THE IMPACT OF INDIVIDUAL, COMMUNITY, AND PUBLIC POLICY FACTORS ON OFFENDER RECIDIVISM IN FOUR STATES: BAD PEOPLE, BAD PLACES, OR BAD POLICY?

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ABSTRACT

Over the past thirty years the U.S. incarceration rate rose at an unprecedented rate, largely due to high crime rates and subsequent changes in sentencing and release policies that enhanced punishment. In the last decade as crime rates notably declined, the portion of former prisoners returning to prison remained high, and the U.S. economy tumbled into a recession, resulting in state governments scrambling to reduce the prohibitive cost of corrections. `One of the reasons that recidivism has remained so intractable may be that our understanding of re-entry and recidivism have emphasized the characteristics of inmates and largely overlooked the social context of the areas to which inmates return and the policies under which they are released to the community. This research accounts for individual, community, and public policy factors in measuring the likelihood of offenders returning to prison. Using the Bureau of Justice Statistics' National Corrections Reporting Program (NCRP) data, Census of Population and Housing data, and crime data from the Uniform Crime Reports, this study follows two cohorts of inmates released from four different states to identify factors associated with returns to prison and finds that all three domains contribute to the rate of recidivism differently, and that effects vary by state and over time.

ACKNOWLEDGMENTS

I would like to thank with the utmost gratitude and appreciation and in order of tenure on this project each of my mentors – Jim Lynch, Rob Johnson, Allen Beck, and Bill Sabol. Thank you for sticking with me through the many challenges in completing this dissertation. It was a privilege and an honor to work with all of you, each of whom has contributed seminal works to corrections research over the last decade while providing me with incredible patience, support, candor, humor, and patience (this merits two mentions given the extraordinary length of time it took me to finish). The shortcomings within this work are mine and mine alone.

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CHAPTER 1

INTRODUCTION

Nearly all commentaries on the prison population begin with a description of the exponential growth experienced since the 1980s. By this point we are all familiar with the spike in crime and subsequent policy changes that fed the growth. We also know a lot about the characteristics and behaviors of those incarcerated, the communities to which they return, the collateral consequences of the high imprisonment rate, and the increasingly prohibitive costs associated with prison. We know that despite the fact that crime peaked by the early-1990s, the prison population continued to grow and the rate of recidivism remained high; according to large recidivism studies, former offenders return to prison on the order of 40% to 50% within three years of release (Beck and Shipley 1989; Langan and Levin 2002). Most persons agree that we cannot continue to accept these high rates of return, but we disagree on the issue of what to do instead. While there is no magical program, risk-assessment tool, or single policy reform that can be implemented to reduce recidivism for all offenders, we can harness what we know to better understand why people come back and translate this knowledge into useful policy changes that, with time and sustained support, can reduce both recidivism and, in turn, the prison population.

Recidivism is a topic often studied and discussed, but rarely explained in a satisfying manner. Recidivism rates are used at the micro-level to assess the success of specific programs and at the macro-level to assess entire correctional systems, but these rates are often not comparable across time and place and often fail to take into account a wealth of variables that we know are correlated with failure following prison release. Many recidivism studies presume that offender characteristics and behaviors are the driving factors in returns to prison – inmates return because there are flaws in their character or socialization or because they are habitual criminals. We imagine that if we could just change these offender attributes by applying the ideal sanction, or implementing an ideal model of substance abuse treatment, education/vocational training, behavior modification, or other intervention, we could solve the problem of people coming back.

Such individual-based approaches largely ignore the roles that community and public policy play in recidivism even though these factors loom large in the criminological literature. Ecological studies of crime explore the influence of one's environment as a series of factors that push an offender toward or pull an offender away from criminal behavior. Past research indicates a plethora of community-based correlates associated with crime – income, employment, education, population density, mobility, supervision levels, and strengths of attachment/investment ties, to name a few (Bursik, 1986, 1988; Bursik and Grasmick, 1993; Sampson, 1985; Sampson and Groves, 1989; Shaw and McKay, 1942). Also established in the literature is that some communities were differentially affected by the incarceration build-up and have suffered numerous unintended consequences such as an increase in female-headed households, decreased social capital, and other measures negatively impacting community stability (Rose and Clear, 1998; Sabol and Lynch, 2003; Sampson, Raudenbush, and Earls, 1997; Western and McLanahan, 2000). An additional body of research focuses on the effects of policy, specifically post-custody supervision, on rates of return to prison (Austin, 2001; Seiter and Kadela, 2003; Solomon, 2006). So while there is ample evidence that individual, community, and public policy factors influence crime and criminal behavior, there is little research that assesses recidivism while controlling for all of these factors at once.

Failing to entertain these factors simultaneously can lead to the misspecification of models of recidivism and yield results that promote and compound our misunderstanding of the recidivism process. If we only include individual level variables in our model, we will attribute success or failure upon release to specific characteristics of the inmate when these outcomes are likely also correlated with supervision policies in a particular jurisdiction and characteristics of the community to which they return. If, for example, a jurisdiction has a strict supervision regime characterized by a low revocation threshold, targets serious offenders for initial incarceration and revocation, and is situated in a community with numerous markers of disorganization such as high crime, unemployment, and residential mobility, it will appear that persons admitted for serious offenses will come back more often than persons with less serious offenses. In fact it is likely the limited opportunities within the community combined with supervision and revocation policies affects the recidivism rate and the type of offender returned. Unless we include community and policy variables in our models of recidivism, we will not be able to sort out the effects of these factors on the recidivism process.

Objectives

Obtaining information on the characteristics of released inmates and the communities to which they are released as well as variation in correctional and supervision policies is not easy. It requires multi-state policies or studies of the same states over periods in which policies have changed. Most recidivism studies are conducted in one jurisdiction at one point in time so they do not have the variation on correctional policies necessary to assess its effect on recidivism. Multi-state studies of recidivism face the additional complexity of obtaining uniform measurement of the dependent variable—recidivism. States differ substantially in how they define and how they record recidivism.

Multi-state recidivism studies conducted by the Bureau of Justice Statistics (BJS) in 1983 (Beck and Shipley, 1989) and 1994 (Langan and Levin, 2002), partially addressed these concerns. BJS used the same definitions of recidivism across participating states, and included demographic information, offense type, and different measures of return (arrest, conviction, return to prison) in its analysis. The objective of these studies, however, was to report the rate of recidivism across the nation rather than to compare rates between states or to assess the impact of community characteristics on recidivism. Individual characteristics such as age, race, number of priors, and length of time served were largely used to describe the variation in return, but not as controls in part of a larger model to explain recidivism.

This research builds upon this work by using another BJS data series, the National Corrections Reporting Program (NCRP), which is made up of individual-level records from participating states on all admissions to and releases from prison in a calendar year. These records include demographic information, criminal justice variables, county of conviction, release type, and the ability to link records between years in the jurisdictions where a state inmate identification number is provided. With this unique data set we will be able to differentiate the effects of individual and policy factors on the likelihood of return to prison. By bringing in county level data from additional sources, we can also include the impact of macro level community factors in the model. The specific questions of interest in this study are:

1. Is recidivism the product of persons, places, or policies, or some combination thereof?
2. How does the impact of individual, community, and public policy characteristics on recidivism differ when modeled in isolation by block and when modeled together?
3. Does the strength and significance of the effects of individual attributes accounting for recidivism differ depending upon the policy context and location?
4. How do these findings inform the debate over how to reduce the size of the prison population within states and as a nation?

5. Can recidivism be reduced with policy changes as opposed to the more difficult task of changing individuals?

Applications of Research

This research has several practical applications. First, the study applies a consistent definition of recidivism to a large number of persons released from state prisons at different periods of time, and from jurisdictions with different release policies and variation in offender demographics and community characteristics. Recidivism is not assumed to be a single-faceted problem with constant predictors across time and place.

Second, multivariate analysis permits the assessment of the impact of various characteristics and conditions while holding other factors constant. It is possible that the characteristics of the individual, often the focus of policy, may not be the primary contributor to subsequent returns to prison once variations in community influences and policy effects are held constant. At the same time, the study offers insight on the degree to which static individual characteristics such as race and age may contribute to recidivism. While such traits may not altered, they can be taken into account in assessing the likelihood of recidivism in conjunction with the characteristics of the community to which released offenders return and the policy regime (e.g. type of release, conditions of post-custody supervision) under which they are released.

Third, state and time-specific models enable us to explore the interactions among individual, policy, and community context variables. The multifaceted model allows us to identify distinctions in correlates associated with recidivism and begin to understand why rates may vary from place to place. For example, there could be several explanations for why drug offenders return at higher rates in one state compared to another. Offenders could have different characteristics, be returned to communities with different level of disorganization and opportunity, be released by mechanisms that accelerate or inhibit their likelihood of return, or some combination thereof. Measuring recidivism without accounting for these population variations only tells us the rates, not the reasons behind them. This research is a first step in identifying the complex variables associated with returns to prison.

Overview of Chapters

This dissertation will identity specific influences on return and the degree to which they predict return to prison, allowing us to direct resources in changing the variables we can, assessing appropriate risk for those we can't, and ultimately reducing the likelihood of return and thereby reducing the prison population over the long term. Considering a wider set of factors as to why people come back can lead to changes in policy that better support those released from prison and decrease their likelihood of return. Chapter 2 provides the background of why and how the incarceration rate grew exponentially since the late 1970s, and this tells us what we have learned about criminal behavior and recidivism. This discussion will explore the contribution of the recidivism to the growth in the prison population and the known factors that affect individual recidivism. Chapter 3 defines recidivism as it is used in this study, lists the hypotheses, describes the data compiled to test these assertions, specifies the measures used to represent individual, community, and public policy factors, and provides an overview of the statistical methods applied. The study results are presented in Chapter 4, starting with descriptive information of the release cohorts, followed by summaries of the various multivariate regressions, results of the final model(s), and hypothesis outcomes. Finally, Chapter 5 summarizes the implications of the findings for how we think about recidivism and discusses the applicability of this research in contributing to future policies designed to reduce the prison population. Also included are recommendations for additional research to further expand the findings.

CHAPTER 2

BACKGROUND

In the foregoing chapter it was asserted that 1) reducing recidivism is an important means of reducing the prison population and 2) understanding recidivism requires going beyond the characteristics of individuals and considering the effects of community attributes and policy variables. This chapter provides support for these assertions and identifies specific attributes of offenders, communities, and policies that should be included in a comprehensive recidivism model.

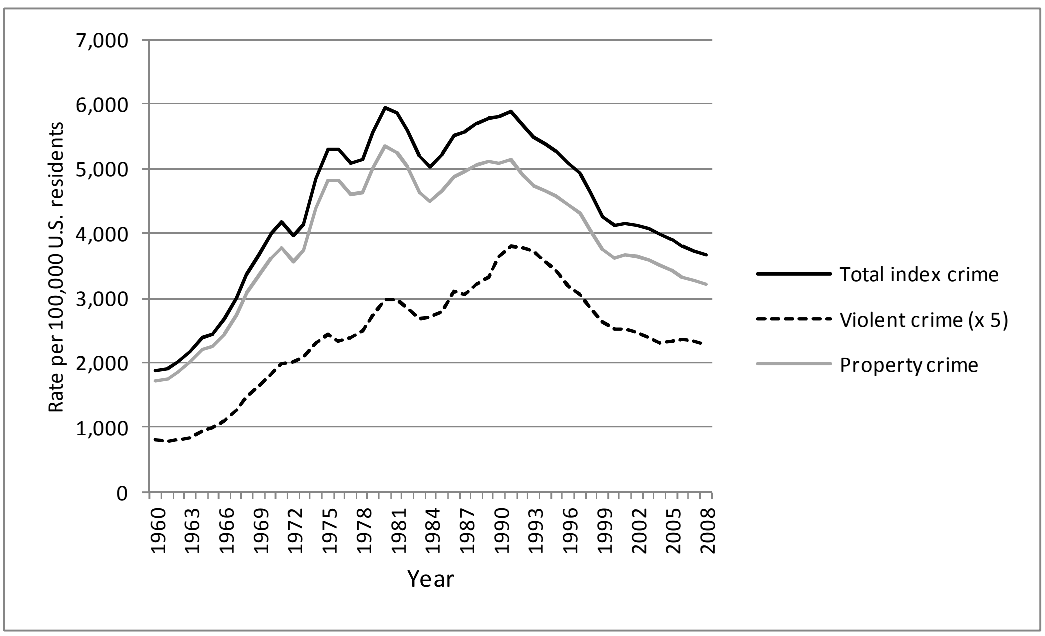
The growth in the prison population, the characteristics of that population, and the role that recidivism played in that growth are summarized and offered as evidence that reducing recidivism can be consequential in bringing the prison population down. The history of the growth in the prison population is also useful for identifying policy variables associated with recidivism and should be included in subsequent recidivism models. This chapter also provides an overview of recidivism and criminal behavior literature to date, and what we know (or suspect we know) about the contribution of individual characteristics, communities, and public policy. This review also suggests variables for inclusion in the recidivism model.

The Rise of the Prison Population

Over the past three decades the prison population increased massively. At the beginning of the incarceration growth, increases in crime and subsequent responses to crime drove the growth by bringing more people in and keeping them longer. We will see that early growth in the prison population can be largely attributed to more new court commitments and increased time served. Over time, parole violators, both for new offenses and technical violations, more than doubled and became a driving force behind prison population growth, underscoring the importance of understanding and reducing recidivism. The increase in crime and subsequent policy reactions are summarized, followed by a discussion of the impact of these policies.

Rise in Crime

The increase in the crime rate between the 1960s through the 1990s is well-documented through the Uniform Crime Reports (UCR), collected annually by the Federal Bureau of Investigation (FBI), which provide the number of crimes reported to police across the nation (Figure 1). In 1960 there were 1,887 total index crimes per 100,000 residents; by 1980 the rate More than tripled to reach 5,950 crimes per 100,000 residents (FBI, UCR, 2011).[1] While the total crime index rate peaked in 1980, violent crime continued to rise; there were 597 violent crimes per 100,000 in 1980, peaking at 758 per 100,000 in 1991. We will see shortly that despite the drop in crime rates the prison population continued to grow, largely due to changes in policy.



1. Part 1Index Crimes include eight specific offense defined within the Uniform Crime Reports: murder, rape, assault, robbery, burglary, arson, larceny, and motor vehicle theft. The index does not include drug offenses, which also substantially increased during this time period.

Figure 1. Crime rate trends per 100,000 U.S. residents, 1960-2008: Violent crime rates were multiplied by 5 in order to better view how violent crime rates trend with property and total crime rates over time. From Uniform Crime Reports query tool (2010), http://www.ucrdatatool.gov.

Changes in Criminal Justice Policies

As crime rates climbed, research proclaiming the failure of rehabilitation received widespread attention (Lipton, Martinson, and Wilkes, 1975), bolstering support for individual accountability through increased punishment for convicted offenders. Throughout the 1980s and 1990s, there was public and political outcry across the nation to protect citizens from violent predators and repeat offenders. Violent crime received substantial media coverage, stoking public fears (Graber, 1980; Warr, 2000) and spurring politicians to advocate for enhanced punishments (Smolowe, 1994; Austin, Clear, Duster, et al., 2007). Justification of increased punishment ranged from retribution (an eye for an eye) to deterrence (both general and specific deterrence in discouraging criminal behavior through increased sanctions) to incapacitation (if we can't stop criminal behavior, we can at least remove them from society for longer periods of time).

The resulting policy shifts increased the likelihood that an offender would be sentenced to prison, expanded the length of stay, and altered the philosophy behind post-release supervision. Mandatory minimums, three-strikes laws, and truth-in-sentencing laws garnered nationwide support through the 1980s and 1990s. Mandatory minimum sentencing was one of the first policy changes to gain popularity beginning with the New York Rockefeller Drug Laws in 1973 and continuing with mandatory minimums for specific crimes, such as those involving guns and crack-cocaine (Comprehensive Crime Control Act of 1984; Omnibus Anti-Drug Abuse Act of 1988). The next widely adopted policy were the various three-strikes laws introduced in the early 1990s with the intent of incapacitating repeat (and presumably the most dangerous) offenders. Between 1993 and 1995, 24 states enacted variations of three-strikes laws (Schiraldi, Colburn, and Lotke, 2004).[2] Around the same time, truth-in-sentencing mandates, which required that a certain portion of sentences be served and restricted or eliminated the use of good time credits, came into widespread use through the 1994 Crime Bill. In 1992 there were 4 states using truth-in-sentencing; by 1998 there were 27 states with such requirements (Spelman, 2009). In combination, these policies resulted in increased likelihood of prison time upon a conviction and more time served by the average inmate.

