxy for crime return, and reflect, at least in part, changes in the criminal justice system policy and practice. And in this case, there is evidence that there were some substantial system changes during the crime decline, at least with respect to the criminal justice system's treatment of drug offenses. Further, insofar as there were real differences in release cohorts' re-offending rates over the course of the crime decline, these behavioral differences may in part have been due to the changing risk profile of prison releasees, in particular, the aging of the prison release population.

The increase in the average and median age of the New York City prison release cohorts from 1990 to the 2000s offers some preliminary and suggestive evidence that the crime participation rates of less experienced or "at-risk" youth dropped more than the personal crime rates of "repeat offenders." If indeed the crime rates dropped more for young offenders relative to older and more experienced offenders, this is consistent with a theory of peer effects. The conventional wisdom in criminology that there is a high proportion of co-offending among the youngest offenders and a decline in percentage of co-offending with increasing age (see e.g., (Zimring 1981; Reiss Jr 1988)). Thus, to the extent that there are peer effects, we should expect larger effects among younger populations.

The paper's analysis has suggested a mixed picture with respect to how we should interpret the declining new felony prison return rate. We cannot simply interpret the 70% drop in the new felony return rate from 1990 to 2012 (28% returned within three years to 8% returned) as a 70% drop in personal crime rates among former prisoners. At the same time, the likelihood of rearrest for a major crime among ex-prisoners released in 2008, an era in which there was 80% less crime in New York City, is lower than for those released in 1990 at the the height of crime in the city, even when including individual controls. This leaves open the question of environmental effects.

That the paper does not establish environmental effects is by no means a demonstration that the contexts to which former prisoners return has *no* effect. In part, this is a function of the data available, which does not include many specifically environmental covariates such as information of neighborhood characteristics or geocoded data. But even with such data, there is the well-established challenge in social science of inferring individual behavior from aggregate data, and the specific challenge of identifying and measuring social and environmental effects.[12]

Identifying and estimating environmental and peer effects is notoriously difficult, and the problem of selection bias may exaggerate peer and neighborhood effects (see e.g. (Angrist 2014; Ludwig and Miles 2007), for example, reanalyze experimental data from the Moving to Opportunity (MTO) housing mobility experiment and show non-experimental ordinary least squares estimates of the effect of neighborhood on the violent crime arrests are substantially higher than the instrumental variable estimates. Kirk's 2009 study of parolees relocated after Hurricane Katrina, described in section 2.1 on recidivism research, offers an important and unusual example of a natural experiment that can speak to the question without the usual selection bias concern (Kirk 2009). The residential destruction from Hurricane Katrina provided an exogenous source of variation that influenced the neighborhoods to which former prisoners returned and thus could be exploited to estimate the causal effect of parolees relocating away from former geographic areas. The study found the chances of reincarceration were significantly lower for those ex-prisoners who relocated relative to those who did not.

Even with credible causal estimates, such as those offered by the natural experiment that Hurricane Katrina introduced, the mechanisms by which residential change (or neighborhoods more generally) effect criminal behavior is necessarily speculative. This is true of causal inference problems generally, and in this case, as in many other applications, qualitative study can offer a useful means of better understanding what drives the effect. Consistent with Zimring's hypothesis, Kirk suggests criminal opportunities (routine activities) and peer associations are likely important determinants of offending behavior and may account for the relocation effects found in the study. But again, causal estimates are only the beginning of the story, this explanation for the effects is necessarily interpretive.[13] In the New York City case, insofar as individuals came to behave differently, understanding how and why demands more direct observation and research closer to the individuals and communities.

Ethnography is one way in which criminologists have tried to make observable behavior and behavior change processes. Much of this criminological work has been on the use and sale of drugs, but there are examples of qualitative study of crime and violence more gen-

[12] The New York City crime decline suggests a degree of behavioral variability and unpredictability that is incompatible with notions of fixed long-term individual propensities to offend and re-offend. And the data presented is not inconsistent with the hypothesis that criminal activity among former prisoners is likely subject to whatever crime-suppressing conditions influenced the general population. But this conclusion can't be clearly drawn from the New York City prison return data.

[13] Kirk notes that unmeasured variation in criminal justice system operations across space and time may offer an alternative explanation.

erally. For example, National Institute of Justice sponsored work by Jeffrey Fagan (1998) used qualitative methods to study violent behavior among adolescents in New York City, examining the "code of the streets" and the contextual variability of violence (Fagan 1998). Shadd Maruna's widely recognized *Making Good: How Ex-Convicts Reform and Rebuild Their Lives* (2001) used extensive interviews to study the determinants of re-offending, specifically, what distinguishes previous criminal offenders who re-offend from those who "go straight" (Maruna 2001). Maruna finds self-narrative characterizes those who are more likely to desist from criminal behavior.

Given the difficulty of identifying and measuring neighborhood and peer effects on criminal behavior, many different approaches and methods of inquiry are relevant and necessary: quasi-experimental research designs when available, qualitative study, and, as has been the subject of this paper, observational and circumstantial evidence.

Finally, this paper, besides speaking to the question of the population composition of the crime decline in New York City, has documented changes in New York City sanctioning policy and practice over the course of the crime decline that have largely gone unnoticed. New York was one of the first states to counter the national trend of relentless incarceration growth: the state prison population began to flatten in the 1990s, and has declined since 2000. The reduction in incarceration was not the product of state policy but was driven exclusively by changes in criminal activity and criminal justice system processing in New York City.[14] New court commitments to prison from New York City began to decline as early as 1992, driven in significant part by declining crime, but also by fewer felony arrests resulting in a prison sentence.[15] The New York City crime decline story is in part so important because imprisonment played no clear part. The city saw dramatic crime reductions while simultaneously reducing the population in prison and jails.

References

Angrist, Joshua D (2014). "The perils of peer effects". In: *Labour Economics* 30, pp. 98–108.

Arbuthnot, May Hill and Zena Sutherland (1947). "Children and books". In:

Beck, Allen J and Bernard E Shipley (1989). *Recidivism of prisoners released in 1983*. US Department of Justice, Office of Justice Programs, Bureau of Justice Statistics Washington, DC.

Benedict, W Reed and Lin Huff-Corzine (1997). "Return to the scene of the punishment: Recidivism of adult male property offenders on felony probation, 1986-1989". In: *Journal of Research in Crime and Delinquency* 34.2, pp. 237–252.

[14]Prison admissions outside of New York City in fact increased slightly during the past twenty years.

[15]While new commitments dropped in the early 1990s, reductions in the prison population were not seen for several years, because the decline in new admissions was partially offset by longer sentences.

Berger, James O (2013). *Statistical decision theory and Bayesian analysis*. Springer Science & Business Media.

Blumstein, Alfred and Joel Wallman (2006). *The crime drop in America*. Cambridge University Press.

Clear, Todd R, Elin Waring, and Kristen Scully (2005). "Communities and reentry: Concentrated reentry cycling". In: *Prisoner reentry and crime in America*, pp. 179–208.

Cook, Philip J and Kristin A Goss (1996). *A selective review of the social-contagion literature*. Tech. rep. Working paper, Sanford Institute of Policy Studies, Duke University.

Cook, Philip J, Robert MacCoun, et al. (2008). "The negative impacts of starting middle school in sixth grade". In: *Journal of Policy Analysis and Management* 27.1, pp. 104–121.

Durose, Matthew R, Alexia D Cooper, and Howard N Snyder (2014). "Recidivism of Prisoners Released in 30 States in 2005: Patterns from 2005 to 2010". In: *Washington, DC: Bureau of Justice Statistics* 28.

Fagan, Jeffrey (1998). "Adolescent violence: A view from the street". In: *Alternatives to Incarceration* 4.3, R25.

Fox, James Alan (1996). *Trends in juvenile violence: A report to the United States Attorney General on current and future rates of juvenile offending*. US Department of Justice, Bureau of Justice Statistics Washington, DC.

Glaeser, Edward L, Bruce I Sacerdote, and Jose A Scheinkman (2003). "The social multiplier". In: *Journal of the European Economic Association* 1.2-3, pp. 345–353.

Jones, Shayne, Donald R Lynam, and Alex R Piquero (2015). "Substance Use, Personality, and Inhibitors Testing Hirschi's Predictions About the Reconceptualization of Self-Control". In: *Crime & Delinquency* 61.4, pp. 538–558.

Kirk, David S (2009). "A natural experiment on residential change and recidivism: Lessons from Hurricane Katrina". In: *American Sociological Review* 74.3, pp. 484–505.

Kirk, David S and Andrew V Papachristos (2011). "Cultural Mechanisms and the Persistence of Neighborhood Violence1". In: *American Journal of Sociology* 116.4, pp. 1190–1233.

Knaap, Leontien M van der et al. (2012). "The predictive validity of criminogenic needs for male and female offenders: comparing the relative impact of needs in predicting recidivism." In: *Law and human behavior* 36.5, p. 413.

Kruttschnitt, Candace and Rosemary Gartner (2003). "Women's imprisonment". In: *Crime and Justice*, pp. 1–81.

Kubrin, Charis E and Eric Stewart (2006). "Predicting who reoffends: The neglected role of neighborhood context in recidivism studies". In: *Criminology* 44, pp. 171–204.

Langan, Patrick A and David J Levin (2002). "Recidivism of prisoners released in 1994". In: *Federal Sentencing Reporter* 15.1, pp. 58–65.

Lanza-Kaduce, Lonn, Karen F Parker, and Charles W Thomas (1999). "A comparative recidivism analysis of releasees from private and public prisons". In: *Crime & Delinquency* 45.1, pp. 28–47.

Lin, Jeffrey, Ryken Grattet, and Joan Petersilia (2010). ""BACK-END SENTENCING" AND REIMPRISONMENT: INDIVIDUAL, ORGANIZATIONAL, AND COMMUNITY

PREDICTORS OF PAROLE SANCTIONING DECISIONS". In: *Criminology* 48.3, pp. 759–795.

Ludwig, Jens and Thomas J Miles (2007). "The Silence of the Lambdas: Deterring Incapacitation Research". In: *Journal of Quantitative Criminology*.

Makarios, Matthew, Benjamin Steiner, and Lawrence F Travis (2010). "Examining the predictors of recidivism among men and women released from prison in Ohio". In: *Criminal Justice and Behavior*, p. 0093854810382876.

Maruna, Shadd (2001). "Making good: How ex-convicts reform and rebuild their lives". In: *American Psychological Association*.

Petersilia, Joan (2002). *Reforming probation and parole in the 21st century*. American Correctional Association Lanham, MD.

— (2006). *Understanding California Corrections*. California Policy Research Center Berkeley, CA.

Reisig, Michael D et al. (2007). "The Effect of Racial Inequality on Black Male Recidivism". In: *Justice Quarterly*.

Reiss Jr, Albert J (1988). "Co-offending and criminal careers". In: *Crime and justice*, pp. 117–170.

Rosenfeld, Barry and Charles Lewis (2005). "Assessing violence risk in stalking cases: a regression tree approach." In: *Law and human behavior* 29.3, p. 343.

Ryan, Caitlin et al. (2010). "Family acceptance in adolescence and the health of LGBT young adults". In: *Journal of Child and Adolescent Psychiatric Nursing* 23.4, pp. 205–213.

Sah, Raaj Kumar (1991). "Social osmosis and patterns of crime: A dynamic economic analysis". In: *Journal of political Economy* 99.6.

Sampson, Robert J, Stephen W Raudenbush, and Felton Earls (1997). "Neighborhoods and violent crime: A multilevel study of collective efficacy". In: *Science* 277.5328, pp. 918–924.

Sampson, Robert J, Christopher Winship, and Carly Knight (2013). "Translating causal claims". In: *Criminology & Public Policy* 12.4, pp. 587–616.

Sarnecki, Jerzy (2001). *Delinquent networks: Youth co-offending in Stockholm*. Cambridge University Press.

Schrag, Joel and Suzanne Scotchmer (1997). "The self-reinforcing nature of crime". In: *International Review of Law and Economics* 17.3, pp. 325–335.

Shaw, Clifford R and Henry D McKay (1942). "Juvenile delinquency and urban areas". In: *Chicago, Ill*.

Shinnar, Shlomo, Raymond J Maciewicz, and Robert J Shofer (1975). "A raphe projection to cat cerebellar cortex". In: *Brain Research* 97.1, pp. 139–143.

States, Pew Center on the (2011). "State of recidivism: The revolving door of America's prisons". In:

Warr, Mark (2002). *Companions in crime: The social aspects of criminal conduct*. Cambridge University Press.

Zimring, Franklin E (1981). "Kids, groups and crime: Some implications of a well-known secret". In: *The Journal of Criminal Law and Criminology (1973-)* 72.3, pp. 867–885.

Zimring, Franklin E (2011). *The City that Became Safe.*

Chapter 3

Estimating California Parole Hearing Outcomes: A Machine Learning Analysis[1]

3.1 Introduction

[The inmate] does not pose an unreasonable risk of danger to society or a threat to public safety and is therefore eligible for parole. - California Parole Hearing for Inmate 15342w34Z

Who gets to hear the above words? Every year, more than 2,000 of the roughly 30,000 inmates serving indeterminate life sentences in California's notoriously overcrowded prisons go before the Board of Parole Hearings (the Board) to make the case for their release. For decades, the process mattered little. Hearings were held, but the outcome was almost never in doubt. The inmate would be denied parole. In the rare case in which the Board granted release, the Governor would almost always reverse the decision. But in recent years there has been a dramatic shift. Now, more than 30% of the hearings result in a parole grant, and Governor Jerry Brown has affirmed over 80% of the release decisions. For the first time in decades, life with the possibility of parole actually contains the possibility of parole.

This paper tells the story of this recent dramatic change in California's parole administration. Additionally, using an original dataset generated from all suitability hearings conducted since 2011 (over 8,000 transcripts), it offers an empirical analysis of current system, evaluating the rationality, uniformity, and defensibility of the criteria and decision-making applied to each claim for release.

The paper proceeds as follows. Section 3.2 provides background on the California parole

[1]Parts of this chapter incorporate material developed in a research project with Ryan Copus, PhD candidate in the program in Jurisprudence & Social Policy.

system for so-called "lifers," inmates serving life sentences with the possibility of parole. This includes a discussion of the legal, political and administrative changes over the last decades. Section 3.3 offers a brief description of the current parole hearing process. Section 3.4 describes the paper's unique dataset constructed using computer text parsing of the universe of California Parole Board hearing transcripts. Section 3.5 examines inter and intra decision-maker inconsistency in the parole hearing process. This includes estimation of the extent to which key system actors – presiding commissioners, deputy commissioners, and psychologists – affect an inmates chances of parole. Additionally, the section analyzes *within* decision-maker variation driven by cognitive biases or extraneous factors that should have no bearing on the decisions. The results suggest there is some variation across decision-makers in the determination of release and risk, but neither "decision fatigue" nor the "gambler's fallacy," cognitive biases researchers have documented in other judicial decision-making contexts, appear to play a role in the California Parole Boards decision-making. Section 3.6 turns from inconsistency to an analysis of the actual parole decisions. This includes estimates of the importance of key variables on which the commissioners are (and are not) supposed to make the release determination: specifically, commitment offenses, risk score, hearing type (i.e. initial versus subsequent), whether the inmate used an interpreter, and the presence of victims at the hearing. These estimates are generated using Targeted Maximum Likelihood, developed at UC Berkeley's biostatistics department. Section 3.6 also includes an instrumental variables *causal* estimate of the effect of risk score on the decision to grant parole, showing risk score is indeed an extremely important determinate in the decision. Finally, 3.6 moves to an analysis of the actual content of the hearing, testing relationships between inmate speech and the Boards decision. Section 3.7 turns from analyzing the Board's decisions to predicting them. The preditive model, built using the "Super Learner" machine learning ensemble approach, performs well in terms of both its ability to correctly classify outcomes (79% accuracy) as well as provide accurate predicted probabilities, suggesting that, although the system contains a significant element of chance, it is in another sense quite predictable. Section 3.7 also offers a discussion of the potential uses of a predictive model as a tool to inform and improve the parole decision process either as a tool for system diagnostics and monitoring, or, more radically, as a tool to guide future decision-making. Section 3.8 concludes.

3.2 Recent History and Trends in California Parole

The system of indeterminate sentencing and release through parole reached a high point in California (and nationally) in the 1970s. At the time, more than 95% of prisoners in California were released by the discretionary decision of the parole board (Petersilia 2003).[2] In 1977, California overhauled its indeterminate sentencing system replacing it with a determinate system for almost all crimes; a life sentences with the possibility of parole remained

[2]More than 70 percent of inmates in the US were released by parole.

for only the most serious offenses.[3] This shift in sentencing reflected broader nationwide changes in criminological thinking and criminal justice policy-making. It was a moment of pessimism about the possibilities of rehabilitation, conservative concerns criminals were being coddled, and progressive worries the discretionary system of indeterminate release led to discrimination and inequality.

Under the current system, the determination of parole suitability for those serving life sentences with the possibility of parole is made by the Board of Parole Hearings ("the Board"), an executive branch agency within the California Department of Corrections and Rehabilitation (CDCR). For decades, indeterminate on the books was meaningless in practice- almost no one faced an actual possibility of parole. Throughout the mid-1980s until the early 2000s, on average, the Board granted parole in only 2% of scheduled hearings. In the rare instances in which the parole board determined an inmate suitable for parole, the Governor almost always reversed the decision. During Governor Gray Davis tenure, from 1999 to 2003, he vetoed 98% of the parole recommendations resulting in a total of only two paroles; between 2003 and 2011, Governor Arnold Schwarzenegger vetoed an average of 73% of the parole recommendations that came before him. This refusal to grant parole contributed to the tripling of the lifer population in Californias prisons since the late 1980s. In the late 1980s, an inmate sentenced to a life term with the possibility of parole for second-degree murder served an average of five years; two decades later, he or she would serve an average of 24 years (Mullane 2012). There are now roughly 30,000 inmates serving life sentences with the possibility of parole, over 20% of the population in prison.[4]

However, there has been a radical shift in the rate of parole release in recent years. As shown in Figure 3.1, the number of grants by the Board has been increasing almost steadily since the early 2000s, with a substantial rise since 2007. The rate of release by the Board has also increased significantly. Because hearings may be scheduled but then postponed or stipulated by the inmate, the best measure of the rate of release is the percentage of cases granted out of the number of hearings actually conducted. Data on this is available since 2007 and is presented in Figure 3.2. In 2007, 8% of hearings resulted in a grant by the Board; in 2014, the rate of release was 36%.[5]

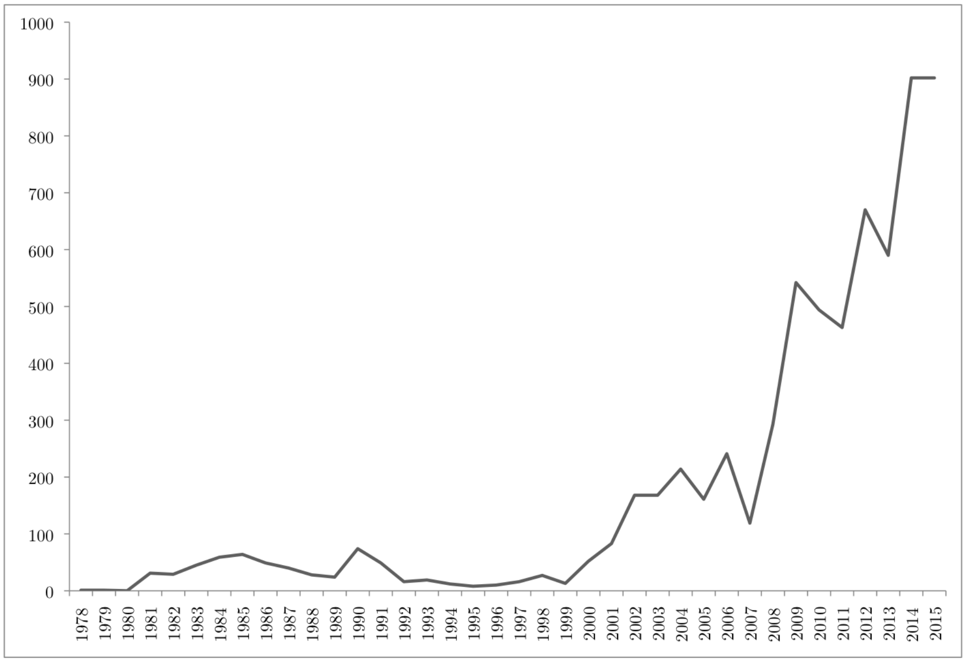
The recent change in the Board's rate of grant tells only part of the story. There has also been a substantial shift in the governor's approval of his appointed Board's release decisions. California is one of only four states – Louisiana, Maryland, and Oklahoma, the others – in which the governor has this power of reversal. This additional layer of administrative

[3]Over 90% of inmates serving life terms with the possibility of parole are in prison for first or second degree murder.

[4]California has the highest proportion of inmates serving life sentences with the possibility of parole than any other state in the nation ((Weisberg, Mukamal, and Segall 2011)).

[5]Data from 2007 - 2008 are from the Stanford Criminal Justice Center *Life in Limbo* Report; 2009-2014 are from this paper's parole hearing transcript dataset.

Figure 3.1: Number of Hearings Resulting in a Grant: 1978-2015



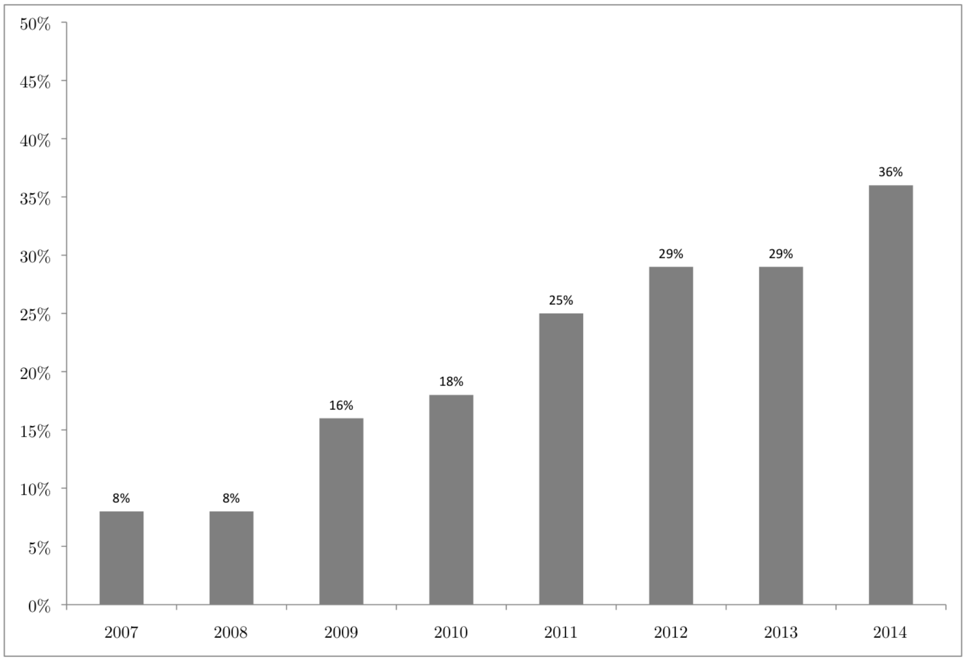
review was instituted in 1988 with the passage of proposition 89.[6]The current Governor, Jerry Brown, has departed from his predecessors practice of routine reversals, affirming over 80% of the Parole Boards release decisions since taking office in 2011. By contrast, Governor Davis, who notoriously vowed that no murderer would ever be set free under his watch, affirmed only 2% of the Board's grants during his term from 1999-2003. Governor Schwarzenegger, who served from 2003-2011, vetoed an average of 73% percent of the Board's parole release decisions.[7] Thus, Governor Brown, rather than compensating for the Board's increasingly leniency, has re-enforced and affirmed the trend in the Board's decisions. The Board and governor appear to work in tandem rather than a true two-stage process.

What has lead to the substantial change in the rate of parole release? And how do we explain the change in the governors' position towards his Board's decisions? At least in some part, these changes may be explained by recent changes in the law brought about by the California Supreme Court. In 2008, the Court held that the Board and the governor must reach the release decision based on an inmates "current dangerousness." Simply citing the heinousness of the inmate's commitment offense is an insufficient basis on which to deny parole (*In re Lawrence* 2008). This new standard, in demanding the Board and governor establish some rational nexus between the evidence and a conclusion the inmate still poses

[6]The Governor has the power to reverse Board decisions in all murder cases. For offenders convicted of a crime other than murder, the Governor can request an En Banc Board review a suitability determination.