Another significant policy change, and a focal point of this research, is the transition from release by discretionary parole (parole boards) to release by statute (supervised mandatory release). Discretionary parole requires inmates to be assessed by a panel of individuals to determine suitability of returning to the community. By yearend 2000, 29 States had abolished discretionary parole, opting instead for either supervised mandatory release governed by statute or, utilized by fewer jurisdictions, expiration of sentence (EOS) with no post-custody supervision (Hughes, Wilson, and Beck, 2001).

The dramatic increase in crime, particularly violent crime, experienced from the 1960s to the early 1990s, strongly influenced public and political opinion on how to best deal with offenders and resulted in the policy shifts discussed above. These changes increased the probability of arrest, conviction, and incarceration (Langan, 1991; Blumstein and Beck, 1999; Sabol, Rosich, Kane, et al., 2002) and increased average lengths of stay (Blumstein and Beck, 2005). At the same time, the release decision shifted from parole boards to the establishment of mandatory release statutes. These factors contributed substantially to the exponential growth in the prison population by bringing more people in, keeping them longer, and expanding the use

2. Three-strikes laws ultimately impacted the prison population far less than expected. Schiraldi et al. (2004) note that in most states the law is rarely invoked – 14 states used three strikes to lock up less than 100 people over the period of a decade. California applies the statute to an average of 10% of eligible cases (Kasindorf, 2002).

of, level of, and length of post-release supervision. These factors also created a policy environment in which recidivism was more likely to occur. The pressure to “get tough” was manifested not only new laws and formal policies adopted during this period but also in the increased punitiveness in the discretionary decisions made by agents in the criminal justice system on a daily basis.

Resulting Growth

The change in specific public policies and the general policy environment regarding crime and sanctions resulted in unprecedented growth in the prison population and impacted the offense distribution of offenders held. As we will see in the subsequent section, changes in release mechanisms (the manner in which prisoners are released back into society) impacted both time served and, in conjunction with post-custody supervision policies, changed the makeup of the incoming populations in terms of admission type. A simulation model is presented to estimate the potential effects of recidivism growth in the population. The simulation compares the actual prison population growth with the growth that would have occurred had the rate of parole violators returned to prison been reduced by half during a key period of growth. Finally, these changes are tied back to the high recidivism rate and why reducing recidivism must be a priority to attain lower incarceration rates in the future.

Incarceration Rate

Prior to the rise in crime, the U.S. enjoyed a fairly steady rate of imprisonment – 79 prisoners per 100,000 U.S. residents in 1925 increased modestly to 96 per 100,000 in 1970 (Blumstein and Cohen, 1973; Bureau of Justice Statistics, National Prisoner Statistics series – BJS, NPS). Figure 2 illustrates how the prison systems grew throughout the 1980s and 1990s, coinciding with the sea changes in sentencing and release policies already discussed. The rate of imprisonment more than tripled from 138 per 100,000 U.S. residents in 1980, or 1 in every 725 residents, to 504 per 100,000 in 2008, or 1 in every 198 residents (BJS, NPS). Based on the change in incarceration rates over time, an estimated 1.9% of U.S. adults born in 1974 will spend time in prison sometime in their life course compared to 6.6% for persons born in 2001 (Bonczar, 2003).[3] The change in the characteristics of the prison population also further compounded growth.

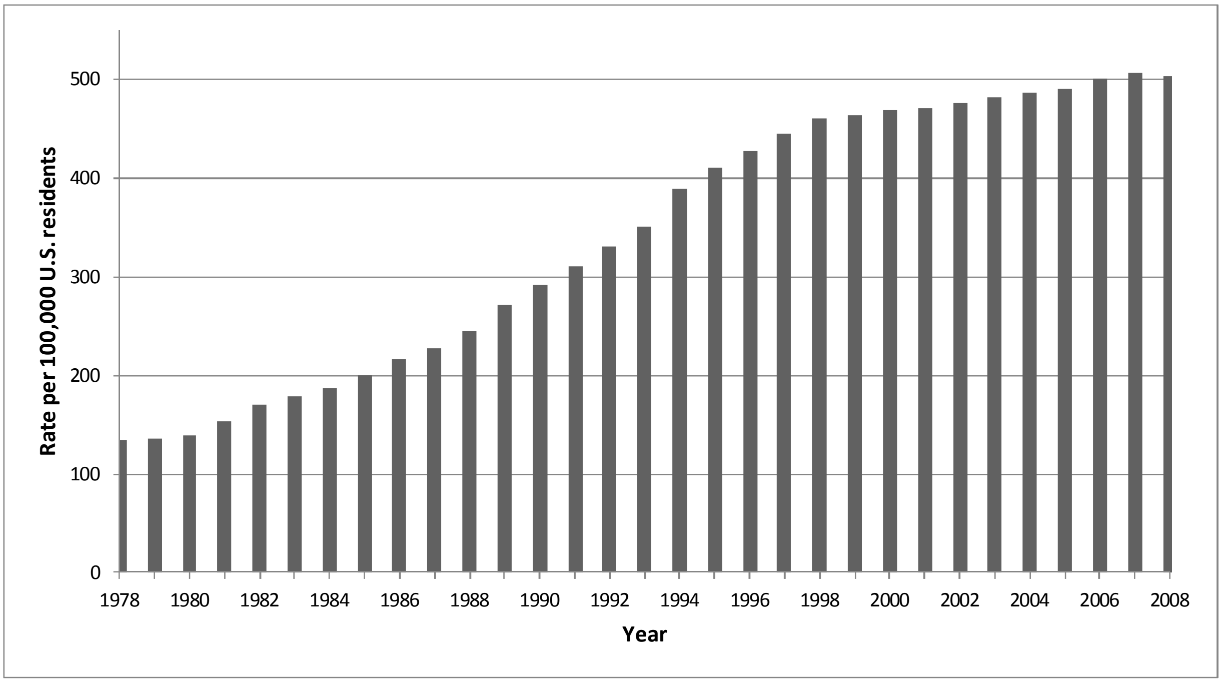


Figure 2. Rate of state and federal prisoners per 100,000 U.S. residents, 1978-2008. From National Prisoner Statistics series, Bureau of Justice Statistics

Change in Offense Distribution and Criminal History

The types of offenders held changed over time. State prisons were and remain largely made up of violent offenders, but the proportion declined from 59% of the population in 1980 to 53% in 2005 (Figure 3). Much of this decline coincided with the rise of drug offenders, which more than tripled from about 6.4% of the population in 1980 to about 22% in 1990, remained

3. This estimate excludes persons who have been arrested, spent time in jail, or served a probation sentence, but did not serve time in state or federal prison.

relatively stable up to 2005, and then declined to 18% by 2009.[4] Public order offenders, largely due to weapons offenses, also more than doubled between 1980 (4%) and 2000 (10%).

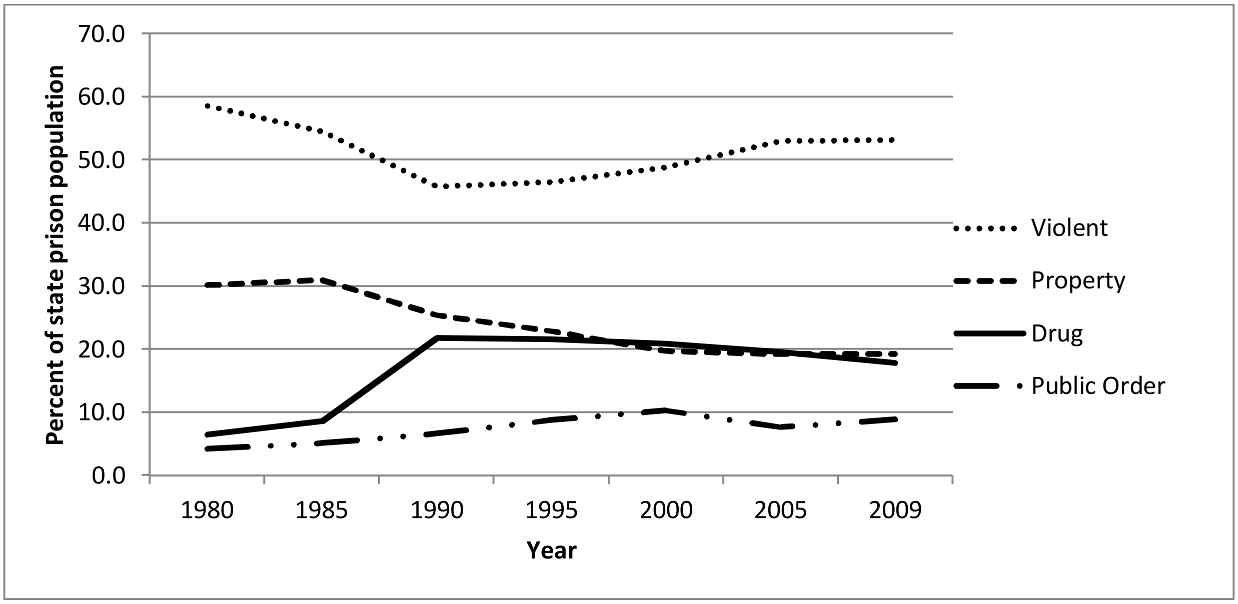


Figure 3. Distribution of state prison population by offense type, 1980-2009. From Bureau of Justice Statistics - National Prisoner Statistics, Survey of Inmates in State Correctional Facilities, National Corrections Reporting Program series.

In addition, state prisoners reporting no previous sentence to probation or incarceration increased from 1 in 5 prisoners in 1991 to 1 in 4 in 2004, indicating that a greater portion of offender were being sent to prison rather than utilizing some intermediary measure and clear evidence that sentencing policies had an effect on prison population growth (Bureau of Justice Statistics, Survey of Inmates in State Correctional Facilities, 1991 and 2004).

Change in Release Type, Time Served, and Impacts on Admission Type

As previously discussed, the use of parole boards declined over the 1980s and 1990s and the use of mandatory release statutes increased. In 1977, the vast majority of prisoners were assessed by a parole board prior to release (72%); by 1999 this had declined to 24% (Figure 4).

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4. In contrast, the federal system became increasingly comprised of drug offenders. Drug offenders made up 20% of the federal prison population in 1980 and 55% by 2005 (Sourcebook of Criminal Justice Statistics, 2006).

During the same time period mandatory releases increased from 16% in 1977 to 41% in 1999 and EOS releases more than tripled from 6% to 18%.

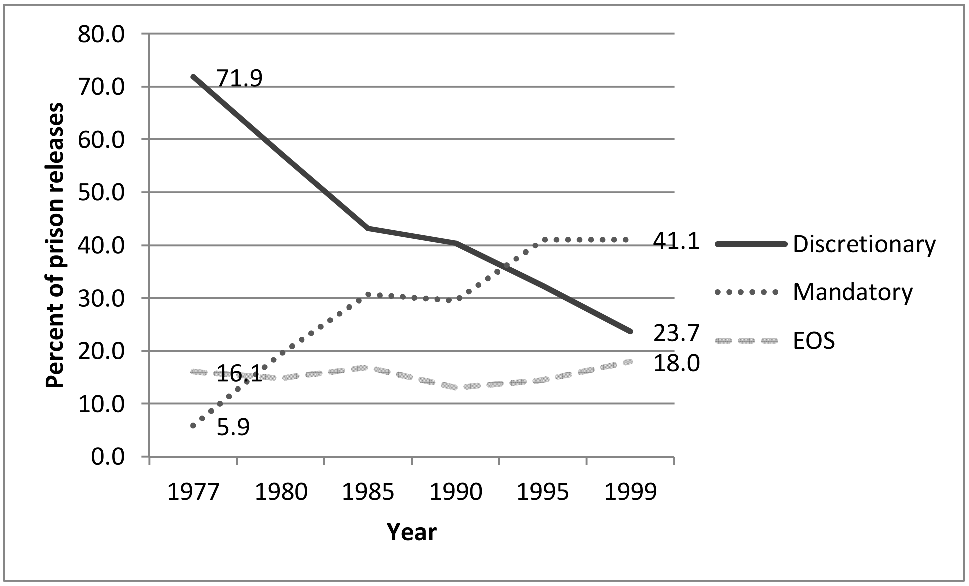

Figure 4. Change in prisoner release type, 1977 to 1999. From Bureau of Justice Statistics, National Prisoner Statistics series.

Another element contributing to the growth of the prison population was the increase in time served. While the average sentence length imposed for convicted offenders decreased from 69 months in 1990 to 65 months in 1999, the average time served increased 6 months and the percent of sentence served went from 38% up to 49% (Hughes, et al. 2001).[5] Austin et al. (2007) estimated that average time served went from 21 months in 1993 to 30 months in 2002, an increase of 9 months. These differences may appear to be small, but when applied to the large population base and the constant influx of admissions serve as a major driver in boosting the stock population.

5. This change can be attributed in part to the violent offender and truth-in-sentencing statutes, which required offenders to serve a certain percent of their sentence in order for states to receive federal funding for prison capacity expansion. The unintended result was that average sentence length imposed decreased, but time served increased, still achieving the desired outcome of more time behind bars. Also of note is the increase in parole violators, who generally serve shorter terms and may well bring down the average.

Time served also varied by release type. Time served went up for nearly every offense type, but the impact varied across release types (Table 1). For instance, between 1990 and 1999 time served among violent offenders increased from 49 to 59 months among discretionary, respectively, from 41 to 47 months among mandatory releases, and from 44 to 52 months among EOS releases in the same time period. Similar differences are observed for other offense types and reinforce the fact length of incarceration vary substantially for similar offense types depending upon the policies in place.

Table 1. Time Served by Release Type and Offense Type, 1990 and 1999

	Time served (months)[a]		
	1990	1999	Change
Total	28	34	+6
Discretionary	29	35	+6
Violent	49	59	+10
Property	25	31	+6
Drug	20	28	+8
Public order	18	21	+3
Mandatory	27	33	+6
Violent	41	47	+6
Property	23	30	+7
Drug	20	27	+7
Public order	19	25	+6
Expiration of sentence	31	36	+5
Violent	44	52	+8
Property	27	30	+3
Drug	21	29	+8
Public order	28	25	−3

Note: From Hughes, Wilson, and Beck (2001).

[a] Includes time served in prison and jail.

As changes in release type and time served occurred, there is evidence that parole success rates changed as well. An estimated 31% of parole releases in 1983 resulted in returns to prison (BJS, Annual Parole Survey, 1983). By 1998 this failure rate increased to 42% (Bonczar and Glaze, 1999). If parole boards were skilled in assessing likelihood of success of parole, then eliminating these panels may well have contributed to an increase of failure rates on supervision and thus impacted recidivism. There is some research that supports this assertion – Hughes et al. (2001) found that success rates for those released in 1999 on discretionary parole (54%) are substantially higher than for those released on mandatory parole (33%).[6] The Urban Institute also found that 54% of discretionary parole releases in 1994 were rearrested after two years, compared to 62% of mandatory releases, and 62% of unconditional releases (Solomon, Kachnowski, Bhati, 2005). It is not that types or levels of subsequent supervision necessarily differ by type of release (although they might), but rather that those assessed by a board of experts as a prerequisite for release may be more successful on parole than those released after serving a time period set by statute.

As more people came into prison, more were subsequently released, increasing the base of persons at risk of return. At the same time, changes in the nature of supervision from an interactive and social-work approach to more authoritarian-oriented monitoring styles (Petersilia, 1999) likely served to accelerate return rates. These changes had inevitable impacts on the manner in which persons were admitted to prison. The volume of both new court commitments and parole violators increased over time, but parole violators accounted for an increasing share of the growth in later years: parole violators were 17% of admissions in 1980, 29% in 1990, and 35% by 2000 (Table 2).

These estimates are also likely an undercount of parole violators since some states include only technical violators in this category and process all other admissions as new court

6. Results vary for first releases and re-releases. For first releases, mandatory releases had greater success (79%) compared to those released by parole board (61%); for second releases the effect flips with parole board releases being more successful (37%) compared to mandatory releases (17%). Much of this is likely due to parole boards being better at assessing risk following an initial failure. These different outcomes achieved by first and subsequent releases will be accounted for in the later models.

Table 2. Admissions to state prison by type, 1980-2009 commitments, while other states may revoke parole for either a technical violation or the commission of a new crime. Parole violators are by definition recidivists, regardless of whether they are returned for a new offense or a technical violation. While the mean time served by parole violators is about half that served by new court commitments (an average of 13 months and 25 months in 1995, respectively), the increase in number of parole violators undoubtedly impacted the growth over time (BJS, NCRP, 1995).

Table 2. New Court Commitments and Parole Violators Admitted to State Prison

Year	All admissions[a]	New court commitments	PVs	PVs admitted (%)
1980	159,286	131,215	27,177	17
1985	240,598	183,131	56,192	23
1990	460,739	323,069	133,870	29
1995	521,970	337,492	175,726	34
2000	581,487	350,431	203,569	35
2005	676,952	421,426	232,229	34
2009	674,836	422,910	237,449	35

Note: PVs = parole violators. Categories do not add to total because returns from appeal/bond and "other" admissions are not listed. From National Prisoner Statistics series, Bureau of Justice Statistics.

[a] Based on inmates with a sentence of more than 1 year. Excludes escapes, AWOL's, and transfers to and from other jurisdictions.

Prison Population Growth Simulation and the Role of Recidivism

To estimate the impact of the increase in parole violator admissions over time on state prison population growth a simulation model is used. First, we strove to replicate the actual increase of the number of persons in state prison by starting with the known standing population at the beginning of each year, adding new admissions by type, and "letting out" releases by type. The assumptions used to replicate the actual population growth between 1988 and 2005 were as follows:

- Based on variations in average time served, it was estimated that 25% of the incarcerated population on January 1 were new court commitments eligible for release between 1990 and 1992. The population eligible-for-release was adjusted downward to 20% from 1993 onward to account for increases in both time served and in the number of parole violators making up the stock as result of the change in sentencing and release policies.
- 10% of new commitments during the year were added to eligible-for-release pool to account for inmates sentenced to less than 1 year.
- These eligible-for-release new court commitment subgroups pools were added together and multiplied by the known rate of new court commitments released in a given year using data from NCRP release records (new court commitment releases in a given year ranged from 60% in 1988 to 65% in 2005, or 0.6 and .065, respectively).
- All parole violators in the January 1 stock population (estimated using the 1991, 1997, and 2004 Survey of Inmates in State Correctional Facilities, BJS) were automatically “let out.” Since the average time served is 12 months for parole violators, offenders that were there on January 1 were granted a 100% release rate.
- The rate of newly admitted parole violators released in a given year was based on the proportion of parole violators admitted and released in the same year from the NCRP data (varying from 20% in 1988 to 28% in 2008, or 0.20 and .28, respectively).

The resulting trend line was consistent with the actual pattern of growth over the time period. Then an alternative growth trend in the prison population was calculated based on the following assumptions:

- The incoming parole violator cohort was halved to simulate conditions under the previous social-worker oriented style of parole supervision (less intense supervision, treatment-focused, and higher thresholds for revocation).
- Had this occurred, the stock population at the beginning of the year would contain a greater proportion of persons serving sentences as new court commitments. In addition, had the time served component remained unchanged, persons would cycle through slightly faster. Thus, the proportion of beginning-year new court commitments eligible for release was boosted from 20% to 50%. Incoming new court commitments eligible-for-release over the year remained at a conservative 10%.
- As before, this eligible-for-release new court commitment pool was then multiplied by the known release rate of new court commitments from NCRP for each year.
- The same assumptions for parole violator releases were applied (all of the beginning year stock and half of the incoming parole violators in a given year).

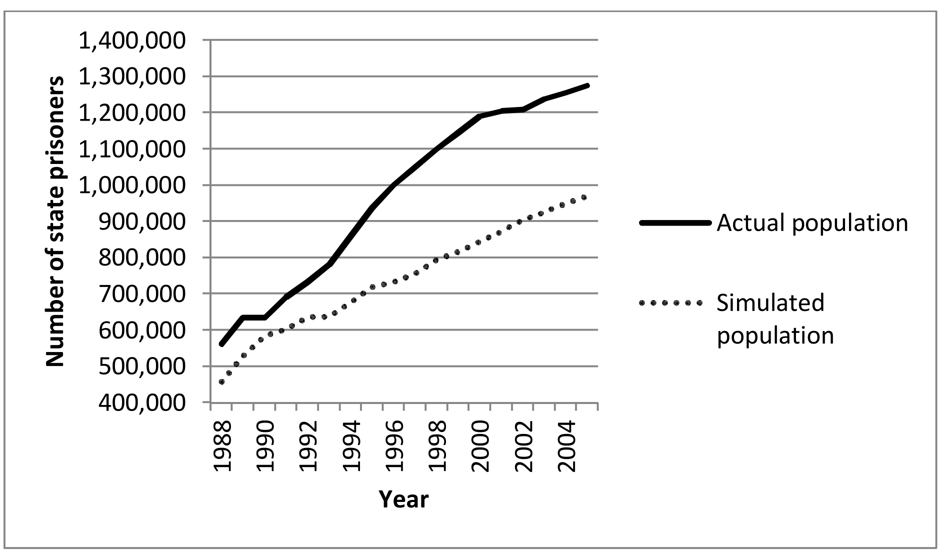

Figure 5. Growth in state prisoners, actual and simulated, 1990–2005. Actual population is based on data from the National Prisoner Statistics and the National Corrections Reporting Program (BJS). Simulated population is based on a 50% reduction in persons returned for parole violations. Simulation also used data from the Survey of Inmates in State Correctional Facilities, 1991, 1997, and 2004.

Figure 5 shows the results of the simulation. Had the increases in time served not occurred and parole violators returned either for new offenses or revocations been halved, the standing prison population in 2005 would be about 970,000 instead of 1,275,000, or 24% lower. The population still rose substantially because no alternative assumption was introduced to diminish the volume of new court commitments entering prison over the time period. However, had the rate of parole violators returned been reduced, the number of persons on prison would be substantially lower.

This exercise illustrates two things. First, that policy changes had real impact on the growth of the prison population. Stricter sentencing increased the probability of being imprisoned given an offense and the length of time served, both of which increased the size of the prison population. Increases in the pool of persons on supervision and changes in supervision policies resulted in high rates of parole revocation. Second, that one can impact the size of the prison population simply by changing how we deal with parole violators. Even if there is resistance to offering alternative to incarceration for persons on parole convicted of a new offense, we could still reduce the population by providing alternative sanctions to technical violators. Better still, we could lower the return rate for both by identifying the reason behind the returns and attempting to address some of them.

These results are consistent with the multi-state recidivism studies conducted in the early 1980s and again in the mid-1990s which indicate offenders returning to prison make up a substantial portion of the standing prison population. Beck and Shipley (1989) estimated from a cohort of prisoners released in 1983 that 41% were reincarcerated within three years. A similar study conducted by Langan and Levin (2002) from the Bureau of Justice Statistics found 52% of prisoners released in 1994 were returned to prison within three years, half for a parole violation and half for a new conviction. We cannot conclude that the difference in recidivism between the studies is significant due to changes in methodology; however, even if the rate of return remained stable, surely a 40% recidivism rate can be improved upon. A more recent national study of recidivism, the largest to date, was conducted by the Pew Center for the States (2011) and looked at 3-year returns for 1999 (33 states) and 2004 releases (41 states) and found 45% and 43%, respectively, were returned to incarceration. While lower than the rates found in the 1994 BJS study, these stubbornly high rates of return reinforce the need to better understand the factors behind why people come back.[7] The simulated model demonstrates the effect of reducing recidivism by half and the results reinforce that this is an endeavor worthy of pursuit.

This review of the factors that gave rise to massive increases in the prison population provides evidence that sentencing and supervision policies likely have substantial effects on the probability that an offender will serve more time in prison and that a released inmate will recidivate. The initial dramatic rise in the prison population occurring in the 1980s and early 1990 was driven by increases in the crime rate and new court commitments, but crime began to decline in the early 1990s and the prison population continued to grow. Recidivism, largely in the form of parole revocation, became an increasingly important factor in the continued growth of the prison population. This suggests that understanding and reducing recidivism is an important factor in any efforts to reduce the prison population. Finally, the simulation model presented reinforces the contention that the policy environment affects the likelihood of return and should be included in models of recidivism.

7. The report also lists rates by state, but since definitions and quality of data varied so widely between states, such comparisons are ill-advised. The study also used a simplistic model of recidivism, failing to account for any variables correlated with recidivism rates; nonetheless ad hoc observations regarding policy differences between states were tied to outcomes.

Studies of Criminal Behavior and Recidivism

A number of empirical studies of criminal behavior and recidivism have identified variables related to both the likelihood of initial involvement in crime and repeat incarcerations. This literature has identified core individual characteristics as well as some community and public policy factors that appear to be correlated with criminal behavior. Many of these factors may inform the design of an expanded model of recidivism.

Individual Characteristics

Some variables associated with criminal behavior and recidivism and are often readily available in individual level data systems include gender, age, race, conviction offense, and prior criminal history. Some additional factors, which are more challenging to obtain at the individual level, are education, employment, substance abuse, participation in treatment programs, and personal attachments, such marital status and family support. Although not all of these factors were available for the study, it is important to understand what was included and excluded in the research and the possible implications on the model.

Males are more likely than females to be criminally involved – one can simply look to the arrest rates in the Uniform Crime Reports and the stock prison population to see this. While males and females each comprise approximately half of the resident population, males make up the overwhelming majority of those arrested and incarcerated, although female criminal involvement has increased over time. In 1980 about 1 in 6 arrestees were female, increasing to 1 in 4 by 2009 (UCR data tool, 2012). Similarly, female inmates have increased over time, from 4% of the prison population in 1980 to 7% by 2010, but they still remain far less likely than males to be incarcerated (National Prisoner Statistics series, Bureau of Justice Statistics).

Age is another factor that is correlated with criminal behavior. In fact, the spike in crime described earlier is believed to be due in part to the baby boomers making their way through the crime-prone age band, ages 16 to 24 (Steffensmeier and Harer, 1991). Age of criminal behavior on-set is also believed to have an influence on criminal career and impact future recidivism – the earlier the involvement in crime, the more likely this behavior will continue through the crime-prone years (Blumstein et al., 1986; Chaiken and Chaiken, 1982; Dembo et al. 1995; Farrington, 1986; Farrington and Hawkins, 1991; Greenberg, 1991; Nagin and Farrington, 1992; Patterson and Yoerger, 1993). Criminal involvement desists with age, as demonstrated by proponents of the aging-out theory (Glueck and Glueck, 1950; Farrington, 1986; Hindelang, Hirschi, and Weis, 1981; Sullivan, 1989), although the reasons for this are a source of debate.[8]

Race is also related to incarceration – black males, particularly young black males, are consistently and significantly more likely to be incarcerated than their white counterparts; although disparities appear to have dissipated somewhat in recent years, the divergence remains marked – black males had an incarceration rate nearly seven times that of white males at yearend 2010 (Guerino, Harrison, and Sabol, 2011). Tonry and Melewski (2008) estimate that 61% of the racial disparity in incarceration rates is due to differential involvement in crime (as measured by arrest rates – that is, 61% of the disparity can be explained by higher arrest rates for blacks), down from the 80% estimate previously estimated by Blumstein (1993). There are, of course, socioeconomic factors believed to interact with race to compound the likelihood of criminal involvement (Krivo and Peterson, 1996).

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8. For example, Gottfredson and Hirschi (1990) argue that desistence in crime is a result of learning self-control, rather than aging out itself. Other researchers say that the average career length is between 6-7 years and is more likely to desist due to life changes, such as marriage, employment, increased ties to the community, or deterrence following a sanction (Tittle, 1980; Sherman and Smith, 1992; Spellman, 1994; Wilson, 1985).

Once incarcerated, blacks appear to be more likely to reoffend, even after controlling for offense and other demographics (Benedict and Huff-Corzine, 1997; Gendreau, Little, and Goggin, 1996; Listwan et al., 2003; Spohn and Holleran, 2002). Prison time has even been declared to be the norm of early adulthood for young black urban men (Freeman, 1996; Irwin and Austin, 1997; Garland, 2001). A lifetime prevalence study estimates that if current age-specific rate of first incarceration remain unchanged, 33% of black males born in 2001 will spend some portion of their life in prison, compared to 6% of white males and 17% of Hispanic males born the same year (Bonczar, 2003).

Additional research shows that some offender types are more likely to return than others. Violent offenders are less likely than property to reoffend (Beck and Shipley, 1989; Kohl et al., 2008; Langan and Levin, 2002). This is likely related in part to the average frequency of crimes committed by offender type. Property offenders are estimated to commit 12 crimes per year, compared to 3.5 for violent offenders (Spelman, 1994). The rate of drug offender returns vary widely across studies (see Beck and Shipley, 1989; Kohl et al., 2008; Solomon, Kachnowski, and Bhati, 2005); it is likely that the differences in return have more to do with supervision policies than the criminality of former drug offenders.

Prior criminal behavior is also a consistently strong predictor of future criminality (Andrews and Bonta, 1998; Blumstein et al., 1986; DeJong, 1997; Gendreau, Little, and Goggin, 1996; Zamble and Quinsey, 1997). Findings from national inmate surveys reinforce this – about 75% of prisoners in 1997 had a previous sentence to incarceration or probation prior to their current admission to prison and 43% had at least 3 prior incarcerations (BJS, 2000). Using this rule of thumb, all persons released from prison have an increased likelihood of returning.

Some recidivism studies take many of the preceding factors into account. Gendreau, Little, and Goggin (1996) looked at 131 recidivism studies with adult offenders conducted between 1970 and 1994 and found the strongest predictors of recidivism to be gender, race, age, priors (measured as any previous interaction with the criminal justice system), social achievement, and family factors. Cottle, Lee, and Heilbrun (2001) assessed 23 recidivism studies with juvenile offenders between 1983 and 2000 and found offense history to be the most significant predictor of recidivism. The most influential pieces in identifying offender characteristics associated with recidivism remain the studies conducted by the Bureau of Justice Statistics (Beck and Shipley, 1989; Langan and Levin, 2002). Findings from the 1994 release cohort confirm that some of the individual characteristics discussed are key elements to include in models of recidivism. Risk factors that appear to increase rates of recidivism are being male, black, young, and convicted of a property crime (Table 3). The report also indicated that the number of prior arrests correlates with future arrests – about two-thirds of the 1994 exit cohort had more than 5 previous arrests and were more likely to be re-arrested compared to those releases with a shorter criminal history (Langan and Levin, 2002).

Measures of gender, age, race, offense, and prior criminal history are common variables in administrative records, which are often the source for large-scale recidivism studies including this one. There are additional variables that have been associated with success and failure, but are more difficult to obtain from administrative data, including employment, education, substance abuse, and participation in treatment.

Employment has been repeatedly linked with criminal involvement and recidivism (Bushway, 1998; Meredith, Speir, and Johnson, 2007; Sampson and Laub, 1993; Western and Beckett, 1999). Uggen (2000) found that employment had a notable dampening effect on arrest for males 27 years and older and Cook (1975) determined that released inmates with jobs were less likely to have their parole revoked for a new offense. The link between employment programs, such as work release and employment assistance, are mixed: some identify little association between such aid and crime desistance (Berk, Lenihan, and Rossi, 1980; Waldo and Chiricos 1977), while others find a significant reduction in recidivism for participants of such programs (Wilson, Gallagher, and MacKenzie, 2001). The picture may be more complex than simply finding employment. Bucklen, Zajac, and Gnall (2004) found in a sample of parolees that most found work without too much difficulty, but had unrealistic expectations about pay in conjunction with debts to pay following their time in prison. Sabol (2007) adds that employment is subject not only to local labor-market conditions, but also the pre-incarceration employment experience (lengthier pre-prison employment is correlated with success in finding post-release employment) and type of release (persons on parole are more likely to find employment).

Employment is associated with race as well. Black males, already challenged in obtaining living wage jobs, experienced a decrease in employment in the 1990s due to crime involvement, transportation challenges, and lack of information on potential opportunities (Hozler and Offner, 2004). Further compounding the problem, Pager (2003) estimated that the effect of a criminal record on the likelihood of an application callback was 40% larger for blacks compared to whites – in fact whites with a criminal record were more likely to get callbacks than blacks without one. Lynch and Sabol (1998) also found that prison release rates had a negative impact on workforce involvement for blacks, but a positive one for whites. That is, as more persons came out of prison, employment went down for blacks but up for whites and vice versa.