[7]http://blogs.sacbee.com/capitolalertlatest/2013/02/jerry-brown-remained-deferential-to-state-parole-board-in-2012.html.

Figure 3.2: Rate of Parole Grant: 2007-2014



a criminal risk, may make blanket denials less likely. At the very least, even if the law does not actually demand a higher threshold, it may offer political cover. Indeed, Brown has explained his lower reversal rate by stating: "I'm bound to follow the law."

The increasing rate of release also comes in the shadow of the state budget crisis and the U.S. Supreme Court's 2011 *Brown v. Plata* decision, which mandated that California reduce its prison population. However, despite speculation by many that prison overcrowding has encouraged more leniency in parole grants, the Brown administration insists lifer releases are unrelated to any efforts to reduce the prison population numbers. On the other hand, Brown has recognized changes in public attitudes on crime. "There's still public safety (as a concern), but there's different dominating issues."

Whatever the causes of these changes in California parole, we are in a moment in which, for the first time in decades, the possibility of parole means a real possibility. With this possibility may come actual incentives that encourage the convicted to reform, the putative purpose of parole, of course. Engaging in productive in-prison programming, avoiding in-prison infractions, and narrating an understanding of past wrongs and future ambitions can have a substantive impact on the chances of release. In short, parole hearings now serve a purpose and represent a real process. In what follows, the paper describes the details of this process and then turns to a rigorous analysis and evaluation of the process as it currently operates in this new era.

3.3 The Parole Hearing Process

California lifer inmates becomes eligible for parole consideration a year before their minimum eligible parole date, a date set at the time of sentencing. As a general rule, the initial and all subsequent hearings are presided over by a commissioner and deputy commissioner. There are twelve full-time commissioners, each appointed by the Governor and confirmed by the Senate for staggered three-year terms with eligibility for reappointment. Deputy commissioners are civil servants who need only to have a "broad background in criminal justice." There are approximately 70 deputy commissioners across the state. Hearings are usually conducted at the prison where the inmate resides and usually take between two and five hours. Commissioners travel across the state to preside over hearings although are more frequently assigned to prisons near their residences. The identity of the commissioners assigned to hearings at a given prison in a given week is kept a confidential until the week's hearings begin.

Before every hearing, the Board receives the central file, which includes the inmate's behavioral record in prison, vocational and education certificates, and the results of the psychological evaluations assessing recidivism risk. The hearing itself generally proceeds in three parts: first with a discussion of the commitment offense and the inmate's pre-conviction behavior and circumstances; then a consideration of post-conviction factors including prison behavior, programs and the risk assessment score; and finally, a review of post-release parole plans and, if applicable, any statements of support for or against the inmates release.

As the California Supreme Court stated in the 2008 *In re Lawrence* decision "[T]he paramount consideration for both the Board and the Governor under the governing statutes is whether the inmate currently poses a threat to public safety." Prior to the 2008 decision, the Board, rarely granting parole, would often cite the incarcerating offense as the sole justification for the denial. The Board may no longer make decisions based on mere retributive impulses; the central question before the Board is whether the inmate poses a risk of future violence and recidivism.

In making this determination the Board considers a host of factors, perhaps most importantly the psychological risk assessment score. Until 2013, psychologists from the Board of Parole Hearings' Forensic Assessment Division (FAD) generated a risk score using a combination of instruments, known as the HCR-20, LS/CMI, and PCL-R and expressed that score in terms of one of five risk levels: low, low/moderate, moderate, moderate/high, and high. Since 2014, the Board has revised its evaluation procedures slightly by ceasing to use the LS/CMI and expressing the risk rating in terms of one of three levels: low, moderate and high.[8] (LSA, Vol. 5-4, April 2014). The psychologist's evaluation may incorporate

[8] Our data mostly does not reflect the shift from a five-level score to a three-level score. It will be some time before the change will manifest itself since most inmates will still be assessed in the hearing based on the risk scores from previous years.

consideration of the commitment offense, historic risk factors, institutional programming, and the inmate's past and present mental state.[9]

In addition to the risk score, the Board may consider factors including whether the inmate has a violent criminal history, exhibits signs of remorse, has plans for the future, has been engaged in institutional activities, vocational and educational certificates, participation in self-help groups such as a Alcoholics Anonymous or Narcotics Anonymous, and the extent of his or her misconduct violations in prison (e.g. infractions for fights, use of drugs, or possession of a cell phone). The Board also considers any letters of support or opposition to the inmates release and testimony from victims or victims kin.

If an inmate is found unsuitable for parole, the law requires that a subsequent hearing be set three, five, seven, ten or fifteen years in the future. At each subsequent hearing the Board reviews transcripts from previous hearings along with an updated record. Despite the fact that fifteen years is the default by law, few subsequent hearings are set for fifteen years: in more than 90% of cases in our dataset the subsequent hearing is set for three years from the time of denial. Under Marsys Law, the Board automatically reviews and may advance a three-year denial one year after the denial was issued. At the same time, an inmate may also request an advanced date regardless of the denial period. If the Board determines there has been a change in circumstances or new information and there exists a reasonable likelihood that consideration of public and victims safety does not require the additional incarceration, a hearing date will be advanced. (BPH; California Penal Code section 3041.5(b)(3)).

If the commissioners find the inmate suitable for parole, the decision is subject to review by the full Board. This rarely happens in practice. Absent action by the full Board, the grant of parole becomes final 120 days after the hearing and then goes to the Governor for his review. Again, in California, the Governor has the unusual power to reverse the decision of the parole board (if the commitment offense was murder).

A parole candidate scheduled to go before the Board may seek to waive, stipulate or postpone the hearing. Waivers may be requested for anywhere between one and five years. A request for a short-term delay (postponement) for exigent circumstances such as emergencies, illness, or incomplete files may also be made. Both waivers and postponements are granted as a matter of course if made 45 days before the scheduled hearing, but there are limits as to the number of waivers and postponements an inmate may request. Alternatively, an inmate may stipulate to unsuitability for a period of three, five, seven, ten or fifteen years in accordance with the current denial periods (California Penal Code, 3041.5(b)). A stipulation is similar in nature to plea bargains, and the Board may choose to deny a stipulation. In practice, however, the Board appears to grant the vast majority.

[9] An evaluation completed after 2009 is valid for five years. If an inmate's petition to advance is granted they are given a new subsequent risk assessment before the next scheduled hearing.

Finally, all inmates are entitled to a state-appointed attorney at the parole hearing if they have not retained an attorney. These panel attorneys are compensated $50 an hour with a cap at $400, which means they spend a maximum of eight hours per case. Advocates and private attorneys with whom we have spoken contend that, not unlike plea bargaining in criminal court, the panel attorneys often try to persuade parole candidates to stipulate to a denial rather than have to spend the time going through the hearing process.

3.4 The Data

The dataset was generated from transcripts, obtained through a public records request, of all parole suitability hearings conducted between 2009-2014.[10] The dataset was built using Python regular expressions to pull key information from each hearing transcript. Table 3.1 summarizes the dataset variables. These include the commitment crime, the psychological risk assessment score as well as the identity of the evaluating psychologist, the minimum eligible parole date, the inmate's lawyer, the district attorney if present at the hearing, the number of victims present at the hearing, whether or not an interpreter was present at the hearing, the results of any previous suitability hearings, the inmate's date of entry into prison, and information concerning how many times the inmate has appeared before the Board, and the inmate's prison. The noise variables extracted for the analysis of inconsistency are presiding and deputy commissioners, the date and time of the hearing, and the results of the immediately preceding hearings.

Notably, there have not been substantial changes in the observable characteristics of inmates going before the Board. The distribution of high and low risk inmates has been essentially constant, as has the type of commitment offense, the rate at which victims appear, and the frequency of interpreter presence at hearings. Thus, the recent increased leniency of the Board described in the preceding section does not appear to be an artifact of differences in the nature of the cases or inmates appearing before the Board.

3.5 Inconsistency in the Parole System

"Justice," the trope goes, "is what the judge ate for breakfast." The problems of inconsistency in judicial decision making have been documented in a number of contexts. Recent research indicates, for example, that the outcome of a football game (D. L. Chen and Spamann 2014), the results of the immediately preceding case (Daniel L. Chen, Moskowitz,

[10]2009 is the first year in which the universe of transcripts are available electronically. Although the available transcripts date back to 2009, the empirical analyses in the paper- estimates of inconsistency, variable importance, and the predictive model of decisions are generating using data from 2011-2014 because of the stark difference in parole board practice since Governor Brown took office. The only exception is that for purposes of constructing the JBM (but not evaluating) we make use of all years.

Table 3.1: Parole Suitability Hearings Data 2011-2013

Variable Name	Brief Description	Further Details
Grant	1: Parole granted 0: Parole denied	1: 28% 0: 72%
Risk	Categorical variable indicating inmate's psychological risk assessment for violent recidivism.	High: 7.4% High moderate: 6.6% Moderate: 28% Low Moderate: 16.7% Low: 32.4% Missing: 10%
VictimD	1: Victim testified 0: No victim present	1: 14.6% 0: 85.4%
Presiding	Categorical variable indicating which of 25 Commissioners presided over the hearing.	
Deputy	Categorical variable indicating which of 50 Deputy Commissioners attended.	
InterpPres	1: Interpreter present 0: Interpreter not present	1: 10.4% 0: 89.6%
Letter	Categorical variable indicating the classification letter associated with inmate. Proxy for time in prison.	
DA	Categorical variable indicating which of 37 district attorneys attended the hearing.	
Hearing	1: Initial hearing 2: Subsequent hearing	1: 16.8% 0: 83.2%
Prison	Categorical variable indicating which of the 27 prisons hosted the hearing.	
Attorney	Categorical variable indicating which of 86 attorneys represented the inmate.	
ResultLag1	Categorical variable indicating the result of the inmate's previous hearing.	Granted Denied Stipulated Waived Postponed Missing
YearsLag1	Categorical variable indicating number of years parole was denied for an inmate's last hearing. (Note: Inmates for whom this is their first hearing will not have a value for this variable)	0: 276 3: 2,067 5: 132 More than 5: 150 Missing: 3,493
Month	Categorical variable indicating month hearing was held	December: 406 July: 480 January: 516 August: 496 February: 509 November: 428 March: 621 October: 552 April: 440 September: 484 May: 495 Missing: 203 June: 516
Year	Categorical variable indicating year hearing was held	2010: 3,396 2011: 1,841 2012: 2,287 2013: 2,018 2014 :2,364
Murder	1: Offense included "Murder" 0: Did not	1: 87.4% 0: 12.6%
First	1: Offense included "First" (i.e. first degree murder) 0: Did not	1: 36.5% 0: 63.5%
Second	1: Offense included "Second" 0: Did not	1: 49% 0: 51%
Attempted	1: Offense included "Attempted" 0: Did not	1: 7.3% 0: 92.7%
Child	1: Offense included "Child" 0: Did not	1: 2% 0: 98%
Sex	1: Offense included "Sex" 0: Did not	1: 1.5% 0: 98.5%
Robbery	1: Offense included "Robbery" 0: Did not	1: 1% 0: 99%
Rape	1: Offense included "Rape" 0: Did not	1: 6.3% 0: 73.7%
Mayhem	1: Offense included "Mayhem" 0: Did not	1: 0.7% 0: 99.3%
ParoleElig	Continuous Variable: Years since inmate's minimum eligible parole date.	Ranges between 0 years - 42 years

and Shue 2014), and the time of day (Danziger, Levav, and Avnaim-Pesso 2011) can substantially affect legal decisions. Also startling are the wide between-judge disparities found in domains including immigration asylum (Ramji-Nogales, Schoenholtz, and Schrag 2007; Joshua B. Fischman 2014), social security disability (Nakosteen and Zimmer 2014), and criminal sentencing (Abrams, Bertrand, and Mullainathan 2012).

The following analyses offer estimates of the extent to which differences between major decision-makers – presiding commissioners, deputy commissioners, and FAD psychologists – affect parole outcomes. The results suggest a process that contains some real element of chance. Who an inmate happens to get as the presiding commissioner or deputy commissioner can alter whether they are released or remain in prison. On the other hand, there is no evidence of *intra* commissioner inconsistency, at least with respect to the time of the decision, which the highly publicized Israeli parole board study (Danziger, Levav, and Avnaim-Pesso 2011) found to be important, and "gambler's fallacy," a psychological effect documented in other judicial decision-making contexts. In sum, the findings, although they cannot speak to the inherent quality of the release decisions themselves or whether the current release rate of roughly a third is the "right", do suggest the parole board appears to be operating in a basically consistent and professional manner.

3.5.1 Inter Decision-Maker Inconsistency

The following analysis of inter decision-maker inconsistency provides two measures of decision-maker differences: average and extreme.[11] The average estimate provides an overall measure of how inconsistency affects outcomes. This estimate of average difference may be interpreted as the probability that a hearing would be decided differently by two randomly selected decision-makers due to one of them being systematically more likely to grant parole than the other. The estimate of extreme inconsistency is the difference in grant rates between the harshest and most lenient commissioner and deputy commissioner. This can be thought of as the percentage of cases that could come out differently if they were assigned to the most lenient decision-maker rather than the harshest.

Estimation Procedure

Estimates are made using year-prison fixed effects with dummy variables for actor identities. Commissioners are assigned to hearings based largely on geography (they are more likely to decide hearings at prisons near their residence), and different security level prisons will have inmates with different characteristics; cases in one year may be hearing very different types of cases than a commissioner hearing cases in another year. Within prison and year, however, commissioners should see the same type of inmates on average, and thus, at least

[11] The method for estimating average inconsistency was developed by Joshua Fischman (Joshua B Fischman 2014).

with an infinite sample, estimates should provide reasonable quantification of actors' relative impacts on the probability that an inmate will be granted parole.[12]

A second stage is needed in the estimation procedure to correct for finite sample bias and to properly estimate confidence intervals. In a finite sample estimates will be biased upwards because there will almost always be differences between decision-makers due to chance even if they would make the same decision in each case. For the measure of average difference in grant rates, we estimate and correct for finite sample bias via subsampling (Joshua B. Fischman 2014; Politis and Romano n.d.).[13] Measures of extreme differences in grant rates are especially susceptible to finite sample bias because we would expect the extremes to regress toward the mean with larger samples. Thus, taking a particularly conservative approach to the estimates of extreme differences, we permute outcomes within prison-year combinations to estimate bias under the null distribution that assumes no actual differences between decision-makers. For both the extreme and average measures of inconsistency, we also guard against finite sample bias by limiting our analysis to decision-makers with at least 100 observations.

Estimates of Inter Decision-Maker Differences

It is worth stressing that these estimates represent lower bounds for inconsistency in decision-making. Insofar as commissioners grant parole differently in different types of cases, the grant rate differentials may understate the degree of inconsistency. For example, one commissioner may decide to grant in 20% of hearings and another in 30% of hearings. While we know that the commissioners decide at least 10% of cases differently, the number could be considerably higher. Imagine, for example, that the first commissioner's grants are all first-degree murder cases while the second commissioners grants are all second-degree murder cases and she denies parole in all first murder cases. The inconsistency between the two commissioners would actually be 30%, but our estimate would only be 10%.

Nonetheless, even the lower bound estimates of inconsistency in decision-making are illuminating. As the estimates presented in table 3.2 show, at least 11% of cases could be decided differently based simply on the presiding commissioner that happens to be assigned to an inmate's case and that at least 15% of cases could be decided differently depending only on the deputy commissioner assigned to hear the case. An evaluating psychologist can

[12] We conduct a randomization check and find support for the assumption that decision-makers are randomly assigned to inmates once prison and year are controlled for. We use the presence of a district attorney at the hearing and whether a hearing is an initial hearing or subsequent as test outcomes. If cases are randomly assigned, district attorney attendance and hearing number should not be related to the decision-maker. We find no evidence of such a relationship.

[13] Our estimates of finite sample bias are slightly responsive to the percentage of the dataset we subsample. For Presiding Commissioner inconsistency, as the percentage subsampled increases from 25% to 55%, our estimate of bias decreases by about .5%. For Deputy Commissioner inconsistency, the estimate of bias decreases by almost 1%. We report bias corrected estimates derived from a subsampling percentage of 40%.

affect an inmates chances of parole by at least 6% despite the fact that they are not involved in the actual parole decision. [14] At the same time, the average differences in parole rates are, as expected, substantially smaller and relatively small: at least 6% of cases would be decided differently if they were randomly re-assigned to a different Presiding Commissioner and at least 7% of cases would be decided differently if assigned to a different Deputy Commissioner.

Table 3.2: Inconsistency in Decision Making: Differences in Grant Rate

Decision-Maker	Average Difference	Extreme Difference
Presiding Commissioners	6.1% (5.0% - 7.2%)	11.3% (7.8% - 14.8%)
Psychologists	3.3% (1.2% - 5.4%)	5.6% (3.3% - 9.7%)
Deputy Commissioners	7.0% (5.7% - 8.3%)	14.6% (10.3% - 18.7%)

Given a substantial literature devoted to the study of how judicial decisions differ by judicial ideology, one might surmise commissioner characteristics could account for the differences in the grant rate. One might expect, for example, that commissioners appointed by Governor Schwarzenegger, a governor known for being "tough on crime," would be less likely to grant parole than commissioners appointed by Governor Brown. But as table 3.3 shows, despite the well-powered dataset, there is surprisingly little difference in grant rates between commissioners with different backgrounds and characteristics: appointing governor, gender, prior employment with the CDCR, military experience, nor prior service as parole panel attorney appear to matter in the likelihood the hearing will result in a grant.

Table 3.3: Associations Between Commissioner Characteristics and Grant Rate

Commissioner Characteristic	Effect Estimate (95% CI)	p-value
Former Panel Attorney	-0.8% (-2.9% - 1.3%)	0.464
Former CDCR Employee	1.8% (-0.4% 4%)	0.108
Former Deputy Commissioner	1.7% (-0.5% 3.8%)	0.124
Military Experience	-0.4% (-3.1% 2.3%)	0.79
Male	0.1% (-2.1% 2.4%)	0.908
Schwarzenegger Appointee	0.2% (-1.9% 2.4%)	0.83
Reappointed	0.2% (-1.9% 2.3%)	0.825

[14] As proceeding sections discuss further, an inmate's risk score is an important determinant of the likelihood they will be released; consistent with In re Lawrence, risk is the primary consideration for the Board. The accuracy of the current instruments used by the Board is one question; a second is whether the tools are applied consistently. If two clinicians administer a tool to an inmate, the score should not reflect the idiosyncratic tendencies of a given clinician.

3.5.2 Intra-Commissioner Inconsistency

A growing body of work in the judicial decision-making literature has been documented intra-judge variation driven by extraneous factors. For example, outcome of the local NFL football team game (D. L. Chen and Spamann 2014), the judge's previous set of decisions in the preceding hours or days (Daniel L. Chen, Moskowitz, and Shue 2014) have been shown to impact decisions. Most relevant to this paper's study of California parole, a highly publicized study of the parole decisions of Israeli judges found the time of day in which the decisions were made in relation to breaks and meals had a significant impact on the parole decision (Danziger, Levav, and Avnaim-Pesso 2011): the rate dropped from roughly 65% to almost zero as a session neared its end and then rose again to 65% after a session break.

The California Parole Board does not take such clear and scheduled recesses. But it is possible to capture and assess the effect of the time of day on release outcomes. Table 3.4 shows the differences in grants for each start hour relative to 8:00 a.m., the earliest time in which hearings are scheduled. Start times are rounded to the nearest hour. The model includes prison-commissioner fixed effects. That is, for each presiding commissioner within a given prison, the model measures differences in release decisions that depend on the time in which the hearing is conducted. The results suggest no such significant differences in the outcome regardless of the time of day the hearing begins. One possible exception is late-starting hearings. There is some evidence that hearings starting between 4:00 pm and 6:00 pm are more likely to end with a grant, but the sample sizes at those times are too small to allow for robust conclusions.

Table 3.4: Effect of Hearing Start Time on Grant Rate

Start Time	Grant Rate (relative to 8:00 a.m.)
9:00 AM	-0.029 (0.018)
10:00 AM	0.005 (0.022)
11:00 AM	-0.010 (0.018)
12:00 PM	-0.010 (0.010)
1:00 PM	0.007 (0.017)
2:00 PM	-0.002 (0.021)
3:00 PM	0.070* (0.028)
4:00 PM	0.062 (0.043)
5:00 PM	0.102 (0.088)
6:00 PM	-0.029 (0.018)

The "gambler's fallacy" represents a second cognitive bias that, although it hasn't been documented or tested for in the parole context, has been been documented in the decisions of asylum judges. The gambler's fallacy is the mistaken idea that the chances of something occurring increases or decreases depending on recent occurrences, despite the fact that the probability of the occurrence is fixed. In the parole context, this would be the tendency to respond to streaks of grants (or denies) by becoming more likely to deny (or grant) in the next hearing, Chen, Moscowitz, and Shue document such negative autocorrelation in the decisions made by asylum court judges and find growing effects as the length of a streak of decisions in one direction or another increases (Daniel L. Chen, Moskowitz, and Shue 2014). However, there is no evidence for such effects in the California parole hearing process. Running a model of lagged release decisions regressed on the present hearing outcome does generate statistically significant lagged coefficients, prima facie evidence that a streak of previous grants (or denies) increases the probability that a commissioner will grant (or deny) the next inmate's request for parole. For every sequential grant, commissioners are about 3% less likely to grant parole to the next inmate. But recent work shows that standard techniques for analyzing the gambler's fallacy are subject to finite sample bias (Miller, Sanjurjo, et al. 2015). And indeed, further analysis reveals the result is not driven by commissioner psychology but is instead an artifact of finite sample bias. Permuting hearing outcomes, thereby randomly reassigning a grant or deny to each hearing, and repeatedly running the same lagged models on the permuted data generates estimates of negative correlation that are essentially equivalent to the initial estimate. In summary, there is no evidence that the gamblers fallacy affects parole decisions.

Under the administration of Jennifer Shaffer, the Parole Board's executive officer appointed by Brown in 2011, the Board has in recent years made efforts towards increasing professionalization. Commissioners are sent to national judicial college for training, and efforts have been made to reduce workloads and day's worked to guard against decision fatigue and to allow for more deliberate decision making[15]. The analyses presented above offers some support that these professionalization efforts may be having the claimed and desired effect.

3.6 What Matters in the Parole Decision

The paper now turns from estimating system inconsistency to assessing the parole decisions. This analysis includes estimates of specific variables associated with the Boards decision to grant or deny parole, a causal estimate of the effect of risk score on the likelihood of grant, and textual analysis of inmate speech at the parole hearing.

3.6.1 Variable Importance Measures

The variables considered in the following analysis include the inmate's commitment offenses, risk score, hearing type (i.e. initial versus subsequent), whether the inmate used an interpreter, and the presence of victims at the hearing. It must be noted, even after adjusting for covariates, there are too many possible unmeasured confounders – variables that may affect both the variable of interest and the outcome - to allow for these estimates to be interpreted

[15]personal communication with Howard Mosely and Jennifer Shaffer, December 2014

causally. At the same time, the measures offer a means of noting important associations that are not easily explained away and thereby raising research questions. For example, why is the presence of an interpreter strongly associated with release even after adjusting for an assortment of other variables? Does speaking through an interpreter actually result in a sharp drop in ones chances of getting parole, or is it instead simply associated with other variables we dont currently have access to that reduce parole chances such as gang membership and race?

Estimation Method

Estimates are generated using Targeted Maximum Likelihood (TMLE). TMLE was developed in the field of Biostatistics, an area in which variable importance is crucial, but randomization or quasi-experimental designs are often not possible. Simple parametric regressions are well-known to be highly sensitive to model misspecification (see e.g. (Ho et al. 2007)). TMLE offers a double robust method, like weighted regression for example, that will be consistent if either the expectation of outcome given treatment and covariates or the conditional probability of treatment assignment given covariates is correctly specified ((Van der Laan and Rose 2011)). TMLE has been shown to less biased and more efficient than other double robust methods and particularly so when estimated with machine-learning tools. For a complete discussion of TMLE we direct the reader to other texts (e.g. (Laan, Polley, and Hubbard 2007)). In brief, TMLE consists of two steps. For the first step, we use the machine learning ensemble approach "Super Learner," described in detail in section 3.7, to estimate the conditional mean release rate given "treatment"(the variable of interest) and covariates. [16] The initial, non-targeted fit of the conditional expectation function will provide an overly biased estimate of a targeted variable's effect. For example, the machine learning algorithm might not use the treatment variable in the initial fit because another variable is highly correlated with both the outcome and treatment, and so including the treatment variable would increase variance without sufficient reduction in bias. The second stage adjusts the initial estimate to take on more variance associated with the treatment of interest, since the entire point is to estimate its effect on release. This second step targets the parameter of interest by exploiting information from the treatment assignment mechanism, i.e., the probability of treatment given covariates. To estimate the probability of treatment, we again use Super Learner, which allows us to estimate the probability of treatment with a nonparametric model.We use the TMLE package in R. ((Knaap et al. 2012)).