Education can be an important factor in obtaining employment and has also been used as a measure of investment in socially-accepted values. However, persons in the criminal justice

Table 3. Characteristics of State Prisoners Released in 1994 and Returned to Prison

	% of state prisoners	
	All released	Return to prison (3 yrs)
All released prisoners	100.0	51.8
Gender		
Male	91.3	53.0
Female	8.7	39.4
Race		
White	50.4	49.9
Black	48.5	54.2
Other	1.1	49.5
Ethnicity		
Hispanic	24.5	51.9
Non-Hispanic	75.5	57.3
Age at release		
14–17	0.3	56.6
18–24	21.0	52.0
25–29	22.8	52.5
30–34	22.7	54.8
35–39	16.2	52.0
40–44	9.4	50.0
45+	7.6	40.9
Offense type		
Violent	22.5	48.8
Property	33.5	56.4
Drug	32.6	49.2
Public-order	9.7	48.0
Other	1.7	66.9

Note: From Langan and Levin (2002).

system typically come from lower socioeconomic strata and have lower levels of formal education compared to the general population, which negatively impacts their marketability and may impact their allegiance to traditional economic values. We know that former offenders with additional education tend to fare better than those without (DeJong, 1997; Tracy and Johnson, 1994), but educational opportunities beyond a GED in prisons are scarce due to resource limitations of facilities, inmate motivation, and the severance of access to Pell Grants per the

1994 Violent Crime Control and Enforcement Act. Overall, inmates have lower levels of educational attainment than those in the general population. Of inmates surveyed in 1997, about 43% had less than a high school education (BJS, 2000) compared to nearly 17% of persons aged 18 and older in the general population (National Center for Education Statistics, 1998). About 44% of prisoners had earned a high school diploma or GED (compared to 33% in the general population) and only 13% of prisoners had any higher education (compared to 48% of the general population). This differentially affects blacks – Pettit and Western (2004) estimate that 30% of all black non-college men served time in prison by their mid-30s; for high-school dropouts this doubled to 60%.

Employment and education are useful measures to predict one's chances of success following release – higher levels of education are associated with greater chance of employment. These factors are also used in conjunction with marital status and family ties to represent broader measures of investment in stakes of conformity, social capital, and attachments to family and community (Hart, Kropp, and Hare., 1988; Sampson and Laub, 1993; Sherman and Smith, 1992; Tittle, 1980; Waller, 1974). It would be ideal to have employment and education available at the individual level for the study; in the absence of this data it is possible to use proxies at the county level to characterize the level of opportunity available to inmates released to a certain area. There is also a large body of research that emphasizes the role of substance abuse in recidivism and the potential successes associated with treatment participation (both in substance abuse treatment and behavior modification treatment). The role of substance abuse on criminal behavior and recidivism is well established in the literature. Wish and Johnson (1986) found that as levels of drug use increased, so did criminal activity. Dembo et al. (1994), Roy (1995), and DeJong (1997) also found substance abuse to be an important predictor of recidivism. We also know that incarcerated persons have greater levels of substance abuse and dependence. According to the 2004 Survey of Inmates in State Correctional Facilities (BJS), about half of all state inmates (and three-quarters of drug offenders) reported using drugs in the month before their arrest, about a third report drug use at the time of the offense, and over half (53%) were determined to have drug abuse or dependence issues, compared to 2% in the general population (Mumola and Karberg, 2006). Alcohol plays a similar role in the lives of inmates; more than 1 in 4 (44%) state inmates in 2004 met the criteria for an alcohol abuse or dependence problem (Noonan and Mumola, 2007).

Substance abuse involvement has serious implications for later success. Spohn and Holleran (2002) found that prison time for felony drug offenders was linked to higher and faster rates of return when compared to felony drug offenders placed on probation while Zamble and Quinsey (1997) found that of released offenders put on drug and alcohol restrictions, about two thirds violated these limits in the first week of release (Zamble and Quinsey, 1997). Clearly, substance abuse has a role in criminal behavior and the likelihood of return. Unfortunately, measures of substance abuse are not often included in administrative record collections.

Similarly, participation in treatment programs, for either substance abuse or other mental health-based treatments, is suspected to be associated with success upon release. In a study based on California parolees receiving treatment in prison combined with post-release care had significantly lower rates of recidivism compared to inmates not receiving such treatment, 35% returned over 2 years compared to 52%, respectively (California Department of Corrections and Rehabilitation, 2009). However, the quality and continuity of care appear to be key in the impact on recidivism (Hiller, Knight, and Simpson, 1999). About 40% of state inmates in 2004 with substance abuse problems reported receiving some type of substance abuse treatment since their admission to prison, but treatment varied – most participated in self-help groups and peer-counseling (28%), while the least prevalent treatment was intensive programming through a residential facility or unit (9.5%) (Mumola and Karberg, 2006).

Other types of treatment have also been associated with reductions in recidivism. Henning and Freuh (1996) found a 20% reduction in recidivism for persons receiving cognitive behavior treatment compared to those not receiving treatment. Gaes et al. (1999) posit that most correctional treatments have at least modest positive effects and should focus on skills-oriented and cognitive-behavioral treatments.

Treatment is a challenging variable to include in recidivism studies not only because the data is rarely available at a state-wide level for released individuals, but also because the modality, quality, and length of the treatment varies so widely from place to place. Neither substance abuse measures nor participation in various treatment programs were available for inclusion in this study in predicting recidivism. These and other factors such as mental health measures, personality scales, and attitudal measures are often included in needs and risk-assessment scales conducted prior to release. Such assessments have had some success in predicting recidivism in recent years, but much debate continues as to the level of accuracy, application across offender types, and assessment modality (Silver, Smith, and Banks, 2000). As with treatment participation, risk needs and assessment tools vary widely by state and scores are rarely included in administrative records. Thus, this information is not included in the present study, but should be considered in future work.

The preceding research establishes individual and criminal justice measures to consider in subsequent studies of recidivism, some of which are readily available and some of which present challenges. We will now look to studies that address the influence of the community on criminal behavior and recidivism.

Community Characteristics

The empirical literature on community factors tends to focus on community influences contributing to delinquency and criminal behavior rather than recidivism. Still, the body of research rooted in ecological theory provides ample evidence that community measures should be included in an expanded model of recidivism. The ecological theory posits that communities are complex organizations that can inhibit or enhance criminal activity (Merton, 1938; Park and Burgess, 1924). Areas susceptible to crime are characterized by high rates of social heterogeneity and mobility such that consensual social order is difficult to achieve, exacerbating crime rates. Shaw and McKay (1969) referred to this condition as "social disorganization."

Social disorganization is believed to both directly and indirectly impact individual criminal activity through lack of positive social control (such as parental supervision, community supervision, the teaching of valued social conventions or norms) and the reinforcement or imposition of negative social controls (such as negative role models, destructive subcultural values, and reinforcement of illegal behavior).[9] A substantial portion of the research in the last few decades represent variations of Shaw and McKay's social disorganization theory (1929; 1969) positing that low socioeconomic status, ethnic heterogeneity, and high levels of residential mobility lead to social disorganization and increased crime.

Ecological theories fell out of favor during the 1970s, but reemerged when Bursik and Webb (1982) applied an updated model to the Shaw and McKay data to reassert the relationship

9. This is directly linked to earlier works by Sutherland and Cressey (1943), Reckless (1961), and Hirschi (1969).

between social disorganization and crime in Chicago communities. This work and the synthesis of ecological theories and social control theory by Bursik and Grasmick (1993) renewed interest in empirical tests of ecological theories of crime and disorganization theory. The second generation of the ecological tradition was marked by the distinction between the social structural position of areas and the direct measurement of patterns of interaction posited to flow from those structural conditions. The concept of social disorganization was broken into its component parts yielding greater evidence that the structural aspects of social disorganization and the resulting patterns of interaction in the community were related in the way the original social disorganization theories predicted.

Since then, social disorganization theory has been operationalized and measured in many ways including: subcultural street codes (Anderson, 1999; Baumer et al., 2003), environmental stressors (Latkin and Curry, 2003), community cohesion (Markowitz et al., 2001), collective efficacy (Lynch et al., 2001; Sampson, Raudenbush, and Earls, 1997), anonymity and mobility (Crutchfield, 1989), alternative exchange interests (Horne, 2004), and limited human and social capital (Cullen, Wright, and Chamlin, 1999; Rose and Clear 1998).

This research included many variables from previous social disorganization work and builds upon it by organizing these complex measures in two main categories – urbanization and opportunity. Traditional social disorganization is classified using a measure of *urbanization*, which includes the well-tested measures of population density, residential mobility, and racial heterogeneity. Other factors that have emerged in the research can be assessed in terms of opportunity. Opportunities can either be consistent with traditional social values (legitimate opportunity, as measured by factors such as education level, income, and employment rate) or can be contrary to them (illegitimate opportunity, measured by factors such as crime rate, unmarried males, and single-female headed households). Generally, a well-functioning community has high levels of legitimate opportunity and low levels of illegitimate opportunity while socially disorganized communities are characterized by low levels of legitimate opportunity and high levels of illegitimate opportunity.

Urban areas are characterized by high levels of population density and mobility and low levels of racial heterogeneity, which in turn are associated with social disorganization and disadvantage. For example, Roncek (1981) linked areas more densely populated with apartment housing to increased rates of violent crime, a finding he attributes in part to increased anonymity. Increased population density has been consistently linked to higher rates of crime (Bursik, 1986, 1988; Bursik and Grasmick 1993; Sampson, 1985; Sampson and Groves, 1989), likely exacerbated by the higher levels of residential mobility that contribute to increased isolation and the weakening of ties with extended family and neighbors (Clear et al., 2004). Racial heterogeneity also appears to contribute to instability. Research indicates that areas with less heterogeneity are more likely to be higher crime areas, particularly when the population makeup is black or foreign-born (Messner and Tardiff, 1986; Sampson, 1987).

Sampson (1987) posited that areas with high rates of single female-headed households are linked to higher crime in the community due to decreased supervision of young males in the area, increasing illegitimate opportunities. Darity and Meyers (1994) found incarceration compounded the prevalence of female-headed families in black areas; Lynch and Sabol (2002) later reinforced this when they estimated that 20% of the increase in single-black-female headed households in the 1980s was due to the effects of incarceration. Disadvantage has also been measured using socioeconomic factors in combination with the urbanization measures summarized above. Krivo and Peterson (1996), controlling for female-headed households, male joblessness, percent of crime-age population (ages 15-24), percent black, and level of community instability (measured by rental and occupancy rates), found that extremely disadvantaged neighborhoods had higher crime rates, and that these structural disadvantages had similar impacts in both black and white disadvantaged neighborhoods. Kubrin and Stewart (2006) and Kubrin, Squires, and Stewart (2007) created a neighborhood disadvantage measure using the portion of residents on public assistance, below the poverty level, or unemployed, as well as median family income – measures also used by Sampson (1997) to gauge community socioeconomic status. This scale determined that a one unit increase in the neighborhood disadvantage index resulted in increasing the odds of recidivism by 12 units (Kubrin and Stewart 2006). Further research found neighborhood socioeconomic status to be significant in explaining variations in rearrest, and that blacks were more likely to come from areas of neighborhood disadvantage (Kubrin et al., 2007).

These findings indicate that community structure and socioeconomic measures are important to include when studying recidivism and that social disorganization is a useful concept for distinguishing communities that may increase the risk of recidivism. For the purposes of this research social disorganization is conceptualized both in terms of urbanization and opportunity measures. As previously discussed, opportunities are available in both legitimate and illegitimate forms for released offenders and may vary substantially by community. For those who want to return to criminal behavior, there are undoubtedly old friends and contacts willing to aid and abet in such illegitimate opportunities; these opportunities may well be greater in areas with lower levels of supervision and higher crime rates. For those who want to try to stay straight, the availability of legitimate opportunities (such as a steady job with a living wage) can help this effort whereas a dearth of legitimate opportunities can foil it, particularly when taken in combination with numerous sources of illegitimate opportunity. Further, the simple status of being on parole criminalizes some activities for former offenders that are otherwise not grounds for incarceration, such as drinking with friends, being seen with known criminals, and failure to attend AA or NA meetings. Released offenders have an uphill battle. They are returned to the negative influences that may have introduced them to criminal behavior, have a criminal record that impedes obtaining a legitimate job, must fulfill a list of conditions as a requirement of parole, also face other challenges such as housing issues, back child-support, and a lack of family support. While it would be ideal to have some of these specific measures for such challenges, previous research indicates we don't necessarily need them, evident in the practice of the extant social disorganization studies using demographic and socioeconomic data at the community level to represent concepts such as social attachments and social capital within a community.

Much of the previous research on social disorganization was conducted based on neighborhood-level measures. This is not possible when studying recidivism across states using administrative data which may be why there is little large-scale research that includes community factors thus far. As we will see in the next chapter, this research uses county-level indicators to measure opportunity and urbanization, which has been used as the unit of measurement by at least one other study that assessed community effects on recidivism (Wilson, 2005). Using country may even be advantageous in that if county-level differences of urbanization and opportunity are correlated with recidivism we may be able to recommend policy solutions that affect a larger population beyond the neighborhood level. We now move on to reiterate and reinforce the evidence that measures of public policy are important to include when studying recidivism.

Public Policy Controls

It has already been established that sentencing policies have played a hand in the unprecedented growth of the prison population – the increase over time in the use of parole, the shift from discretionary parole release to mandatory release by statute, and the movement of parole away from support and programming services to law-enforcement type surveillance have increased the rate of return of parole violators to prison and compounded the growth of the population. We have previously argued for the importance of these policies in predicting recidivism on the basis of macro-level decompositions of the prison population and its increase over time. Additional evidence for the importance of release policy on recidivism can be found in individual level recidivism studies previously discussed. The increase in time served, instituted with the expectation that more time has greater deterrent effects, is another way in which the sentencing policy changes contributed to growth of the prison population; research outcomes on the success of this strategy will also be discussed.

Recidivism research to date does not yield much support for the shift away from the use of parole boards. While subsequent supervision levels do not necessarily differ by release type, but those formally assessed for risk by a board of experts as a prerequisite for release *may* be more successful on parole than those released by statute, but the research is mixed. Solomon, Kachnowski, and Bhati (2005) found release type had little impact on the probability of being rearrested. Persons on discretionary release did slightly better than mandatory releases, who did no better (and sometimes worse) than those released without any supervision. Solomon (2006) and Bonta et al. (2008) proclaim there is no evidence to date that parole in general has either systematically reduced recidivism or increased public safety and called for the need to study classification, type, length, and quality of supervision more carefully.

There is some research that begins to do so. Georgiou (2011) took advantage of a programming error in a classification instrument used to determine level of post-custody supervision in Washington State to show that persons mistakenly allocated to higher levels of supervision were not more successful than those properly classified to lower levels of supervision. Around the same time an overview of recidivism studies conducted by state adult and juvenile departments of correction between 1995 and 2009 by the Sentencing Project (2010) found mixed results of parole supervision and rates of return. Recidivism was higher for those on released to supervision compared to those released unconditionally in Arizona, Kentucky, Massachusetts, Oklahoma, and West Virginia; but supervised releases were more successful than outright (unsupervised) releases in Connecticut, Iowa, and North Carolina. The definitions of recidivism, size of sample, type of offender included, and characteristics used varied between studies, making outcome comparisons difficult. We can also assume that definitions and levels of supervision varied widely across states.

Wilson (2005) used a model similar to the one adopted in this research to investigate why recidivism rates in Tennessee increased between 1993 and 1999. He controlled for individual demographics, the area to which they returned (county of conviction), and type of release and found the increase in recidivism was due to neither criminal behavior nor demographics, but rather an increase in technical violations. In other words it was policy and not personal attributes that most affected recidivism. Parolees returning to urban areas had higher rates of recidivism, and recidivism was highest for property offenders. These findings are key to informing efforts to reduce the prison population, but require further testing to ensure this finding is not specific to Tennessee.