Variable Importance Results

Table 3.5 presents the TMLE estimates as well as the simple difference in mean release rate between groups.

[16]We use GLMs, a Bayes GLM, and elastic net models, Random Forests, several screening and stepwise algorithms in the Super Learner model.

Table 3.5: Likelihood of Grant Variable Importance Measures: 2011-2014

	Bivariate Regression	TMLE Regression
Murder	0.045 (0.015)	0.004 (0.014)
Robbery	-0.001 (0.02)	0.031 (0.019)
Kidnap	-0.033 (0.019)	-0.004 (0.019)
Attempted	-0.012 (0.018)	0.013 (0.018)
Sex Crime	-0.186 (0.028)	-0.125 (0.02)
Interpreter	-0.032 (0.016)	-0.066 (0.015)
Initial Hearing	-0.237 (0.014)	-0.195 (0.012)
Low-Moderate Risk (Relative to Low)	-0.242 (0.013)	-0.243 (0.016)
Moderate Risk (Relative to Low)	-0.42 (0.012)	-0.42 (0.015)
High-Moderate (Relative to low)	-0.534 (0.018)	-0.535 (0.013)
High Risk (Relative to Low)	-0.552 (0.02)	-0.552 (0.012)
0 vs 1 Victim	-0.015 (0.04)	-0.001 (0.044)
0 vs 2 Victims	-0.008 (0.03)	-0.02 (0.033)
0 vs 3 Victims	-0.058 (0.027)	-0.057 (0.028)
0 vs 4 Victims	-0.073 (0.031)	-0.06 (0.031)
0 vs 5 Victims	-0.085 (0.039)	-0.073 (0.038)
0 vs More than 5 Victims	-0.139 (0.033)	-0.141 (0.027)

Victim Presence

The role victims play in the parole suitability hearing has been the subject of considerable debate since the passage of Marsys Law (Proposition 9) in 2008. Marsys law, among many things, gave victims and their next of kin expanded rights to receive notice and testify at suitability hearings. It was also under Marsys Law, ostensibly in an effort to relieve the hardship placed on victims of attending hearings, that the deferral lengths between hearings was extended to the current three to fifteen years period.

The Stanford Criminal Justice Center Report, the first and only report to date offering a empirical portrait of the California parole process, used a sample of data from 2007-2010 and found the overall grant rate when victims attended hearings was 5% as compared to 14% when victims did not attend. The estimates presented here look at the importance of victims ranging from zero in attendance to more than five. This analysis shows that victim attendance at the parole hearing is an important predictor of an inmates parole chances. While there is minimal difference when one or two victims are at a hearing as compared to zero, the chances of parole drop precipitously as more victims are in attendance: hearings with more than five victims result in a grant roughly 14% less often than hearings with no victims in attendance, even after adjusting for highly predictive variables (Weisberg, Mukamal, and Segall 2011).

Crime Type

In most cases, the grant rate does not appear to vary with the commitment offense. One clear exception, however, are commitment offenses that included a sex crime. The grant rate is an estimated 13% lower when the inmates commitment offense included a sex crime. This finding comports with evidence presented in the Stanford report (2011) and conventional wisdom among attorneys and advocates, who suggest the Board is particularly unlikely to release an inmate whose crime involved sexual violence, especially if the crime involved a child.

Hearing Type

Not surprisingly, the chances of release are substantially lower at an initial hearing as compared to a subsequent. After accounting for important covariates we estimate a 20% lower average grant rate for initial hearings as compared to subsequent. This substantial difference is likely explained by a number of factors, including, for example, experience presenting before the Board and understanding what they are looking for, more time engaging in positive in-prison activity, making post-prison plans, and simply getting older and thus presenting a lower criminal risk.

Interpreter

The estimate of the rate of release at hearings conducted through an interpreter is 7% lower than at hearings in which an interpreter was not present. Again, it cannot be concluded that speaking through an interpreter actually causes the Board to be less likely to grant parole. It may be that unmeasured factors, such as gang membership and race, are associated with having an interpreter and with lower chances of parole. Or perhaps the need for an interpreter represents a broader set of disadvantages faced by inmates who do not speak English and therefore have a harder time engaging in prison programming and planning for post-prison release.

Risk Score

The strongest predictor of the release outcome is the inmates risk score. The estimates presented in table 3.5 shows the difference in average grant rate for inmates with a low risk score rating relative to low-moderate, moderate, high-moderate or a high risk score. The bivariate and adjusted estimates are remarkably close and reveal a substantial difference in the rate of release as the risk severity increases. We estimate the difference in the grant rate between an inmate with a low risk score and an inmate with a low-moderate risk score is 24%; the difference in the rate of release between a low and a high risk inmate is 55% – effectively no inmate with a high risk score is granted parole (a total of 9 inmates, or 2% of those given a high risk score). The following sections offers a causal estimate of the effect of risk score on the likelihood of release using an Instrumental Variables approach. The different estimation methods produce remarkably similar results.

3.6.2 The Causal Effect of Risk Score on Parole Release

Currently, risk assessments are completed by one of the 46 psychologists in the Board of Parole Hearings Forensic Assessment Division (FAD). The FAD psychologists work exclusively on conducting these assessments for use in suitability hearings. Evaluations are conducted in-person using a combination of instruments – HCR-20, LS/CMI, and PCL-R – as well as "clinical judgment." The process of pairing inmates with psychologists is based solely on geography, thus, within a given prison and year, an inmates assignment to one of the 46 psychologists is essentially random. It is thus possible to use the systematic differences in psychologists penchants for assigning higher (or lower) risk ratings to instrument for risk measured as a cardinal variable from a score of 1 - 5, with 1 being "low risk" and 5 high. Table 3.6 presents the estimate of the average effect of moving down a risk score level on the likelihood of parole release. Notably, the causal IV estimate is slightly smaller and the confidence interval wider than a simple regression estimate, but the two estimates are remarkably similar: the average of moving up each risk assessment score category (i.e. from low to low-moderate) causes a 15% reduction grant chances.

Table 3.6: Effect of Risk Score on Grant Chances

	IV Estimate	Naive OLS Estimate
Risk (1-5)	-0.154*** (0.023)	-0.161*** (0.004)

3.6.3 Inmate Text Analysis

The following section moves beyond pre-hearing information to parse the spoken words of inmates during their parole suitability hearings to identify patterns of speech (i.e., word usage) that are predictive of parole. This represents an initial effort to capture some of the more human aspects of the parole process; aspects that may matter to the Boards decision-making but are not clearly captured in a risk checklist or the variable importance analysis. It is clear from speaking with former lifers and lifer support groups that they view much of the hearing preparation work as learning to express and narrate the trajectory of their life: to recognize past wrongs and the ways in which they have reformed. You have to show the Board that youre a mench, explained a former lifer at a Life Support Alliance workshop held for family and friends of current lifers trying to help their loved ones prepare for their suitability hearings.

This preliminary exploration involves a series of bivariate regressions of inmate spoken word indicators on the hearing outcome. Table 3.7 below presents the top 40 words spoken by an inmate at the suitability hearing that have the largest significant positive association with grant likelihood. Table 3.8 shows the top 40 words with the largest negative association. So, for example, if an inmate used the word yes at a hearing, as compared to never uttering the word yes, the average grant rate is 29% higher.

Many of the words that are most negatively associated with grant are negative conjunctions: wasn't, couldn't, shouldn't, havent, for example. A number of other negatively associated words express informality in other ways: dude, aint, yep, and oh for example. This comports with longstanding research on the power of language in legal decision-making. For example, Morrill and Facciolas experimental study found judges given identical case scenarios but for the speech style of the defendant where significantly more likely to find guilt in cases in which speech was powerless as compared to powerful (Morrill and Facciola 1992). The analysis also shows words that are likely not in and of themselves problematic but rather reflect activities that decrease the chances of release: tobacco or 115 a prison rule violation. Cellie is another such word. A reading of a handful of transcripts suggests that an inmate often refers to their cellie in the context of blaming the cellmate for particular rule violation or write-up.

A number of the words positively associated with grant are words connected to programming and training in prison and to post-release preparation and work. These words include externship, internship, refrigeration (an in-prison vocational training program), seminar, and mentor. But there are also a number of significant words that appear to have content in and of themselves and suggest the narration of reform is an important dimension in the parole consideration process. These words are related to ideas of redemption, spirituality, and self-reflection: sobriety, pastor, spirituality, esteem, empathize, and shame.

Table 3.7: Top 40 Words Positively Associated with Release

Word	coefficient	se	p-value
chrone	0.291	0.086	0.001
promptli	0.153	0.029	0.000
backup	0.145	0.029	0.000
network	0.135	0.021	0.000
disassoci	0.124	0.028	0.000
principl	0.123	0.019	0.000
extern	0.122	0.026	0.000
empathi	0.120	0.021	0.000
disappoint	0.117	0.021	0.000
refriger	0.114	0.027	0.000
resum	0.112	0.028	0.000
confid	0.111	0.020	0.000
recoveri	0.110	0.014	0.000
governor	0.109	0.028	0.000
resent	0.106	0.016	0.000
sponsor	0.102	0.012	0.000
dysfunct	0.102	0.025	0.000
cga	0.101	0.020	0.000
model	0.096	0.021	0.000
walden	0.096	0.029	0.001
restor	0.095	0.022	0.000
satisfi	0.094	0.028	0.001
technolog	0.094	0.023	0.000
stressor	0.093	0.028	0.001
facilit	0.092	0.015	0.000
specialist	0.090	0.028	0.001
numb	0.090	0.025	0.000
ministri	0.089	0.025	0.000
sobrieti	0.089	0.018	0.000
grandson	0.088	0.029	0.002
root	0.087	0.027	0.001
secondari	0.086	0.028	0.002
paul	0.086	0.028	0.002
pastor	0.086	0.020	0.000
ident	0.084	0.027	0.002
intern	0.082	0.017	0.000
spiritu	0.081	0.015	0.000
tabernacl	0.081	0.026	0.002
mindset	0.081	0.021	0.000
isol	0.080	0.026	0.002

Table 3.8: Top 40 Words Negatively Associated with Release

name	coefficient	se	PValue
theyv	-0.196	0.081	0.015
commission	-0.182	0.049	0.000
wouldnt	-0.171	0.048	0.000
havent	-0.165	0.051	0.001
doesnt	-0.156	0.049	0.002
theyr	-0.148	0.049	0.002
ive	-0.143	0.041	0.000
couldnt	-0.142	0.044	0.001
maam	-0.134	0.062	0.030
cant	-0.133	0.046	0.004
wasnt	-0.130	0.037	0.000
dont	-0.130	0.027	0.000
gonna	-0.128	0.040	0.001
presid	-0.123	0.031	0.000
didnt	-0.111	0.032	0.000
wa	-0.107	0.052	0.038
explan	-0.102	0.024	0.000
like	-0.096	0.035	0.006
go	-0.093	0.042	0.026
anytim	-0.089	0.029	0.003
know	-0.087	0.041	0.035
farm	-0.085	0.026	0.001
interpret	-0.084	0.016	0.000
im	-0.081	0.034	0.016
underneath	-0.081	0.027	0.003
said	-0.080	0.021	0.000
time	-0.079	0.036	0.027
disput	-0.079	0.025	0.002
salina	-0.079	0.026	0.002
hmm	-0.077	0.021	0.000
one	-0.075	0.038	0.049
verifi	-0.075	0.029	0.010
tobacco	-0.072	0.028	0.011
error	-0.072	0.023	0.002
supposedli	-0.072	0.024	0.003
voc	-0.071	0.029	0.014
tripl	-0.070	0.025	0.005
stipul	-0.070	0.028	0.013
sergeant	-0.069	0.017	0.000
upstair	-0.068	0.029	0.019

3.7 Predicting the Board's Decisions

The paper now turns from analyzing parole decisions to predicting them, and argues for the potential of decision-predictive algorithms to aide and improve release determinations.