Another form of public policy control that resulted from policy changes – the increase in time served – is also hotly debated within the literature and has been included in a number of recidivism studies. If time served has a limited impact on whether offenders return, a reduction in the average incarceration period could aid in reducing the prison population in the same way it contributed to the growth. The increase in time served is one of the cornerstones of the get-tough movement and presumes that keeping offenders longer will either deter future criminal behavior or simply incapacitate longer and thus reduce the frequency of their criminal activity. Determinate sentencing, mandatory minimums, three-strikes, and truth-in-sentencing were all motivated at least in part by the belief that more time would reduce crime. Yet, few studies have indicated that an increase in time served has a dampening effect on recidivism. Langan and Levin (2002) identified an effect only on inmates serving more than 5 years; the median time served was 20 months, indicating if there was indeed an impact, it was only being applied to a subset of the population. In a smaller study, Kuziemko (2007) estimated that for each month served by inmates in Georgia, recidivism was reduced by 1.5%, independent of other control factors. These studies support the contention that increased time served can decrease the likelihood of return.

However, the theory that increased time served either has no impact or increases recidivism appears to have more support. Even before the changes in sentencing policies, evidence indicated that time served had either no effect (Beck and Hoffman, 1976) or actually increased recidivism (Gottfredson, Gottfredson, and Garafalo, 1977). Studies of early release in the 1980s found that reducing sentences had no impact on recidivism (Berecochea, Jaman, and Jones, 1974; Sims and O'Connell, 1985; Austin, 1986). Gendreau et al. (1999) conducted a meta-analysis of studies comparing length of time served and recidivism as well as the use of prison or less severe sanctions on recidivism and concluded that more punishment either had no effect on recidivism or actually increased likelihood of return. In a more recent study, Frederique (2005) found that increased time served among violent offenders in Pennsylvania released from 1997 to 2001 were more likely to return.

The mixed results promulgated from the body of research on the impact of release type and time served on recidivism indicates that these variables should be considered when assessing why people come back to prison. It is also important to acknowledge that these two policies are not the only ways in which policy differences over place and time can affect the likelihood of recidivism, but they are the most accessible in terms of data measures. Other measures, such a level of supervision, conditions of release, and official thresholds for parole revocations would be valuable measures to include, but are not available within the data sources used here.

In the beginning of this chapter, a number of other specific policies that contributed to the increase in the prison population were identified, such as mandatory minimum sentences and three-strikes laws. It is difficult to assess the effects of these policies on an individual's likelihood of returning to prison, since data on sentencing type and structure is not readily available at an individual level. In some sense, however, policy effects are greater than the sum of individual policies that we can identify. The "get tough" movement involved not only new, specific practices such as the imposition of mandatory minimum sentences, but also impacted many smaller policy decisions that affect recidivism. For example, the shift in the approach of parole supervision policies in a locale, both large (the shift from discretionary to mandatory release) and small (the number and nature of technical violations that can trigger a revocation) likely impacts the size of the prison population substantially at any given time. Other places may have instituted a practice to divert all drug offenders to treatment and allow greater latitude and discretion in parole revocations, resulting in lower recidivism rates. The amalgamation of such changes in the policy climate may be more important than any single or specific change in sentencing or supervision policy. In this analysis, we will not only assess the effects of specific policies on the likelihood of an individual inmate's recidivism, but also the effects of changes in the policy environment by using both release type and state dummy variables that encompass the definite, but difficult-to-measure differences in practice between states.

Summary

The majority of empirical recidivism studies have emphasized attributes of inmates as the determinants of whether a released prisoner succeeds or fails. These studies provide strong evidence that different personal and criminal justice characteristics of individuals are related to different probabilities of recidivism. At the same time, the changing sentencing and release policies, resulting in the creation of more persons on parole, changes in supervision, and lower thresholds of revocation, contributed to the massive increases in the prison population in the last several decades.

The foregoing review suggests that recidivism influences the size of the prison population and that specific policies affect the likelihood of re-imprisonment. This raises the prospect that what appears to be the effect of inmate characteristics on recidivism may be the result of different policies being in force in different places or at different times. Moreover, the ecological tradition in criminology and more recent studies on the collateral consequences of imprisonment argue that the residential community an inmate comes from and returns to may influence subsequent success or failure. The evidence for including individual, policy and community variables in models of recidivism is compelling, but to date has only been conducted in a study of one state (Wilson, 2005), who found that the increase in recidivism between 1993 and 1999 in

Tennessee was correlated with neither county measures nor criminal behavior, but was instead a result of technical violations. This study will bring variables from each of these domains to bear on the question of recidivism across several states and test the relative contributions of these domains to recidivism and whether these impacts vary over time and place.

CHAPTER 3

RESEARCH DESIGN AND METHODOLOGY

Based on the review of the literature, it is reasonable to believe that recidivism is influenced by attributes of offenders, the characteristics of the residential communities from which inmates come and to which they return, and the sentencing and supervision policies in the jurisdictions in which inmates live. Previous work on recidivism and offending suggest that these classes of factors can affect the likelihood of reoffending both individually and in combination. However, the specific relationship between these variables and recidivism is not known because few studies have included all three categories in their models. This chapter describes how these relationships are operationalized beginning with the definition of recidivism, followed by the statement of the hypotheses. The chapter also includes a description of the data sources, the construction of the dataset, and the methods applied to test the hypotheses.

Defining Recidivism

As previously mentioned, one of the greatest challenges in comparing recidivism rates across studies is the variation in definitions used. Maltz (1984:1) offers a broad definition of recidivism:

> Recidivism is the reversion of an individual to criminal behavior after he or she has been convicted of a prior offense, sentenced, and (presumably) corrected. It results from the concatenation of failures: failure of the individual to live up to society's expectations–or failure of society to provide for the individual; a consequent failure of the individual to stay out of trouble; failure of the individual, as an offender, to escape arrest and conviction; failure of the individual as an inmate of a correctional institution to take advantage of correctional programs–or failure of the institution to provide programs that rehabilitate; and additional failures by the individual in continuing in a criminal career after release.

It is notable that the term "failure" is repeatedly applied to the individual, with the exception of minor allocations of responsibility assigned to society for failing "to provide" (the term "provide" could refer to social supports ranging from education to equality and opportunity) and institutions for failing "to correct" (modifying behaviors to fit within socially acceptable norms). The contribution of specific policies to "failure" is conspicuously absent from this lengthy definition. This definition is consistent with the traditional view of criminal behavior – that responsibility lies largely with the individual.

Recidivism is usually operationalized in terms of a rearrest, a reconviction, or a return to incarceration. Studies using rearrest as a measure of recidivism (Schmidt and Witte, 1988; Lanza-Kaduce, Parker, and Thomas, 1999) rely upon the lowest threshold (probable cause) to define failure. As Maltz (1984) notes, this can result in Type I errors by including those who are not guilty.[10] Other studies reconviction or re-imprisonment to measure recidivism (Carr-Hill and Carr-Hill, 1972) and still others (Beck and Shipley, 1989; Langan and Levin, 2002) use all three to provide a range of measures. This study is concerned with reducing the prison population by decreasing the rate of persons returning to prison; therefore, the appropriate recidivism measure used is a subsequent admission to prison after release.

Researchers in the past have also disagreed on the risk period by which to measure recidivism. Time to recidivism has been measured in increments of months, years, and even lifetime. Due to the time lapse necessary for an offender to reoffend or violate parole and be re-processed through the criminal justice system, a one-year return may be too short for some systems.[11] The common practice is to use a 3-year recidivism measure and thus this will be the threshold used in this research (Beck and Shipley, 1989; Langan and Levin, 2002; Pew Center for the States, 2011). Specific time to return, type of return, and number of times returned were

10. All recidivism studies suffer from Type II errors in that those who are not re-arrested, convicted, or incarcerated have not necessarily ceased criminal behavior.

11. Some persons previously released may be held in jail following a re-conviction or revocation of parole and may not appear in the prison system database until they are actually transferred to a prison facility.

additional dependent variables that were considered. While each of these can be a valid measure, states vary in their classification of return types and also in their processing times to admit a recidivist back to prison. For instance, in some states all admissions are categorized as new court commitments (this phenomenon was discovered while searching for states to include in the study). Other states use the parole violator status to revoke conditional releases picked up for a new crime because it saves the court processing time. Time to return is also an unreliable measure because states vary widely in processing time for returning offenders. Some states re-admit parole violators to prison quickly, while other states take longer to officially re-admit inmates (we will see evidence of this later in the descriptive data of the states used in the study). It is possible to use re-admission type and time to return as dependent variables, but one must understand the classification and processing differences between states in order to do so effectively. Finally, the main objective of this study is to identify the reasons people return to prison *at all* rather than the question of when a return occurred, whether the return was for a new crime or revocation, or how many times persons are returned over a set period.

Finally, parole violators may include both technical violators and persons returned for new offenses, depending upon the jurisdiction. However, the NCRP data does make this distinction in the type of return variable. Even if this data were available, we know from the explanatory notes provided by states accompanying submitted data that they have different classification systems for how a parole violator is recorded within their own systems. While it would be preferable to make a distinction between new offenses and technical violators, that was not possible for this study.

Hypotheses

The following hypotheses are based on findings from previous research and the supposition that sanctions and release policies should have similar effects across places, even though there is some evidence to the contrary. The hypotheses are presented under the same blocks used to summarize the existing literature: individual and criminal justice factors, community factors, and public policy factors. Brief explanations of the underlying assumptions for each hypothesis are provided.

Individual and Criminal Justice Factors

Hypothesis 1 – Males, minorities, and younger released inmates will have significantly higher rates of recidivism compared to females, whites, and older released inmates. This assumption is consistent with prior research findings; this study will determine if this effect holds true for these cohorts and whether it is consistent across states and over time.

Hypothesis 2 – Property offenders will have significantly higher rates of recidivism than other offender types. This assumption is also consistent with previous research. This hypothesis is of particular import given some of the current initiatives to reserve prison for exclusively violent offenders and sanction non-violent offenders within the community. If fail to reject this hypothesis we must then consider whether we are willing to accept higher rates of non-violent crime in exchange for a reduced prison population.

Hypothesis 3 – Previous failure will be correlated with subsequent failure. As previously demonstrated, first releases are generally more successful than subsequent releases. We will see if this holds true even after holding individual, community, and policy factors constant.

Hypothesis 4 – Greater time served will result in lower probability of return. Increasing time served was a conscious policy decision under the assumption that more time would serve to deter future offending. Time served could also be assessed as a policy variable, but because it is commensurate with the offense it was designated as a criminal justice domain. The literature on the relationship between time served and recidivism is mixed. The study will allow us to identify if there a consistent effect across states and over time.

Community Factors

Community measures as a whole are used to measure the environment to which inmates return upon release. Rooted in the theory of social disorganization these variables are organized in terms of legitimate opportunity, illegitimate opportunity, and urbanization, each of which are summarized here and discussed in greater detail later in the chapter.

Hypothesis 5 – The more legitimate opportunities in the community, the lower the rate of recidivism. A common theme in previously modeled theories of social disorganization is that stable communities have lower levels of disorganization. One way to operationalize the level of community organization is by assessing the level of legitimate opportunities available to residents, which can measured by factors such as low levels of unemployment and high levels of education and household income. A stable community is more likely to provide legal and pro-social opportunities to a released offender which may serve to inhibit a return to prison.

Hypothesis 6 – The more illegitimate opportunities in the community, the higher the rate of recidivism. Much as legitimate opportunities can reduce recidivism, illegitimate opportunities are indicators of community instability that may increase recidivism. Illegitimate opportunity can be measured by factors such as the prevalence of unmarried males, female headed households, and high crime rates. Areas with high levels of such factors present released offenders with the peers, lack of supervision, and criminal opportunity that may encourage or reinforce behaviors that increase their probability of returning to prison.

Hypothesis 7 – Higher levels of urbanization will be correlated with higher levels of recidivism. Finally, and most closely associated with the extant social disorganization literature, is the assumption that the degree of urbanization within a place, which can be measured by factors such as the minority population, population density, percent of renters and vacant housing, impacts recidivism. Urbanization is associated with reduced levels of social cohesion, investment in social norms, and personal attachments, all of which may serve to exacerbate community instability and increase recidivism.

State and Public Policy Factors

Hypothesis 8 – Type of release (i.e. discretionary parole, mandatory release, or expiration of sentence - EOS) will have no impact on rates of recidivism. There is already evidence that we may reject the null for this hypothesis – there appears to be a difference in recidivism rates between inmates released through various mechanisms. However, as the Sentencing Project found in their analysis of recidivism studies conducted from 1995 to 2009 the results are mixed – sometimes post-custody supervision was found to reduce recidivism and other times to increase it. This hypothesis will serve as a test to see if type of release impacts the likelihood of recidivism and if there is a consistent effect across places and time while accounting for other factors correlated with recidivism.

Hypothesis 9 – State will have no significant impact on recidivism. In an ideal world, a return to prison is based on specific behavior of the individual and not where one resides. We are already controlling for type of release, which we have seen varies across places and is a jurisdictional determination. However, there is ample evidence that jurisdictions also handle offenders differently in terms of diversion, supervision, and revocation policies. Because we don’t have measures for these and other state-specific policy differences that likely exist but may be less formalized, the state dummies will provide a general measure to account for residual state-level factors comprising a policy climate that could explain differences in recidivism between states.

Hypothesis 10 – Recidivism will decrease between the 1992 and 1999 cohorts for all states. Many of the policies introduced in the 1980s and 1990s were based on the belief that increased likelihood of incarceration, time served, and post-custody supervision would deter future criminal behavior. Based on this, it is reasonable that given the sea changes in policy regimes the recidivism rate would decline if such measures were successful. At the national level, we have evidence that the rates seen in the 1994 BJS recidivism study were higher than those from the 1983 study, but results from all states were aggregated together and the studies were conducted differently, which may account for this disparity in results. This hypothesis will test whether a decline in recidivism was achieved across states included in the study.

Data

The main data source used to build the research dataset, the National Corrections Reporting Program (NCRP), is collected by the Bureau of Justice Statistics. The NCRP provides both the individual and state level measures used in the models, and also provides the county of conviction, which was used as the location to which offenders would return following release. The NCRP data were merged with the variables from the decennial censuses and the Uniform Crime Reports on the county variable. Following is an explanation of how the states in the study were identified, how the individual records were linked over time from the NCRP data, and what county level variables were merged into the dataset.

State-Level Data

Initiated in 1983, the NCRP is comprised of electronic data files from participating states containing individual level records on all admissions to prison (A records), releases from prison (B records) and releases from state parole (C records), along with demographic characteristics, offense, sentence length, release type, and other information central for a recidivism study. The dataset was built by linking together records from the NCRP A and B records from 1992 to 2002.[12] It proved to be a challenge to identify states that 1) consistently submitted both admission and release records for over a decade; 2) had comparable reporting over the years and; 3) included core data elements each year. States without the required baseline data were eliminated from the study.

Participation in the NCRP is voluntary; the number of states participating from 1983 to 2002 ranged from 32 to 42. Because the current study focuses on the changes in sentencing and release policies in the 1990s, 1990 was the initial target release cohort for the baseline year. However, inmate identification numbers (inmate IDs), essential for tracking subsequent admissions following release, were not collected until 1992, so the first release cohort year became 1992.[13] A release cohort for 1999 was also used in order to measure changes, if any, in both rates of recidivism and the variables associated with likelihood of recidivism.[14]

Of the 35 states submitting data for each year from 1992 to 2002, two states submitted partial records; that is, either admission records or prison release records. Since both records

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12. Much of the code used was adapted Allen Beck's syntax that linked NCRP records for his work on population growth in prisons between 1980 and 1996, which he generously shared (Blumstein and Beck, 1999).

13. In order to include more states, probability matching on variables such as date of birth and race could likely be used to overcome the ID issues.

14. When this study began, 2002 was the most recent available year for NCRP and a 3-year recidivism followup was required.

were required to build the dataset these states elimination from the study. The next cut, identifying states submitting uniquely assigned inmate IDs, was the largest. Nine states submitted inmate IDs in the files from 1992 to 2002, but several either instituted a new alpha numeric scheme over the time period or assigned a new inmate ID to every inmate admitted, making individual record linking based on ID impossible. Finally, there were some variables required to generate a basic recidivism model – date of birth, race/ethnicity, date of admission, admission type, offense, date of release, time served, and type of release. States that did not include all of these variables were excluded from the study.

In the end, four states met all of the necessary requirements for inclusion in the study: California, Michigan, New York, and Pennsylvania. Fortunately, there is sufficient variation over the decade in sentencing and release practices among the selected states to test the effect of policy on recidivism. Information on the prison population, sentencing and release policies, and basic descriptors of the inmate release cohorts of each state are presented in the next chapter.