3.7.1 Building the Predictive Model

There is increasing recognition of the advantages of Machine Learning over the traditional regression approach when the task at hand is that of prediction. Machine Learning uses the data itself to decide how to make the bias-variance tradeoff and allows for search over a rich set of variables and functional forms thereby offering a means to capture more signal. The predictive model presented belwo was built using "Super Learner," an ensemble machine-learning method developed in University of California Berkeley's Biostatistics department (Laan, Polley, and Hubbard 2007). Super Learner takes as input any number of user-supplied non-parametric and parametric models (e.g., a simple linear regression, random forest, lasso, etc) and combines those models' predictions to generate "super" predictions. Specifically, the Super Learner proceeds in two steps: (1), validation-set predictions are generated for each candidate model; (2), the true outcome is regressed on the candidate models' predictions to assign each model's predictions a weight. Details on the Super Learner method generally and the specific implementation used in this paper are offered in the appendix.

Evaluating the Model

The model performs well in terms of both classification and calibration. It correctly predicts validation-set 2011-2014 suitability hearing decisions with 79% accuracy.[17] The Area Under the Receiver Operator Curve (the "AUC"), a measure of model performance that goes beyond classification accuracy, shows the model also offers valuable information with respect to the *probability* that an inmate is granted parole. The AUC provides the probability that a randomly selected case with a positive result (a hearing that ended in a grant) would have a higher predicted probability than a randomly selected case with a negative result (a hearing that ended in a denial). A model with an AUC score of 1 can perfectly discriminate between grants and denials; a model that is no better than random would score a 0.5. The model has a cross-validated AUC of .80. This means there is an 80% probability that a randomly selected hearing that results in a grant was given a higher predicted probability than a randomly selected hearing that resulted in a denial.

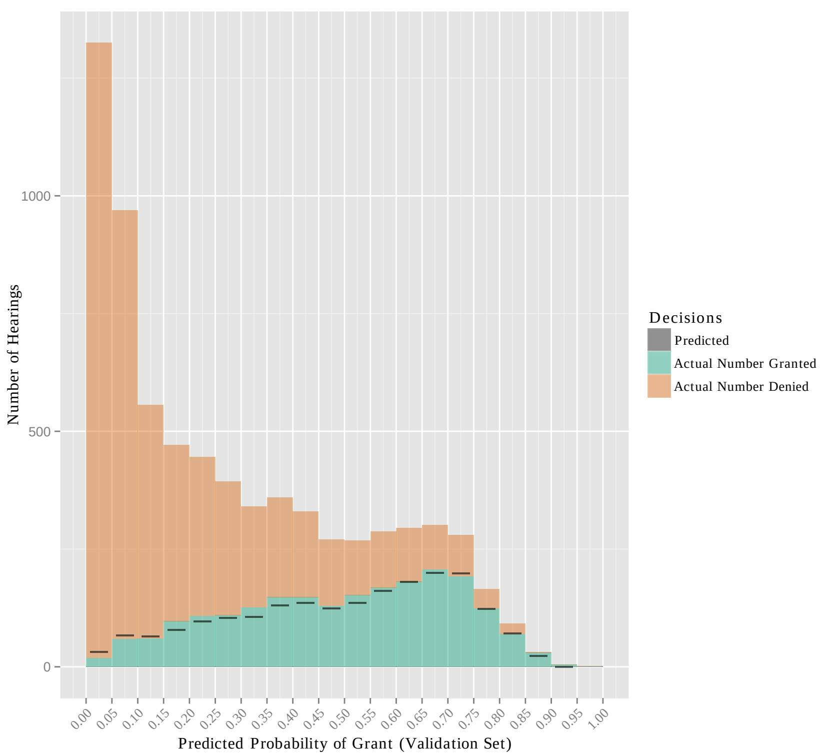
Figure 3.3 offers a graphic representation of the model's predictions.[18] It shows the

[17]Correct classification rates have been the primary metric by which recent high-profile efforts to predict legal decisions, the Supreme Court's in particular, have been assessed (Ruger et al. 2004; Katz, Bommarito, and Blackman 2014).

[18]For the predictive model to be useful in either system diagnostics or as a decision-making tool, it must only include variables available pre-hearing and excludes noise variables - those variables that should be unrelated to the merits of the case, or at least unrelated to variables that are plausibly related to the merits

actual number of hearings that resulted in a grant or denial against the model's predicted probabilities. The graph reveals the wide distribution of accurate predicted probabilities provided by the model. It also shows the particularly robust performance of the model in identifying hearings that have a very low probability of resulting in a grant. Note that an uninformative model would have simply one bar over the unconditional mean; a perfectly predictive model would have one red bar at zero and one green bar at one.

Figure 3.3: Validation Set Parole Predictions: 2011 - 2014

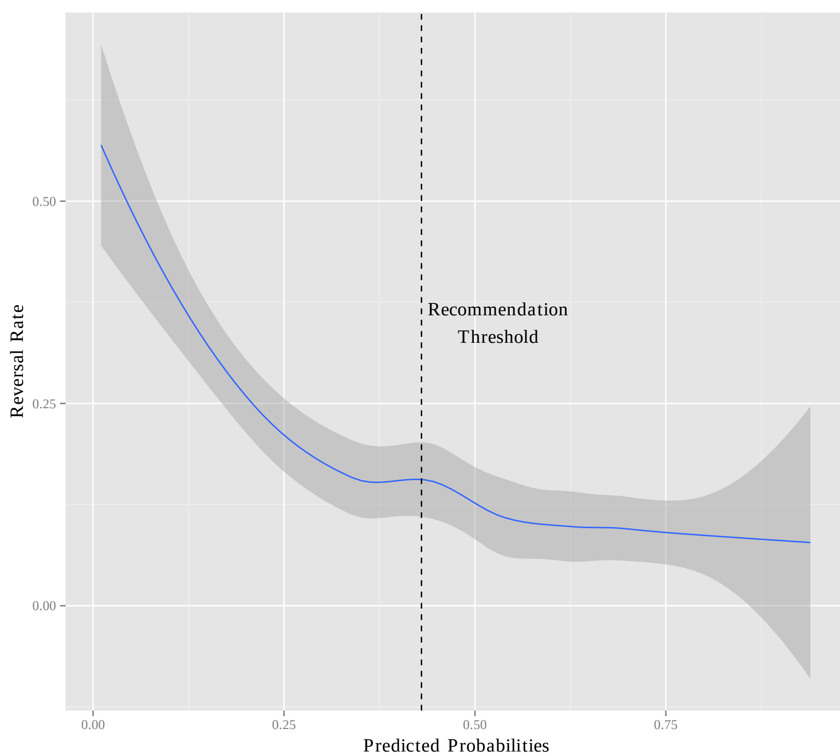


Besides these metrics and graphics showing the algorithms predictive capacity, there is also some external evidence or "correspondence" criteria validating the quality of the predicted probabilities. Data on future offending would be an obvious means of assessing whether the predicted probabilities generated by the model actually correspond with criminal risk – i.e. if low predicted probabilities of release generated from the model corresponded

of the case. Thus, the predictive model presented here uses only pre-hearing variables. Information about the verbal exchanges that occur during the hearing is not included in the model. While text analysis of inmate speech could only increase predictive power of the model, such speech may partly reflect the commissioners' idiosyncrasies or inclinations to grant or deny parole. For example, an inmate who said "no" repeatedly might be facing questions from a tough commissioner or a commissioner who is otherwise in the mood to deny parole to the inmate. Using text analysis to help inform predictions might therefore give commissioner idiosyncrasies – arbitrary elements of the system that predictive model is designed to eliminate – an improper role in the model.

with re-offending likelihood. Unfortunately, we do not yet have access to this data. But Governor reversals are available, and this gives some external confirmation the model is correctly identifying high and low probability of release cases. Or at least it suggests Governor Brown tends to agree with the model predictions. Figure 3.4 shows the relationship between the validation set predicted probabilities and the Governor's reversal rate.[19] If the model recommended against parole, the Governor was two and a half times more likely to reverse the Board's decision. There is a high probability of governor reversal if an inmate was paroled when the model predicted a low chance of parole offers some external validation the model is

Figure 3.4: Relationship Between Model Predictions and Governor Reversal Rate (Loess Smoothed)



What does the governor reversal data offer with respect to our understanding of the CA parole system and the relationship between the Board and the governor, issues raised in section 3.2. The data may be interpreted in different ways. It could be seen as some evidence of remnants of retribution and political posturing in the parole process. The Board

[19]As a proxy for governor reversals, we denote a case as reversed if an inmate's parole is granted but the inmate reappears in another hearing at a later date. In order to avoid problems of potentially biased missingness, the analysis is restricted to 2011 and 2012 hearings so that there is sufficient passage of time for inmates to show up in the dataset again if their parole is reversed.

is prohibited by law from denying parole based solely on the commitment offense. At the same time, we know cases involving sex crimes are, for example, are less likely to be granted by the Board and are likewise cases that are notoriously reversed by the governor. The governors tendency to reverse such cases might represent evidence that the governor is bringing in the element of retribution and outrage that the courts have tried to prohibit. On the other hand, if we think the governors reversals are justifiable, the decisions might not be seen as purely political but rather understood as "quality assurance." The governor may be denying parole to the higher risk inmates that "slip through" the parole process.

3.7.2 The Uses of Decision Predictive Algorithms

This paper has show it's possible to predict California parole decisions with a relatively high level of accuracy using just pre-hearing variables that could be pulled from the hearing transcripts.[20] Now, what are the uses of such a tool? A decision-predictive model could be used in several ways to improve the parole process. One such use is as a tool to vet the quality of the parole decision process. Comparing model predictions to individual commissioner decisions offers a means to identify commissioners who frequently depart from the standard or norm and a means of monitoring commissioner decisions. Commissioners might not see the actual predicted probabilities, but it could serve as a means of easy administrative review. A second and more novel use is to employ a decision-predictive algorithm as an aide in the actual decision-making process itself. This might take many forms, but most straightforwardly, model predictions could be given to commissioners as a suggestive anchor. Commissioner decisions would remain discretionary, but more closely tethered to algorithm recommendations, which, as the proceeding section will argue, could help to generate better and more consistent release decisions. The following discussion is devoted to this second more novel application.

Judgmental Bootstrapping

The idea of using a statistical model of decisions to help individuals make decisions is not new. So-called "judgmental bootstrapping" was conceived in the early 1900s in relation to predicting corn crop quality and developed in a variety of fields in the 1960s (Dawes 1971) and the term itself was coined by the American psychologist Robyn Dawes in a review of the research in the late 1970s.[21] The central insight is that the fitted values from a regression model of expert judgments, by eliminating the uninformative variance or noise, will often be more highly correlated with the outcome variable being predicted than are the actual expert judgments themselves. Scholars in disciplines including psychology, education, marketing, and finance have applied judgmental bootstrapping to contexts ranging from school admissions decisions (Dawes 1971), predicting loan defaults (Abdel-Khalik and El-Sheshai

[20]It is likely the model would perform even better with access to the full set of variables to which the Board administration has access.

[21]Judgmental Bootstrapping is also sometimes referred to as "policy capturing" (Armstrong 2006).

1980), criminal sentencing appeals decisions (Simester and Brodie 1993), and forecasting the number of advertising pages a magazine will sell (A. H. Ashton, R. H. Ashton, and Davis 1994). The method of modeling decisions to assist future decision-making has also been employed in settings outside of the academy: used by sports teams in making draft picks, for example, by corporations making business decisions, and in contemporary contexts such as the development of "robo-reader." [22]

More formally, Condorcet's Jury Theorem, although not referenced in the judgmental bootstrapping literature, provides a conceptual framework for understanding the potential effectiveness of the method.[23] The central idea of the classic political science theorem is that a group operating under majority rule is more likely to make an accurate decision than any random member of the group deciding alone. In the classic form, this is shown to hold true so long as (a) each individual's probability of making the right decision is greater than 50% and (b) the group members' votes are cast independently of one another. The requirement that all individuals must have a probability of making the right decision greater than .5 can be relaxed considerably: one only need to assume that the average of the individuals' probabilities is greater than .5 for the central insight of Condorcet's Jury Theorem to apply (Dietrich 2008). For simplicity, the weaker theorem is presented below showing the probability that N individuals each with probability p of making the right decision collectively arrive at the correct decision:

$$P(N,p) = \sum_{k=N/2}^{N} \binom{N}{k} p^k (1-p)^{N-k}$$

As the formula makes clear, the probability that a group will make an accurate decision increases as the size of the group increases. Intuitively, if votes tend to be correct, then more votes are better because any one vote might be randomly mistaken. Judgmental bootstrapping leverages this central insight. Modeling across and within judges, a judgmental bootstrapping model attempts to simulate a world in which (1) each judge votes in each case, to address inter-judge inconsistency, and (2) a judge casts multiple votes for each case under different circumstances (e.g. different times of day, in different moods, following different decision streaks), to address intra-judge inconsistencies.[24] By averaging out deviations in judgment that stem from random influences – such as the idiosyncrasies of the judge assigned

[22] These grading algorithms are developed by mimicking the grades given by human readers: sorting, recognizing, and categorizing text features associated with what teachers deem is an A essay, or B essay, etc, and so on. The success of automated essay scoring systems is gauged with respect to their ability to produce scores similar to those given by actual readers, as there is no clear "right" grade independent of human judgment.