Person-Level Data

The core dataset was created by taking the entire exit cohort from the release records in each state for 1992 and 1999, using the inmate ID to find any subsequent record of the same inmate through admission records, and appending the new admission data record to the release record. Before data cleaning, there were 124,723 releases among the four states in the 1992 cohort and 160,636 releases in the 1999 cohort. A subset of inmates was returned more than once in a single year; as a result programs were run to append multiple returns to the original release record in order of re-admission date. Multiple returns occurred in each state for every year. California had a handful of inmates coming back five to six times in each year, an early indication that the California system may be different than other states (see Appendix A for number of iterations each year by state).[15]

Data cleaning included purging deaths, transfers, and escapes from the release cohorts, as these are not releases for the purposes of the study (that is, a legal release from custody with opportunity to return). Overall, this reduced the total number of cases to 117,340 for the 1992 cohort and 156,061for the 1999 cohort (a decrease of about 6% of cases in 1992 and 3% in 1999). Once the links between individual inmate releases and returns were made, the original id was destroyed and the case was assigned a new id to decrease the probability of identifying individuals in the dataset.

Additional data cleaning was necessary to allow for state comparison, such as recoding date of birth and race and ethnicity. Finally, since county and community effects on recidivism are being tested in the study, a threshold of at least 20 cases per county was set in order for a county to be included in the analysis based on the assumption that county level measures applied to groups of fewer than 20 would be unreliable.[16] See Appendix B for listing of counties removed.

County-Level Data

Various data elements from the Census of Housing and Population were downloaded from the Census Bureau website by county, which are described later in more detail (U.S. Census Bureau, 1990, 2000). The 1990 and 2000 decennial information are reasonably close to

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15. While the focus of this study is not frequency of return, the information may prove useful for future research on the characteristics of persons with high-frequency returns and the wisdom (or limitations) of managing a prison populations by a revolving door method.

16. Initially, county-level dummies were also going to be used in HLM modeling which was another reason for the 20 case threshold. However, HLM modeling no longer made sense with 4 states and preliminary regression analyses using the state dummies were difficult to interpret. Thus, it was decided that the social organization scales would represent county differences.

the 1992 and 1999 cohorts, respectively, and served as an approximation of county characteristics at the time of each cohort release. The Uniform Crime Reports data on arrests and crimes by type and county for the years 1990 and 2000 (to match the periods used from the decennial census data) were also downloaded online and merged into the county dataset. The county data from the censuses and the UCR crime and arrest measures are both used to describe environmental characteristics that could impact the likelihood of recidivism for released inmates. These variables are discussed in more detail in the next section.

Variables

The individual, county, and public policy variables culled from the data sources described in the foregoing section are detailed below.

Individual Factors

All available variables in the NCRP were downloaded for the release cohorts from the four states and then assessed for usability. Some of the variables were not used due to data issues – education, participation in substance abuse treatment programs, and prior jail and prison time variables all proved to be unusable due to missing or inconsistent data.[17] Up to three offenses are collected per individual in the NCRP. The first offense, which has the greatest sentence length, was used as the controlling offense. This will obscure some information. For instance, a person convicted of an assault and a drug offense will be classified as a violent offender for the assault, thereby excluding the less serious drug offense from consideration as a control variable in the

17. The variable for prior time served (a numeric recorded in months) proved to be inconsistent across states. Some states appeared to be reporting jail time served prior to transfer to prison for the current offense, others appeared to be reporting time served on prior sentences, and others had no reported value at all. Due to the nature of these inconsistencies, it was also impractical to convert the continuous variable to a binary one (yes/no for prior time) because of the uncertaingly whether “prior time” was associated with the current offense, previous offenses, or both.

model. In addition, the offense of record serves as the controlling offense for which an individual was released, and does not include previous offenses (the NCRP does not collect detailed information on prior criminal history). This means someone released for a drug offense may have a violent conviction in the past, but this information was not available. While it is tempting to categorize offenders into general subgroups (i.e. violent, property, drug, public order) we must remember that this category is based on the current offense with the longest sentence.

The individual attributes included in the full dataset were sex, race/ethnicity, date of birth, county of conviction, offense, admission type, time served, and type of release. Race/ethnicity data were not submitted consistently between states; see Appendix C for a listing of percent of cases missing race variables by state. Due to differences in systems, it was not possible to classify inmates by white non-Hispanic, black non-Hispanic, and Hispanic across states. In addition, Pennsylvania did not submit offense data in 1992 and New York did not submit time served or admission type variables in 1992. Individual attributes were divided into individual characteristics (sex, age, race) and criminal justice characteristics (offense, time served) and county of conviction was used to bring in measures of social disorganization.

Frequency distributions (Table 4) reveal that time served varies substantially for first releases (those entering as new court commitments) compared to re-releases (parole violators). About half of parole violators serve less than 6 months, compared to about 10% of new court commitments. Were we to use a continuous or categorical time served variable with no adjustment for admission type, these disparities would be obscured and introduce error in the model as result of misspecification (for example, average time served for released offenders in a state like California with a large proportion of parole violators would be lower compared to that of states with fewer parole violators exiting prison).

Table 4. Time Served by Admission Type and Release Year

	% released by time served			
	1992		1999	
Time	NCs	PVs	NCs	PVs
0–6 months	9.9	47.0	9.8	49.5
6–12 months	34.6	31.2	30.2	27.7
1–2 years	32.6	15.1	29.3	11.2
2–5 years	19.0	5.6	23.0	7.6
5+ years	3.8	1.1	7.7	3.9

Note: Total may not add due to rounding. NCs = new court commitments. PVs = parole violators.

To take into account the difference in time served between new court commitments and parole violators, an adjusted time served variable was computed. Quintiles of time served by admission type were produced and then incorporated into a new time served categorical variable. Cutpoints are displayed in Table 5. Dummies were then created from the categorical variable to represent new time served tiers adjusted for admission type. The impact of this adjustment is discussed in the next chapter.

Table 5. Adjusting Time Served for Differences by Admission Type

	Time served (months)	
Quintile	New court commitment	Parole violator
1	0 to 7.7	0 to 2.7
2	7.8 to 11.7	2.8 to 5.0
3	11.8 to 17.8	5.1 to 7.8
4	17.9 to 30.4	7.9 to 12.9
5	30.5+	13.0+

Additional variables that could indicate social bonds and socioeconomic status, such as marriage, children, employment, and income were not available. Education, treatment, and prior time, all variables requested as part of the NCRP, were also not useable. State Departments of Correction, the source of the NCRP administrative data, generally do not include such information in their data systems because this information is not core to their mission of safety and security. Some parole and probation departments collect this information because it can be used in risk assessments for supervision classification, but access to these data was not possible for the study.

County Factors

A variety of county level data elements were extracted from the Census of Population and Housing and the Uniform Crime Reports to account for community factors that previous research indicated may be correlated with crime and recidivism. A full list of the variables downloaded and entered into factor analysis is provided in Appendix D.

These county attributes were used to characterize the social environments to which inmates return. The literature reviewed previously identified a number of community characteristics that could affect recidivism. As previously discussed, the county variables were conceptualized into discrete measures to capture different aspects of social disorganization or community stability: legitimate opportunity, illegitimate opportunity, and urbanization. Each of these dimensions of social disorganization may to influence subsequent behavior following prison, either in a positive or negative manner by reinforcing or discouraging criminal behaviors and behaviors that, while not criminal per se, may result in a revocation because they violate conditions of post-custody supervision (such as mandatory treatment attendance, obtaining and maintaining employment, and avoiding known drug users, to name a few).

Legitimate opportunity is operationalized as factors that contribute to the ability of an individual being able to attain a reasonable standard of living through legal means. For example, areas with higher average education and wages and lower rates of unemployment would represent counties with more legitimate (non-criminal) opportunities for residents, including released offenders. Even if the offender and the immediate family of the offender have lower levels of education, earnings, and employment than the county average, the relative success of others in the county could increase their own changes of success through legitimate means, such as by learning of job leads or educational opportunities through family or social connections.

Conversely, there are also factors that may inhibit success or encourage criminal behavior – these are characterized as illegitimate opportunities. Measures such as the crime rate and the portion of the population made up of unmarried males and female-headed households are examples of factors that can affect involvement in crime and subsequent recidivism for released offenders. High crime rates are indicative of prevalent opportunities to commit crime. A high percent of unmarried males could also increase illicit opportunities as unmarried males may be more likely to be young, have unmarried peers, and have more time and opportunity to engage in criminal behaviors or behaviors that violate parole conditions (e.g. alcohol and drug use). As in previous research, a high prevalence of female-headed households in a community can be used as an indicator of lower informal supervision levels.

Law enforcement responses to crime were also included, but may impact opportunity in ways difficult to predict. For example, areas in which drug activity is low-risk due to limited law enforcement intervention provide more illegitimate opportunities for interested persons. But the chances of being caught could be higher for released offenders for a variety of reasons. They may be on the radar of police officers due their recent release. They could fail to pass the regular drug tests that are a condition of their community supervision. Even if former offenders intend to go straight after release, they have to contend with the reality that legitimate employment may be elusive due to a criminal record and limited education and experience. At the same time, they may be surrounded by friends and family trying to get them to go back to their old ways.

The traditional measure of social disorganization most often used – population density, racial heterogeneity, and residential mobility – is conceptualized as a measure of urbanization, the third element of the model that, in conjunction with legitimate and illegitimate opportunities, can be used to characterize the stability (or instability) of the environment to which released inmates return. Places with greater population density, a high percent of foreign-born residents and renters, and higher rates of unoccupied housing are likely more urban and less stable.

Factor analysis was utilized to determine if the variables would cluster into uni-dimensional scales to represent each of these conceptualizations of social disorganization. All variables were standardized prior to factor analysis and were either identified in previous research as appropriate measures of general social disorganization or disadvantage or were believed to be appropriate measures to represent legitimate opportunity, illegitimate opportunity, urbanization, or law enforcement measures at the county level. Some variables could be theoretically included in more than one scale. In these cases, they were entered into both and ultimately included in the scale in which the loadings were superior. Percent black and violent crime rate, for example, could be operationalized as a measure of either illegitimate opportunity or urbanization; percent black loaded best in the urbanization scale and the violent crime rate loaded best with other illegitimate opportunity measures.

Standardized variables were entered into a principal components analysis without rotation and the component loadings and Eigenvalues were used to assess how well the individual measures worked together as a scale measurement. After a series of iterations that produced scales with loadings significant in both the 1990 and 2000 scales, the variables comprising each of the county scales were identified.[18] Table 6 lists the loadings of the final scales for legitimate

18. There is one exception – foreign born loaded well within the urbanization scale with the 1990 data, but not with the 2000 data. The variable was used in the scale for both years for consistency.

Table 6. Factor Analysis Loadings

	1990		2000	
	Component 1	Component 2	Component 1	Component 2
Median household income	−0.820	—	−0.677	—
% adults unemployed	0.886	—	0.862	—
% households with public assistance	0.850	—	0.876	—
% high school diploma or higher	−0.771	—	−0.788	—
% below poverty level	0.915	—	0.911	—
Eigenvalue	3.6	—	3.4	—
% of variance	72.3	—	68.4	—
Violent crime rate per 1,000 residents	0.827	—	0.836	—
% unmarried males	0.691	—	0.776	—
% single moms as head of household	0.851	—	0.870	—
Eigenvalue	1.9	—	2.1	—
% of variance	62.8	—	68.6	—
% Black	0.738	0.344	0.730	−0.243
% foreign born	0.866	−0.389	−0.070	0.941
% speaking English at home	−0.835	0.422	−0.711	−0.328
% renters	0.889	−0.145	0.871	0.175
% using public transportation to work	0.845	0.465	0.882	−0.007
% occupied housing units	0.696	−0.360	0.684	−0.212
Population per square mile	0.776	0.543	0.798	0.011
Eigenvalue	4.6	1.1	3.7	1.1
% of variance	65.4	15.9	52.6	16.1

Note: Dash indicates no Component 2 matrix in output.

illegitimate opportunity, and urbanization. For legitimate and illegitimate opportunity the analysis only produced 1 component. A second component was produced in the urbanization scale for both years that included all the same variables with an Eigenvalue of 1.1. The drug arrest rate per 1,000 county residents did not load significantly in any one scale, but was retained for use in the regression models to measure the impact, if any, that local law enforcement reactions to drug crime may have on recidivism of offenders released into the community.

Thus, community factors in this study are measured in terms of factor-weighted county scales representing legitimate and illegitmate opportunities and urbanization, and by county drug arrest rates. This approach is a departure from the conventional application of social disorganization; however, it is hoped that by expanding the scope of environmental factors possibly correlated with recidivism, we will be able to better understand how characteristics of the community impact the likelihood of return to prison.

Public Policy Factors

As previously discussed, the role of public policy in impacting recidivism is complex. Offenders are subjected to numerous sanctions that may differentially impact their success upon release. As stated earlier, ideally all offenders would be treated similarly in accordance with the specific crime, as well as the nature and length of criminal history. We know, however, that this is not case simply by looking at the many differences in sentencing and release policies used across the nation. What remains unknown is whether these policy differences have significant and consistent effects on recidivism across states, net of individual and community effects. Type of release is a key policy measure used in this analysis. There are also other practices, such as supervision type, duration, and revocation threshold that make up a policy climate but for which data were unavailable. In an effort to account for these differences, state dummies are used.

Type of release is an important measure in characterizing policy. Persons released by mandatory statute are all subject to post-custody supervision; persons released by parole boards are evaluated by a board to assess the preparedness for reentry, and then subject to post-custody supervision; other persons complete their term and are released under an expiration of sentence status without post-custody supervision. While the hypotheses predicts no difference in recidivism between persons released in these various ways, it is suspected that the model outcomes will result in a rejection of the null, indicating that there is indeed a difference. We will also be able to determine if the outcomes are consistent across place and time after controlling for other correlates.

There are many other policies and practices within a state that together constitute a policy climate but are more difficult to measure. Supervision policies and requirements, for example, are not available at the offender level but may well influence the likelihood of being returned to prison. For example, parole offices with low tolerance thresholds for technical violations such as positive drug tests or a missed appointment with an officer will return more persons than an office that only revokes parole for a new offense. In addition, officers with heavy workloads may not be able to supervise every person with the same rigor. Classification systems and risk assessment tools aid in assigning parolees to different levels of supervision, but officers may know additional details about individuals on their caseload that cause them to informally re-classify their charges and supervise accordingly. The time and resources necessary to pursue absconders (persons who fail to report following release from prison) may not exist, so such persons may elude revocation in some systems. Alternatively, there may be an emphasis on locating absconders and other types of violators, but the county jail is already crowded and officers know the parolee will be re-released within hours making an arrest not worth the time of the paperwork involved. These are just a few examples of practices at the supervision level that can affect rates of recidivism.

These underlying activities can have noticeable impacts on rates of recidivism but are very challenging to measure. Because such practices are so difficult to identify and measure in a consistent way across states, a dummy variable for state will be used to represent the policy climate beyond that of release type. Most parole rules and regulations stem from the state-level, so the state dummy may be able to represent some of the nuances in parole practices between states. By studying the variable coefficients within each state over time, we can also see if the national-level shift in supervision and revocation practices occurred consistently or only in some states. It is also possible that the more severe policies may impact different types of offenders differently. For example, drug offenders may have higher rates of return in 1999 simply because the tolerance for drug violations declined over time. Alternatively, perhaps violent offenders return to prison at higher rates because facilities were crowded and bed space was reserved for the biggest public safety threats. By looking at outcomes across the various correlates we may be able to offer theories about the underlying policies at work.

Limitations in the Data

Measures for individual, community, and public policy characteristics have been identified for inclusion in the recidivism model. Before we proceed, however, it is important to consider the limitations in the data and the approach. First, there are limitations in using the administrative records. Related to this issue is the problem of missing data that may result in inconsistent measurement across jurisdictions, particularly for individual level characteristics. Second, the model necessarily assumes that county is a sufficient representation of community and that released offenders return to the county in which they were convicted. Third, the NCRP only allows the tracking of those offenders reincarcerated in the same state. Finally, a focus on return to prison excludes persons who may re-offend, but who are not arrested, convicted, or may be sentenced to community supervision or held in local jails rather than sent to state prison.