[23] Scholars have heretofore understood judgmental bootstrapping's efficacy as coming from its ability to infer "robust decision rules...which are not subject to the inconsistencies which can occur in human decision patterns due to various factors such as fatigue or distraction" (Lafond et al. 2015).

[24] So, for example, a perfect model that generates a predicted probability of .63 for a particular parole

to a case, whether the case happens to be scheduled before or after a judges lunch break, or the judge happened to grant parole in the three cases preceding an individual's case – judgmental bootstrapping models can boost the signal of the good judgments, isolating those judgments from the contamination of the random influences. [25]

A final point on using machine learning (in this particular case, Super Learner) to build a judgmental bootstrapping model as compared to the traditional regression approach. The traditional method "involves developing a model of an expert by regressing his forecasts against the information that he used" in order to "infer the rules that the expert is using" (Armstrong 2006). This approach offers the advantage of interpretability, but in contexts where decision-making requires nuanced judgments, it has substantial shortcomings. Most importantly, often we can't measure much of the information that experts use in a complex decision task, such as a legal decision. Without that information, a traditional judgmental bootstrapping model will, along with removing noise, remove much of the signal that it is designed to capture. A machine-learning approach builds a flexible, non-parametric model of decisions that leverages variables that may merely be correlated with the signal in order to better capture it. [26]

Statistical Risk Assessments in the Criminal Justice System

The use of algorithms to help guide and inform criminal justice system decisions is of course not new. Statistical risk assessments have been used for decades and are becoming increasingly common at all stages of the criminal justice system process. Given their increasing prevalence, in particular, the rise of evidence based sentencing, it is worth noting some under-appreciated problems with these sorts of forecasting instruments and thus the potential for a decision-predictive algorithm to supplement and thereby triangulate risk prediction algorithms.

One under-appreciated problem criminal risk forecasting models must confront is that of

case is indicating that, were these extensive set of hypothetical votes to be cast, 63% of votes would be in favor of release. In almost tautological phrasing, so long as those hypothetical votes would be correct more often than not, the perfect judgmental bootstrapping model coupled with a majority rule threshold (i.e., grant parole if the predicted probability is greater than .50) becomes increasingly likely to generate a correct decision as it accurately simulates more votes.

[25]It should noted, however, just as judgmental bootstrapping models will improve outcomes if decision-makers tend to make good decisions, aggregation will also intensify the signal of the bad judgments if judges tend to make poor decisions (Kerr and Tindale 2011). Given the history and evidence of racial bias and concerns about disparate racial impact in the criminal justice system, there is particular reason to worry about boosting racial biases. If this is case, it will be of little solace that aggregation is working well overall. Separate efforts are needed to estimate the disparate treatment and remove the effect if present.

[26]Noise variables – those variables that we have good reason to believe are statistically unrelated to the actual merits of a case – should be excluded, however. These variables may include, for example, the judge to which one happens to be assigned, the results of the immediately preceding cases, the time of day, whether the judge's football team won the night before, the weather, and the judge's mood.

selection bias. The problem of selection bias has long been recognized in the criminological literature (Smith and Paternoster 1990; Loughran et al. 2009), and more recently, in current work on machine learning forecasting in the criminal justice system (Berk 2016). The crux of the problem is the mismatch between the dataset used to build an empirical risk instrument and the set of individuals to whom the model is applied. For simplicity, consider models used to assist parole decisions, although the argument also applies to bail and sentencing decisions. The model is fit on a dataset of individuals granted parole – the group for which there will be recidivism data – but the model is applied to all parole-eligible inmates. Information about paroled individuals may not provide accurate forecasts for individuals that a commissioner would not have paroled. It is like fitting a model on apples to forecast both apples and oranges to help decide who should be an apple. Judges do not, presumably, release observably similar individuals randomly, so there is reason to worry about the application of forecasts of paroled inmates to the entire population of parole-eligible inmates. [27]

A second challenge risk instruments must confront is that of measurement. Risk instruments offer forecasts of future criminality. Yet criminality can only be imperfectly measured with arrests, convictions, or prison return data. The problem of what should count as recidivism - what type of future criminal activity we actually care about – has long plagued criminal justice system researchers and administrators. This is a particular concern now as jurisdictions are increasingly turning to evidence based sentencing (and risk assessments more generally). The recent Pennsylvania proposal for evidenced-based sentencing illuminates these problems of definition and measurement. The Pennsylvania Commission on Sentencing, in compliance with a law that requires it to develop a instrument to assist the court in sentencing, has begun developing predictive models of recidivism. In its current form, the Commission uses "re-arrest and, for offenders sentenced to state prison, re-incarceration *on a technical violation*." Although reports indicate the Commission intends to analyze different types of recidivism risk (i.e., for violent and nonviolent crimes), in the eleven reports it has so far completed, they have only addressed the bluntest of questions: what are an individual's chances of recidivating in any way? Thus, while "recidivism" may be measurable, the choices over how it is measured reflect value judgments, and claims to objectivity should be treated with suspicion.

This problem of measurement also dovetails with concerns about racial biases in the criminal justice system. If recidivism includes crimes that are subject to police discretion, instruments such as Pennsylvania's can compound racial disparities by producing artificially high risk scores for individuals in heavily policed and supervised minority communities. If, as evidence shows (Beckett et al. 2005), black men are more likely to be caught for drug possession than their white counterparts, and "recidivism" includes re-arrest for drug

[27]It is important to distinguish between data-driven risk assessment instruments and psychological risk assessments. In the case of the psychological assessments, the assessment is theoretically grounded and constructed a priori. Because recidivism data is not used in the construction of the tool, but is instead used only to validate it, our selection-bias objection does not apply to psychological risk assessments.

possession, risk scores for black males will be erroneously inflated. Similarly, if black men are more frequently penalized for technical parole violations, a measure of recidivism that includes such violations will unfairly increase risk scores for black men.

The problems outlined above are not necessarily arguments against the use of criminal risk forecasting models in the criminal justice system. But they do point to the potential for an additional decision-making tool that can help triangulate the question of who should be released. A system might implement both tools at once - one offering a risk score, the second a summary statistic of what judges had decided in like cases in the past. The decision-predictive model is in effect a version of recent institutional memory.

Finally, it should be noted, the basic idea of judgmental bootstrapping - the deployment of past decisions to inform future decisions - is also not without precedent in the criminal justice system. The Federal Sentencing Guidelines can be understood as a primitive form of bootstrapping in both aim and method. As stated in the U.S. Sentencing Guidelines Manual, a primary aim was to narrow "the wide disparity in sentences imposed for similar criminal offenses committed by similar offenders,"(2014), and the method used resembles a rudimentary form of judgmental bootstrapping. The Commission generated guidelines using:

> an empirical approach that used as a starting point data estimating pre-guidelines sentencing practice. It analyzed data drawn from 10,000 pre-sentence investigations, the differing elements of various crimes as distinguished in substantive criminal statutes, the United States Parole Commission's guidelines and statistics, and data from other relevant sources in order to determine which distinctions were important in pre-guidelines practice. After consideration, the Commission accepted, modified, or rationalized these distinctions. (United States Sentencing Guidelines 2014).

Although it's unclear exactly how the Commission implemented the Guidelines, its approach had the essential characteristics of judgmental bootstrapping: the use of a large dataset of previous judgments to derive uniform recommendations in order to reduce inconsistency in future decision making.

The Federal Sentencing Guidelines have been controversial. Perhaps most problematically, they offered a means for easily increasing sentencing lengths, which helped to generate the massive prison expansion of the 1980s and 1990s. Is this also an argument against this paper's suggestion that decision-predictive algorithms could be useful in the criminal justice system? Not necessarily. Such algorithms also present a unique opportunity to quickly update a system in accordance with new values. A simple adjustment to the algorithm, such as lowering the release recommendation threshold could effect change that might otherwise come only with slow shifts in judicial attitudes. As the California parole trends indicate -

current attitudes are changing and in the direction of leniency. Any tool that systematizes decisions has the risk of systematizing them in a way we don't like. But this is less an argument against the tool so much as what is done with it.

3.8 Conclusion

The parole of those sentenced to prison for life with the possibility of parole was for decades a process without a purpose. Parole hearings were held, but almost no one was actually let out on parole. Things have changed. It now represents an important release valve in the California criminal justice system, yet it has received relatively little attention. With a unique dataset, this paper has offered a rigorous account of release decisions. The results suggest a process that is both highly predictable – the outcome of a hearing can be predicted with almost 79% accuracy – but at the same time, the system contains a real element of chance. Who an inmate happens to get as an evaluating psychologist or commissioner can alter whether they are released or remain in prison for many more years. Further, the analysis of variables suggests that, at least to some degree, factors that by law should not matter in the parole decision, such as the presence of victims at the hearing, may well have a substantial impact on how the Board decides. On the other hand, the psychological risk score, a measure of an inmate's dangerousness and risk of re-offending, which is the central criteria upon which the Board is required to make its decision, is indeed of great importance in the decision, as revealed by the causal estimate and its importance in the predictive model. Further, there is no evidence that the California parole commissioners exhibit the psychological effects that researchers have discovered in other adjudicators: the gamblers fallacy and decision fatigue appear to play little to no role in the California Parole Boards decision-making. Thus, in sum, it is a system that could be improved. And this paper has suggested one way in which this might be done with the incorporation of a bootstrapping model. But it is also a system that is generating release decisions in a way that it hasn't since its inception, and doing so in a relatively rational and consistent manner.

References

Abdel-Khalik, A. Rashad and Kamal M. El-Sheshai (1980). "Information choice and utilization in an experiment on default prediction". In: *Journal of Accounting Research*, pp. 325–342. URL: `http://www.jstor.org/stable/2490581` (visited on 10/07/2015).

Abrams, David, Marianne Bertrand, and Sendhil Mullainathan (2012). "Do Judges Vary in Their Treatment of Race?" In: *Journal of Legal Studies* 41.2, pp. 347–383. URL: `http://papers.ssrn.com/sol3/Papers.cfm?abstract-id=1800840` (visited on 10/07/2015).

Armstrong, J. Scott (2006). "Findings from evidence-based forecasting: Methods for reducing forecast error". In: *International Journal of Forecasting* 22.3, pp. 583–598. URL: `http:`

//www.sciencedirect.com/science/article/pii/S0169207006000537 (visited on 10/05/2015).

Ashton, Alison Hubbard, Robert H. Ashton, and Mary N. Davis (1994). "White-collar robotics: Levering managerial decision making". In: *California Management Review* 37.1, p. 83. URL: http://search.proquest.com/openview/8590459ba0156326aa9c3ad830c53746/1?pq-origsite=gscholar (visited on 10/07/2015).

Beckett, Katherine et al. (2005). "Drug use, drug possession arrests, and the question of race: Lessons from Seattle". In: *SOCIAL PROBLEMS-NEW YORK-* 52.3, p. 419. URL: http://socpro.oxfordjournals.org/content/socpro/52/3/419.full.pdf (visited on 10/05/2015).

Chen, D. L. and H. Spamann (2014). *This morning's breakfast, last night's game: Detecting extraneous factors in judging*. Tech. rep. Working paper, ETH Zurich.

Chen, Daniel L., Tobias J. Moskowitz, and Kelly Shue (2014). "Decision-Making Under the Gambler's Fallacy: Evidence from Asylum Judges, Loan Officers, and Baseball Umpires". In: *Loan Officers, and Baseball Umpires (November 4, 2014)*. URL: http://papers.ssrn.com/sol3/papers.cfm?abstract-id=2538147 (visited on 10/05/2015).