Weis (1986) states official criminal records of criminal behavior are one of the most reliable of methods in measuring criminal behavior, but acknowledges problems with official records include varying police practices and laws, changes in recording practices, and incomplete records (Weis, 1986). Many of these are minimized by the definitions imposed by BJS to streamline the data collected, but inconsistencies remain. When core data elements were completely missing or unreliable, the state was excluded from the study. Still, there are some remaining data issues with the final four states. Pennsylvania did not submit offense data for the 1992 cohort. About a third of race data and all of the time served and admission type data for New York was missing in 1992, and Hispanic origin was unavailable for most cases in both Michigan cohorts and the majority of Pennsylvania cases (Appendix table C). While there are a sufficient number of cases to conduct analysis, this missing data may affect the model outcomes and must be considered in interpreting the results.

The study assumes that the released prisoner returns to the county of conviction. Inmates under supervision are required to check in with the local parole office and keep their officer apprised of their address, employment, and treatment – many list a family member or friend as the contact address upon release as family, friends, and children can provide a support network for housing, financial aid, and employment. The assumption that persons return to the county from whence they came is supported by findings from the Urban Institute (2008). Overall, released prisoners tend to return to certain cities in each state upon release and these same cities are the source of the majority of admissions. Half of all prisoners released in Illinois and

Maryland in 2001 returned to Chicago and Baltimore, respectively (Baer et al., 2006). Houston was home again to a quarter of prisoners released in Texas, and 2 of New Jersey's 21 counties re-welcomed a third of released state prisoners (Baer et al., 2006). Further, offenders tend to return to where they have family, which is most likely to be from whence they came – most prisoners in Maryland (80%) and Illinois (88%) were living with a family member two months after their release (Urban, 2008). In terms of mobility, just over a quarter of released prisoners in Chicago moved at least once in the two years following release; but the average distance was only 2.8 miles away from their initial address (LaVigne and Parthasarathy, 2005). While such moves were often to different census tract (92%) or neighborhood (75%), they still resided in the same county (Urban, 2005). Finally, there is precedent for use of county of conviction as a measure to place persons following release from prison (Wilson, 2005).

The assumption that inmates return to the county in which they were sentenced also has implications for the accuracy of the recidivism measure. In the case of a released inmate moving to another county, a reentry to state prison would still be captured in the data through the assigned state inmate ID. Those who are re-committed in another state will go undetected through this data collection; according to a national level recidivism study by Langan and Levin (2002) about 1 in 8 of the 1994 release cohort were rearrested in other states. Of these, a portion would have been re-incarcerated. Thus, while the current dataset does have some potential slippage in the detection of readmission to prison, the vast majority of those coming back are accounted for in the data.

Finally, the study's focus on re-imprisonment rather than rearrests or reconvictions uses a higher bar than some previous studies in defining recidivism. Maltz (1984) would likely add that success should be based on positive accomplishments rather than the absence of negative findings, particularly since it is not clear that those who have not reentered the criminal justice system have actually ceased criminal activity—perhaps they just got better at avoiding detection. However, the goal of this research is to reduce the prison population by identifying factors which impact the likelihood of return to prison, so defining recidivism as a subsequent admission to state prison is appropriate; if one were measuring public safety instead, subsequent crime commission or arrest would be a more appropriate measure.

Statistical Methods

The objective of the analysis is to identify some of the factors that impact recidivism of persons released from state prison, and determine whether these influences are consistent across several states and over time. These factors have been classified into individual, personal, community, and policy attributes. The effects of each block of variables on the probability of return to prison will be assessed while holding constant the effects of the other blocks of variables. In addition, we are interested in identifying the interaction among these categories of variables. We want to know if specific types of inmates are more likely to return under specific policies than others. Finally, we want to see if these effects are different among states and over time.

The models tested in the next chapter are first run in a series of linear logistic regressions as "pooled" models that aggregate all states by cohort year to determine the overall effect of variable blocks and identify changes over time. This approach will also demonstrate whether the state dummy variables, which represent the underlying policy climate in each state, are significant. State and time-specific models are also estimated to see if the effects of individual and community attributes and release type vary across place and over time. Then logistic regressions are run by state and cohort since it is likely that recidivism is not a linear function.

While much empirical research has been conducted in the area of recidivism, the simplistic approach of using a handful of individual attributes (or none at all, as in the recent Pew study) to control for recidivism rates persists. The multi-faceted model used here offers an integrated, comprehensive model that allows for individual, community and public policy effects. By controlling simultaneously for these variable blocks, this study aims to improve what we know about why so many offenders come back.

CHAPTER 4

RESULTS

In this chapter the release cohorts are generally described in terms of the variable blocks in the model – individual characteristics, criminal justice factors, and public policy factors (type of release) – as well as by state and year.[19] We provide basic descriptive information on the variables in the models. The univariated distributions are presented as well as the simple bivariate relationships between the predictor variables and recidivism so that we may include these variables appropriately in the model and better understand the multivariate results. The multivariate models will be estimated with the linear probability models first to identify collinearity problems and the relative contribution of variable blocks. Logistic regression models will be presented last to provide the coefficients and effect sizes for individual variables in the models.

Multi-variate models will be estimated first with pooled data from all of the states for each of the two time periods, 1992 and 1999, in order to assess the relative contributions of the variable blocks and the stability of these contributions over time. State specific models will then be estimated to determine if the effects of predictor variables differ across policy environments. A final model will be run using the data pooled across states and time to obtain a formal test of the effects of time or epoch on the probability of recidivism while holding other factors constant.

Descriptive Data

The descriptive data are provided in two parts: the predictor variables used in the models and the rates of recidivism without controlling for any characteristics.

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19. Community characteristics are not assessed at the state level in the descriptive statistics, as these are more appropriately attached to the individuals released. The average score on a social disorganization scale is not very useful in the aggregate because it obscures the variation between counties.

Predictor Variables

Based on the data reported from the National Prisoner Statistics the cases included in the dataset represent approximately 30% of offenders released nationally in 1992 and 1999 (Bureau of Justice Statistics). California cases represent the largest share of releases included in the dataset in 1992 (65%) and 1999 (71%), followed by New York (20% and 16%, respectively), Michigan (about 8% each cohort year), and Pennsylvania (6% each cohort year). Gender distributions varied slightly among states, with a high female population representation in the 1999 California cohort of 10% and low of 6% in the 1999 Pennsylvania cohort (Table 7). The female representation of an average 8% in the two exit cohorts is slightly above the national average of the 6.6% in the stock population in 1999 (Beck, 2000).

In 1999 the racial distribution of the standing inmate population for the nation was 33% white, 46% black, 18% Hispanic, and 3.4% other (Beck, 2000). The four states in the study illustrate how the racial distribution can vary substantially across states, but this should be viewed with caution due to the missing data problem with race in New York and Hispanic origin in Michigan and Pennsylvania – Hispanics are likely also included in the white and black race classifications for these states (see Appendix table C). The data show California and New York released the greatest proportion of Hispanics in 1992 and 1999 (between one-fourth and one-third of the exiting cohorts) while over half of released inmates in Michigan and Pennsylvania were black. California had the highest proportion of white releases. The other three states had much higher proportions of black releases than California, while New York had the lowest percentage of white releases (about half that of the other states).

The mean age of release did not vary much across state, but did increase an average of two years for all four states between the 1992 and 1999, with California and Pennsylvania releasing the oldest average population (a mean age at release of 35 years old). The proportion of

Table 7. Demographic Characteristics of Persons Released from Prison, by Release Year and State

	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
Number of cases	77,169	111,451	9,362	10,297	23,998	24,913	6,811	9,400
% of cases in dataset, by year	66 %	71 %	8 %	7 %	20 %	16 %	6 %	6 %
Gender								
Male	92 %	90 %	92 %	92 %	92 %	92 %	93 %	94 %
Female	8	10	8	8	8	8	7	6
Race								
White	30 %	39 %	39 %	43 %	15 %	16 %	36 %	32 %
Black	37	37	60	55	51	52	55	56
Hispanic	33	23	1.3	2	33	31	9	11
Other	0.8	1.3	0.4	0.5	0.4	0.6	0.2	0.5
Age at release								
Under 20	0.5 %	0.6 %	2.8 %	2.1 %	4.2 %	2.3 %	0.5 %	0.4 %
20–24	16	12	23	16	21	16	16	13
25–29	26	18	23	19	27	18	23	21
30–34	25	21	20	18	22	21	23	20
35–44	26	35	24	31	20	32	28	31
45–54	6	11	5	11	5	9	7	11
55 +	1.6	2.0	1.5	2.1	1.2	2.2	2.2	2.9
Mean age at release (years)	32.7	35.0	31.5	34.3	30.9	34.0	33.2	35.0

Note: About 33% of race data was missing for the New York 1992 cohort, approximately 98% of ethnicity data was missing from both Michigan cohorts, and 81% and 69% of ethnicity data was missing in Pennsylvania for the 1992 and 1999 cohorts, respectively.

youngest inmates, those under 20 years old, decreased in the release cohorts between 1992 and 1999 with the exception of California. New York experienced the most significant decline in young inmates released from 4.2% in 1992 to 2.3% in 1999 (this could be due to a number of factors, including an increase in time served or increased diversion of young offenders to probation or the juvenile system). About one-third of the released population in each state was between 35 and 44 years of age by 1999. At the same time, released inmates aged 45-54 years increased in all four states between 1992 and 1999 in California, Michigan, and New York (an average of 6% of the released population to about 12%).

Criminal justice variables also varied by state (Table 8). Admission type for offenders in the 1992 and 1999 cohorts shifted during the decade. In 1992 the most prevalent type of initial admission for the exiting cohort, with the exception of California, was new court commitments, accounting for about two-thirds of admissions in Michigan and Pennsylvania. This is consistent with the national trend – about 70% of all state prison admissions in 1990 were new court commitments, dropping to 60% by 1999 (Beck, Karberg, and Harrison, 2002). As new court commitments declined, state prison admissions through parole revocations increased across the board, from 29% in 1990 to 35% in 1999 (Beck et al., 2002). This trend is also consistent in the exit cohorts, but there was variation between states. Two-thirds of admissions in California were parole violators by 1999, compared to roughly one-third of admissions in the other three states.

Type of offense for the exiting cohorts was largely consistent between states – overall, about one-quarter of the released inmates served time for a violent offense, one-third for property offenses, and one-third for drug offenses. There were a few notable differences between states,

Table 8. Criminal Justice Characteristics for Release Cohorts, by Release Year

	California		Michigan		New York		Pennsylvania	
Criminal justice variables	1992	1999	1992	1999	1992	1999	1992	1999
Admission type								
New court commitment	46	38	66	57	—	54	63	60
Parole revocation	**53**	**62**	23	33	—	40	33	37
Other	1	0	11	11	—	6	4	3
Offense type[a]								
Violent	24	25	25	28	29	26	—	38
Property	32	30	43	37	22	19	—	24
Drug	32	37	24	22	43	48	—	30
Time served in prison								
0–3 months	**16**	**14**	3	3	1	14	6	4
3–6 months	**15**	**24**	5	10	3	10	10	3
6–12 months	**35**	**33**	19	16	21	22	20	7
1–2 years	23	18	32	29	30	22	26	16
2–5 years	9	10	33	28	35	26	30	30
5 + yrs	2	2	8	13	10	7	7	**40**
Mean time served (months)	**12.3**	**12.5**	25.7	32.0	30.1	22.8	24.6	**61.2**
Release type								
Mandatory	**98**	**98**	0	5	13	**28**	0	0
Parole board	0	0	94	**83**	84	**64**	90	**72**
Expiration of sentence	2	2	6	**12**	3	**8**	10	**28**

Note: All figures are percentages. Dash indicates that data were not available.

[a] Offense for which offender was released in 1992 or 1999.

however. About 4 in 10 Pennsylvania releases in 1999 were violent offenders (offense data for 1992 were not reported), higher than in other states. Drug offenders released over the decade increased in California and New York; over a third of California releases and nearly half of New York releases were drug offenders in 1999. Concomitantly, property offenders declined as a proportion of releases over time in California, Michigan and New York.

Time served estimates are based on all admission types to identify aggregate level differences between states (the adjusted time served variables that account for new court commitment or parole violator status are discussed shortly in the bivariate table). There was some variation in time served by the exiting cohorts among the states in the study. California had much shorter time served than any other state with a mean of 12.4 months, while other states vary between 23 and 32 months (except for Pennsylvania in 1999 with a mean time served of 61 months). California remained constant, Michigan increased average time served by 6 months, and Pennsylvania increased by 37 months.[20] New York was the only state with a decline in average time served over the period (2 months), likely partially due to the increase in drug offenders released in 1999. Not only did California offenders serve less time, over one-third (38%) of the 1999 cohort served less than 6 months, compared to 24% in New York, 13% in Michigan, and 7% in Pennsylvania. By time served without adjustment for admission type, the mean time served decreases, particularly in California. These differences reflect in part the choices by the state systems in offender sentencing and release policies and population management strategies.

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20. This substantial change between 1992 and 1999 in Pennsylvania was verified using data reported in the Annual Statistical Report issued by the Pennsylvania Department of Corrections (Emory and Lategan, 1999). This increase may be due to the of the 1999 release cohort were violent offenders, who serve longer than other offender types.

As previously discussed, release type changed through the 1990s. Nationally, the trend moved away from parole board releases toward mandatory statute releases. Between 1990 and 1999, parole board releases decreased from 39% to 24%, while mandatory parole releases increased from 29% to 41% (Hughes, Wilson, and Beck, 2001). At the same time prisoners serving their entire terms (maxing out and released by EOS without post-custody supervision) increased from 13% in 1992 to 18% in 1999 (Hughes et al., 2002). The states included here provide variation in release types utilized. California remained consistent through the decade, releasing 98% of their population by mandatory release. New York increased the use of mandatory release, but parole boards remained the main release mechanism. Meanwhile, EOS releases increased in Michigan and Pennsylvania through the 1990s. If formal state control (release type and subsequent supervision) affects recidivism, there should be significantly different rates of return between states.

Recidivism

The basic rates of recidivism without controlling for other variables in the model demonstrate that there is significant variation in returns to prison between states (Figure 6). California had the highest rate of return for both the 1992 and 1999 release cohorts (over 60% of releases were returned to state prison within 3 years). Pennsylvania had the lowest rate of return in 1999 (around one-third of releases came back within three years), followed by New York and Michigan (38% and 41%, respectively).

Although time to return is not used as a dependent variable in the recidivism modeling, it is a useful analytic in comparing how the states may differ in terms of post-custody supervision and revocation/new offense processing. Overall, California inmates come back more quickly compared to inmates released in Michigan, New York, and Pennsylvania (Table 9). Nearly 40%

of inmates coming back in California returned within 6 months, most likely a reflection of the high parole violator portion of the population and the catch-and-release policy utilized to manage the correctional population. The other states in the study do not display increases in recidivism until the 6-12 month and the 1-2 year period. It is unlikely that offenders from these states take notably longer to re-offend or violate parole than those in California. More likely is that offenders in other states are processed differently (such as being formally processed for new charges, longer terms in jail before return to prison, and violating several times before revocation occurs). Recall that this is why we didn't use time to return as a dependent variable.

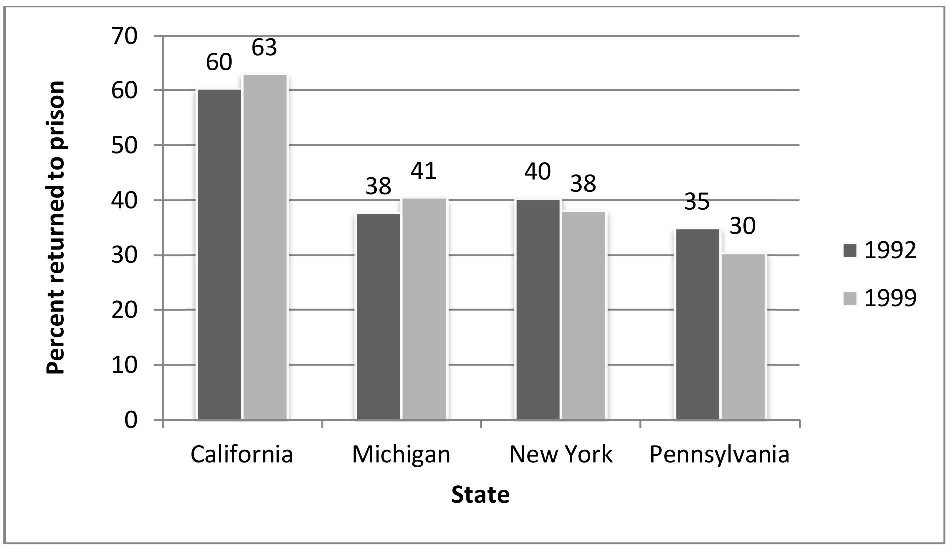

Figure 6. Percent of inmates returned to prison within 3 years, by release year and state.