Danziger, Shai, Jonathan Levav, and Liora Avnaim-Pesso (2011). "Extraneous factors in judicial decisions". In: *Proceedings of the National Academy of Sciences* 108.17, pp. 6889–6892. URL: http://www.pnas.org/content/108/17/6889.short (visited on 10/05/2015).

Dawes, Robyn M. (1971). "A case study of graduate admissions: Application of three principles of human decision making." In: *American psychologist* 26.2, p. 180. URL: http://psycnet.apa.org/journals/amp/26/2/180/ (visited on 10/07/2015).

Dietrich, Franz (2008). "The premises of Condorcet's jury theorem are not simultaneously justified". In: *Episteme* 5.01, pp. 56–73. URL: http://journals.cambridge.org/abstract-S1742360000000927 (visited on 10/05/2015).

Fischman, Joshua B (2014). "Measuring inconsistency, indeterminacy, and error in adjudication". In: *American law and economics review* 16 (1), pp. 40–85.

Fischman, Joshua B. (2014). "Measuring inconsistency, indeterminacy, and error in adjudication". In: *American law and economics review* 16.1, pp. 40–85. URL: http://aler.oxfordjournals.org/content/16/1/40.short (visited on 10/05/2015).

Ho, Daniel E. et al. (2007). "Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference". In: *Political analysis* 15.3, pp. 199–236. URL: http://pan.oxfordjournals.org/content/15/3/199.short (visited on 10/07/2015).

In re Lawrence (2008). {:jurisdiction: Cal}.

Katz, Daniel Martin, Michael James Bommarito, and Josh Blackman (2014). "Predicting the Behavior of the Supreme Court of the United States: A General Approach". In: *Available at SSRN 2463244*. URL: http://papers.ssrn.com/sol3/papers.cfm?abstract-id=2463244 (visited on 10/05/2015).

Kerr, Norbert L. and R. Scott Tindale (2011). "Group-based forecasting?: A social psychological analysis". In: *International Journal of Forecasting* 27.1, pp. 14–40. URL: http://www.sciencedirect.com/science/article/pii/S0169207010000166 (visited on 10/05/2015).

Knaap, Leontien M van der et al. (2012). "The predictive validity of criminogenic needs for male and female offenders: comparing the relative impact of needs in predicting recidivism." In: *Law and human behavior* 36.5, p. 413.

Laan, Mark J. van der, Eric C. Polley, and Alan E. Hubbard (2007). "Super learner". In: *Statistical applications in genetics and molecular biology* 6.1. URL: http://www.degruyter.com/view/j/sagmb.2007.6.1/sagmb.2007.6.1.1309/sagmb.2007.6.1.1309.xml (visited on 10/05/2015).

Lafond, Daniel et al. (2015). "Capturing Non-linear Judgment Policies Using Decision Tree Models of Classification Behavior". In: URL: http://www.researchgate.net/profile/Francois-Vachon/publication/279204793-Capturing-Non-linear-Judgment-Policies-Using-Decision-Tree-Models-of-Classification-Behavior/links/562ffb8708ae01bbaedd390f.pdf (visited on 11/21/2015).

Loughran, Thomas A. et al. (2009). "Estimating a dose-response relationship between length of stay and future recidivism in serious juvenile offenders*". In: *Criminology* 47.3, pp. 699–740. URL: http://onlinelibrary.wiley.com/doi/10.1111/j.1745-9125.2009.00165.x/abstract (visited on 10/07/2015).

Miller, Joshua B., Adam Sanjurjo, et al. (2015). *Surprised by the Gambler's and Hot Hand Fallacies? A Truth in the Law of Small Numbers*. Tech. rep. URL: ftp://ftp.igier.unibocconi.it/wp/2015/552.pdf (visited on 10/05/2015).

Morrill, Calvin and Peter C. Facciola (1992). "The power of language in adjudication and mediation: Institutional contexts as predictors of social evaluation". In: *Law & Social Inquiry* 17.2, pp. 191–212. URL: http://onlinelibrary.wiley.com/doi/10.1111/j.1747-4469.1992.tb00610.x/full (visited on 10/05/2015).

Mullane, Nancy (2012). *Life After Murder: Five Men in Search of Redemption*. PublicAffairs.

Nakosteen, Robert and Michael Zimmer (2014). "Approval of social security disability appeals: analysis of judges' decisions". In: *Applied Economics* 46.23, pp. 2783–2791. URL: http://www.tandfonline.com/doi/abs/10.1080/00036846.2014.914147 (visited on 10/05/2015).

Petersilia, Joan (2003). *When prisoners come home: Parole and prisoner reentry*. Oxford University Press.

Politis, D. N. and J. P. Romano. *M. Wolf, 1999. Subsampling*. Springer, New York.

Ramji-Nogales, Jaya, Andrew I. Schoenholtz, and Philip G. Schrag (2007). "Refugee roulette: Disparities in asylum adjudication". In: *Stanford Law Review*, pp. 295–411. URL: http://www.jstor.org/stable/40040412 (visited on 10/05/2015).

Ruger, Theodore W. et al. (2004). "The Supreme Court forecasting project: Legal and political science approaches to predicting Supreme Court decisionmaking". In: *Columbia Law Review*, pp. 1150–1210. URL: http://www.jstor.org/stable/4099370 (visited on 10/05/2015).

Simester, Duncan I. and Roderick J. Brodie (1993). "Forecasting criminal sentencing decisions". In: *International Journal of Forecasting* 9.1, pp. 49–60. URL: http://www.sciencedirect.com/science/article/pii/016920709390053P (visited on 10/07/2015).

Smith, Douglas A. and Raymond Paternoster (1990). "Formal processing and future delinquency: Deviance amplification as selection artifact". In: *Law and Society Review*, pp. 1109–1131. URL: http://www.jstor.org/stable/3053663 (visited on 10/07/2015).

Van der Laan, Mark J. and Sherri Rose (2011). *Targeted learning: causal inference for observational and experimental data*. Springer Science & Business Media. URL: https://books.google.com/books?hl=en&lr=&id=RGnSX5aCAgQC&oi=fnd&pg=PR3&dq=Targeted+Learning:+Causal+Inference+for+Observational+and+Experimental+Data&ots=FPb9cuAT7B&sig=P-RCh8efs-QtJYp1duNsq2W7Tbw (visited on 10/05/2015).

Weisberg, Robert, Debbie A. Mukamal, and Jordan D. Segall (2011). *Life in Limbo: An Examination of Parole Release for Prisoners Serving Life Sentences with the Possibility of Parole in California*. Stanford Law School, Stanford Criminal Justice Center. URL: https://www.ncjrs.gov/App/Publications/abstract.aspx?ID=264072 (visited on 10/05/2015).

Appendices

Super Learner Details

To generate validation-set predictions, Super learner breaks whatever data it is given into ten separate random "chunks."[28] The first chunk, the first 1/10th of the data, is then set aside and the underlying models are built using the remaining 9/10ths of the data. The left-out 1/10th of the data, the "validation set," is then plugged into the underlying models and used to generate model predictions. The same process is repeated for each of the remaining chunks. That is, the second 1/10th chunk of data is set aside, and Super Learner builds the models on the remaining 9/10 of the data (the first chunk is now being used to help build the model) and then generates validation set predictions for the second 1/10th chunk of data. And so on for all ten chunks. The appeal of these validation set predictions is that they allow us to estimate how the underlying model would perform on data it has never seen.

The first step generates validation set predictions for each data point for each underlying model. In the second step, Super Learner then leverages the cross-validation information on model performance to assign weights to each model according to how well their predictions match the true outcome. It does this by regressing the true outcome on the underlying model predictions.[29]

The predictive model of the Parole Board decisions consists of fourteen candidate algorithms. We cross-validate the candidate algorithms as well as the Super Learner itself. In all cases, the Super Learner performs at least marginally better than any of the individual underlying models. Table 3.9 displays statistics for cross-validated mean squared error and

[28] Ten-fold cross-validation is the default. Users may choose other fold numbers, but ten-fold cross-validation is generally regarded as an appropriate choice (cite).

[29] As a default, Super Learner runs a non-negative least squares regression.

Table 3.9: Cross-Validated Performance of Super Learner and Candidate Models

Model	Avg MSE	Min MSE	Max MSE	Weight
Super Learner: weighted composite of the below candidate models	0.134	0.124	0.143	NA
The overall average grant rate	0.187	0.172	0.200	0.002
Logistic regression with all variables	0.136	0.125	0.146	0.049
Logistic regression with the 33% of variables with smallest t-test p-vals	0.136	0.126	0.146	0.079
Logistic regression with the 50% of variables with smallest t-test p-vals	0.136	0.126	0.148	0.079
Logistic regression with the 66% of variables with smallest t-test p-vals	0.135	0.124	0.146	0.010
Logistic regression with interaction of the 6% of variables with smallest t-test p-vals	0.144	0.137	0.151	0.040
Classification and regression tree	0.149	0.140	0.160	0.000
Random Forest with default parameters (mtry = 33% of variables)	0.142	0.133	0.152	0.012
Random Forest with mtry = 10	0.138	0.130	0.147	0.043
Random Forest with mtry = 20	0.139	0.131	0.147	0.198
Bayesian generalized linear model with default parameters	0.136	0.125	0.146	0.198
LASSO regression	0.135	0.124	0.144	0.038
Elastic-net regularized generalized linear model with alpha=.1	0.135	0.125	0.145	0.021
Stepwise model selection by AIC	0.136	0.125	0.146	0.232

ensemble weights for the models. Three of the fourteen candidate models – a Random Forest, a Bayesian linear model, and a stepwise AIC-based model selector – account for more than 60% of the Super Leaner.

Conclusion

This dissertation offered three studies on criminal behavior among high rate and high risk offenders. The first chapter provided a review of the criminological literature on the theory and policy of incapacitation, and empirical research efforts to estimate incapacitation effects. The chapter considered the New York City crime decline as a case controverting the notion that long prison sentences to incapacitate "career criminals" is the only (or primary) available strategy to successfully reduce crime rates. The chapter described the theoretical and policy implications of the shift from "supply-side" accounts of crime to conceptions of criminal behavior and behavioral change that recognize criminal behavior to be deeply social, situational, and contingent.

The second chapter turned to an empirical analysis of New York City recidivism data from 1990 to the near present. The aggregate prison return data indicated a decline in reoffending; the chapter analyzed individual cohort release data to assess the question of whether individual propensities to engage in serious criminal behavior changed during the crime decline and the kind of environmental effects this might imply. The chapter concluded that there were changes in the New York City court's sanctioning responses to crimes over the two and a half decade period of study, and offenders leaving prison aged over this period, both of which partially explain the the fall in measured recidivism. To some degree, the individual behavior of high rate offenders likely did fall, but the prison entrance data suggests there was substantially larger drop in offending rates among high risk youth as compared to experienced felons.

The third paper analyzed the judgments of criminal justice system actors regarding criminal risk among serious known offenders. Specifically, the chapter used computer text processing of California Parole Board hearing transcripts for inmates serving life sentences with the possibility of parole to offer a rigorous account of release decisions. The chapter showed a process that contains a real element of chance - who an inmate happens to get as an evaluating psychologist or commissioner can alter whether they are released or remain in prison for many more years. Further, the parole hearing analysis suggested that factors that by law should not matter in the parole decision, such as the presence of victims at the hearing, may well have a substantial impact on how the parole board decides. On the other hand, the paper tested and found no evidence that California parole commissioners exhibit the psychological effects researchers have documented in other adjudicators. Specifically, neither the the gamblers fallacy nor decision fatigue appear to play a role in the California Parole Boards decision-making. The chapter concluded that while the California parole system could be improved, overall, the parole board appears to be making decisions in a relatively rational and consistent manner. The chapter did not find vast disparities in decision outcomes, which have been documented in nationwide criminal case decisions, nor the intra-judge inconsistencies, documented in a variety of contexts including the well-known Israeli study of parole decisions. The chapter also offered an analysis of risk assessment instruments currently used at various stages of the criminal justice system process, including parole. Pointing to problems with these risk assessment instruments, the chapter proposed a novel algorithmic approach - statistical models of past decisions to help judges make better present decisions. This algorithmic approach can help mitigate inconsistency and bias in decision-making, and avoids some of the problems associated with the current risk prediction instruments such as selection bias, poor proxy measure for re-offending, and embedded racial discimrination.