We can begin to decompose why recidivism differs between states by looking at the bivariate relationships between recidivism by specific characteristics of inmates and policies. Bivariate tables 10a and 10b compare recidivism rates by individual characteristics, criminal justice characteristics and community measures. Males have higher rates of return than females across all states and both sexes came back at higher rates in 1999 compared to 1992, excepting males in the 1999 Pennsylvania cohort. Overall, California females (over half) were more than twice as likely to return to prison compared to females in New York and Pennsylvania.

Table 9. Time to First Return to Prison for Released Inmates, by Year and State

	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
Total returned	60	63	38	41	40	38	35	30
0–90 days	10	13	2	2	1	1	2	1
91–180 days	14	13	5	5	3	4	2	3
6–12 months	20	19	11	11	11	12	9	9
1–2 years	13	14	15	16	17	15	15	12
2–3 years	3	4	6	8	9	7	7	6

Returns by race showed some consistency across states. Black inmates had higher rates of return than other race groups in all states, while the differences in recidivism within races persisted across states. Hispanics released in 1999 were less likely than those released in 1992 to return in both California and Michigan. California had the highest rate of return for all races. Overall, 6 in 10 whites in California were returned compared to half that in the other states.

The magnitude of recidivism by age varied between states, but overall offenders under 20 had the highest rates of return, with declines in rates as offenders aged, most notably in releases aged 45 and older. Again, differences in recidivism rates across states persisted within age groups. Return rates for those older than 55 in California (35% to 47%), however, were similar to the highest rates or return for the other three states.

Consistent with extant literature, parole violators returned at higher rates than new court commitments in every state, again excepting the 1999 Pennsylvania cohort. The differences in recidivism rates across states were reasonably consistent within type of admission with a slightly greater variation between years for the new court commitments. Property offenders had the highest rate of return among offense types in New York and Michigan, but were slightly exceeded by the "other" offense category in California and Pennsylvania.

We begin to see the nuances in the time served outcomes across states and over time because time served is presented both in terms of an average among all admission types and the adjusted time served variables that account for the differential time served between new court commitments and parole violators. When looking at average time served among all offenders, California releases serving less than 6 months appear to return most frequently. These short-timers also have high return rates in Michigan and New York. The relationship between time served and recidivism generally appears to be negative—as time served increases recidivism

Table 10a. Rate of Return within 3 Years of Release by Individual and Criminal Justice Characteristics

	Rate of return by characteristic							
	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
Total return rate	60	63	38	41	40	38	35	30
Sex								
Male	61	64	39	41	37	39	36	31
Female	52	56	27	35	26	29	22	23
Race/ethnicity								
White	60	65	33	36	30	35	29	28
Black	67	70	41	46	40	42	40	32
Hispanic	54	48	34	27	34	33	27	27
Other	58	68	30	35	35	30	14	21
Age at release								
Under 20	61	70	43	52	53	50	34	54
20-24	64	68	39	39	41	40	41	33
25-29	62	62	40	39	38	37	40	33
30-34	61	64	41	46	36	41	36	32
35-44	59	63	37	43	30	39	32	30
45-54	50	59	21	34	23	31	20	24
55+	35	47	15	17	16	21	13	14
Admission type								
New court	50	54	31	34	--	31	32	31
Parole violator	69	69	53	52	--	47	40	28

Table 10a (continued)

	Rate of return by characteristic (%)							
	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
Offense type								
Violent	59	62	33	34	37	38	--	29
Property	66	68	46	50	43	46	--	33
Drug	57	60	30	39	33	36	--	30
Public order	51	61	34	32	28	29	--	24
Other	68	56	7	24	8	18	--	34
Time served								
0–6 months	67	66	47	45	41	44	36	19
6 months–1 year	60	64	40	42	38	37	36	33
1–2 years	55	59	39	45	39	37	35	33
2–5 years	52	56	35	38	34	36	35	28
5+ years	57	55	32	33	28	34	26	33
Time served (quintiles)[a]								
1	59	58	40	41	--	37	34	33
2	59	64	36	41	--	39	36	32
3	69	70	53	54	--	47	46	19
4	61	63	35	42	--	37	37	31
5	62	64	39	39	--	38	32	29

Note: Dash indicates that data were not available.

[a] Categories in months, by new court commitments (NCs) and parole violators (PVs): Q1 = 0–7.7 (NCs), 0–2.7 (PVs); Q2 = 7.8–11.7 (NCs), 2.8–5.0 (PVs); Q3 = 11.8–17.8 (NCs), 5.1–7.8 (PVs); Q4 = 17.9–30.4 (NCs), 7.9–12.9 (PVs); Q5 = 30.5+ (NCs), 13.0+ (PVs).

decreases. However, once time served is adjusted, we see that the relationship is generally curvilinear with the highest recidivism rates in the third quartile of the time served distribution. New court commitments serving approximately 12 to 18 months and parole violators serving approximately 5 to 8 months have the highest rate of return (again, in all but the 1999 Pennsylvania cohort). About 7 in 10 of California offenders in the third time-served quintile come back to prison. Modifying the time-served variable to account for admission type sheds a different light on the variation in recidivism rates and should prove useful in later modeling.

Table 10b provides recidivism rates by release type and community factor scales for each state and release cohort. Absent of other factors, there appears to be little difference between rates of return among releases by mandatory statute and parole boards in states other than California. There is a substantial difference between the recidivism rates of parole board and mandatory releases in California. Overall, EOS releases fared best in terms of return to prison, varying from 1% in the 1992 Pennsylvania cohort to 26% in the 1992 Michigan cohort.

Community scales were recoded into quartiles for the purposes of the bivariate table to standardize scores across states. Quartiles were created using scores across all counties among the four states.[21] As in other measures, California is different than the other 3 states in terms of rate of return. There is some variation within state among return rates by quartile for the three scales, but no consistent trend (e.g. as the scale goes up, the recidivism rate always goes up). Judging by these outcomes, levels of opportunity and urbanization within a community do not appear to have notable differential impacts on the likelihood of return.

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21. One could create quartiles for each state based on the county scores for that state as well. This was considered, but not implemented because one of the purposes of this study is to standardize common variables among states (as we did for time served).

Table 10b. Rate of Return within 3 Years of Release by Release Type and County Scales

	Rate of return by characteristic							
	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
Release type								
Mandatory release	61	64	—	39	38	38	—	—
Parole board	~	~	39	44	37	40	38	41
Expiration of sentence	—	—	26	19	11	24	1	3
Community scales (quartiles)								
Legitimate opportunity								
Q1 (low)	60	66	38	40	35	36	32	29
Q2	67	65	36	37	36	40	37	31
Q3	56	59	36	47	30	39	29	29
Q4 (high)	61	65	39	—	37	37	35	31
Illegitimate opportunity								
Q1 (low)	60	63	36	37	35	36	32	29
Q2	62	67	35	41	36	42	40	32
Q3	68	69	—	—	—	35	—	—
Q4 (high)	68	59	42	44	37	39	36	31
Urbanization								
Q1 (low)	60	64	35	38	36	40	34	30
Q2	62	65	—	47	32	30	—	—
Q3	58	60	42	—	33	35	—	—
Q4 (high)	68	70	—	—	36	38	36	31

Note: Dash indicates no cases in this category. Tilde indicates too few cases to include.

In sum, states vary substantially in their crude recidivism rates with California having by far the highest rates. States also vary in the demographic composition of their populations with New York having a much higher proportion of minorities in their release cohorts than other states. The composition of state release cohorts differs more in terms of their criminal justice characteristics. NewYork, for example, has a greater proportion of drug offenders than other states. Average time served is much lower in California than other states, and the proportion of release previously failing at supervision is much higher there as well.

The relationship between attributes of release cohorts and recidivism are largely consistent with what we would expect from the literature. Men are more likely to recidivate than women, blacks more than other races, property offenders more than other offender types, and parole violators more than new court commitments.

The curvilinear nature of the adjusted time served variables was not expected; we will see how this bears out in the fuller models. In the following section, multivariate models incorporating individual factors, criminal justice factors, community factors, and public policy controls (release type) will be applied – first to the aggregate data, and then to specific states – to determine if they assist in explaining these differences in recidivism across states and over time.

Identifying the Best-Fit Models

Modeling was carried out in steps, the first of which pooled the state data by release cohort and entered each block of variables iteratively into various combinations of linear regression models with a three-year return as the dependent variable. The linear probability model results were used to a) identify collinearity between variables and scales and b) assess the impact of the state dummies to detect an underlying difference in policy climate. Aggregate models were also run without California to identify whether California cases, which comprised much of the dataset and are overwhelmingly comprised of mandatory releases, were driving the results and obscuring the policy climate effects of the other states. Variable blocks were modified to account for collinearity and then used in logistic regressions by state and release cohort to identify differential impacts. Results from the binary logistical regressions by state are summarized separately by fit and notable predictors, and final state models are compared and contrasted.

Linear Regression Results

The linear regression models were estimated with data pooled from all four states, then with the pooled data from just Michigan, New York, and Pennsylvania to determine whether the amount of the variance explained changed after taking out California. This was done because California accounts for so much of the pooled sample and, based upon the descriptive statistics and bivariate data, is markedly different from the other states. Table 11 provides a summary of the variables initially included in each block for the linear regressions.

Before describing the overall model fit for the aggregated states and whether effects changed when California cases were removed, the collinearity issues between variables in the model must be addressed (Table 12). When models were run with all states, several collinearity issues appeared.

The first issue of collinearity arose between the urbanization and opportunity scales. Illegitimate opportunity was not collinear with urbanization and legitimate opportunity in the 1992 4-state models, but it was in the 3-state models (with a VIF for illegitimate opportunity of 7.6 and 11.7, respectively). In order to keep the models consistent over time, we decided that collinearity in either period was unacceptable. Of the three subsequent variations run to identify the scales that were most independent of one another, legitimate opportunity and urbanization did best in terms of tolerance and VIF scores. Thus, illegitimate opportunity was removed from the county scale measurement block.[22]

Table 11. Key to Variable Blocks

Block name	Variables included in blocks
State (as measure of policy climate)	• Used in the aggregate linear regression models only. • Dummies for Michigan, New York, and Pennsylvania (reference category is California). • State models were also run without California (reference category is New York).
Individual characteristics (ID)	• Dummies for male, black, Hispanic, other race (reference categories are women, whites). • Age of first release in categories (reference category is releases under 25 years old).
Criminal justice demographics (CJD)	• Offense type dummies (reference category is violent offense) • Admission type dummies (reference category is new court commitment). • Adjusted time served dummies (reference category is Quartile 1, the shortest stay group).
County factors (CF)*	• *Legitimate opportunity*: median household income, percent adults unemployed, percent of households with public assistance income, percent of adults with high school degree or higher, percent of households in poverty. • *Illegitimate opportunity*: violent crime rate, percent unmarried males, percent single mother households[a] • *Urbanization*: percent black, percent foreign born, percent speaking English as home, percent renters, percent using public transportation to work, percent occupied housing, population per square mile. • Drug arrests per 1,000 county residents[a]
Public policy controls (PPC)	• Dummies for parole board release, expiration of sentence release, mandatory parole release (mandatory parole release was reference variable in aggregate models and California models; parole board release was the reference category in Michigan, New York, and Pennsylvania models).

[a] Illegitimate opportunity and drug arrest variables are excluded in subsequent models due to collinearity with other variables identified in the linear regressions, shown in next table.

22. In retrospect it makes sense that illegitimate opportunity would be related to legitimate opportunity and urbanization. A place with a high score on the illegitimate opportunity scale would likely score low on the legitimate opportunity scale and high on the urbanization scale.

Table 12. Collinearity between Variables Blocks in Linear Regressions

	1992		1999		1992		1999	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
NY	0.205	4.878	0.408	2.449	-	-	-	-
MI	0.303	3.297	0.461	2.170	0.896	1.116	0.858	1.165
PA	0.374	2.672	0.473	2.112	0.898	1.114	0.809	1.235
Mandatory release	0.137	**7.313**	0.227	4.411	0.939	1.065	0.869	1.151
Expiration of sentence	0.835	1.197	0.779	1.284	0.985	1.015	0.935	1.069
State alone								
NY	0.959	1.043	0.973	1.028	-	-	-	-
MI	0.969	1.032	0.980	1.020	0.938	1.066	0.920	1.087
PA	0.976	1.025	0.981	1.019	0.938	1.066	0.920	1.087
Public policy alone								
Mandatory release	0.942	1.062	0.838	1.193	0.996	1.004	0.970	1.031
Expiration of sentence	0.942	1.062	0.838	1.193	0.996	1.004	0.970	1.031
Legitimate opportunity	0.404	2.476	0.605	1.652	0.218	4.597	0.304	3.292
Illegitimate opportunity	0.132	**7.588**	0.310	3.222	0.085	**11.702**	0.247	4.054
Urbanization	0.210	4.760	0.412	2.429	0.192	5.216	0.427	2.341
Variation 1								
Legitimate opportunity	0.495	2.022	0.609	1.642	0.289	3.458	0.311	3.214
Illegitimate opportunity	0.495	2.022	0.609	1.642	0.289	3.458	0.311	3.214
Variation 2								
Illegitimate opportunity	0.257	3.890	0.414	2.413	0.254	3.930	0.437	2.286
Urbanization	0.257	3.890	0.414	2.413	0.254	3.930	0.437	2.286
Variation 3								
Legitimate opportunity	0.788	1.268	0.808	1.238	0.649	1.541	0.539	1.856
Urbanization	0.788	1.268	0.808	1.238	0.649	1.541	0.539	1.856
Legitimate opportunity	0.788	1.269	0.763	1.310	0.632	1.582	0.480	2.084
Urbanization	0.450	2.221	0.365	2.738	0.083	**12.114**	0.096	**10.419**
Drug arrests	0.517	1.933	0.349	2.861	0.081	**12.393**	0.086	**11.687**

County drug arrest rate was collinear with urbanization in the 3-state models for both 1992 and 1999. This is likely because urban areas are more closely monitored for drug activity transactions that occur on the street. Because the urbanization scale includes the conventional measures of social disorganization applicable to a broad range of economic crime and not simply drug offenses, the urbanization scale was retained and the drug arrest variable was dropped.

The linear probability models shown in Table 13 presents variance explained when specific blocks of variables were included and excluded from the models. The greater the amount of variance attributable to a specific block of variables when other factors are held constant, the more important those variables are for explaining recidivism. Although specific models are better examined using the final models presented later in the logistical regressions, the linear models offer a preliminary and easily interpretable indication of the predictive power of each variable block on recidivism and highlight the difference between California and the other four states.

State dummies and release type (PPC) are both strong predictors in the 4-state regressions when modeled separately, but when they are both included in the model, the state dummies add little predictive power to the model. Release type seems to account for much of the differences in recidivism across states. Once California is removed in the 3-state model, the state dummies have little to no impact when modeled alone. This has two implications – that there may be some residual policy effects brought to bear on the 4-state model in California beyond the impact of mandatory release and that policy climate as measured by the state dummies in the 3-state model adds little to the policy influence already accounted for by release type. This is also consistent with the recidivism distributions presented earlier – California releases are more likely to return compared to the other three states, which have more comparable rates. Overall, method of

Table 13. R-Squares for Linear Regression Models for Aggregate States, by Release Year

Model number	Variable blocks entered	R2 for 3-year return: CA, MI, NY, PA[a] 1992	CA, MI, NY, PA[a] 1999	MI, NY, PA[b] 1992	MI, NY, PA[b] 1999
1	State	0.052	0.057	0.000	0.006
2	Individual demographics (ID)[c]	0.013	0.021	0.023	0.014
3	Criminal justice demographics (CJD)[d]	0.064	0.042	0.017	0.022
4	ID/CJD	0.078	0.058	0.040	0.035
5	Community factors (CF)[e]	0.004	0.005	0.000	0.001
6	Public policy control (PPC)[f]	0.065	0.077	0.010	0.037
7	State/PPC	0.069	0.085	0.011	0.039
8	State/ID/CJD/CF	0.105	0.107	0.041	0.040
9	ID/CJD/PPC	0.126	0.135	0.053	0.082
10	ID/CJD/PPC/CF	0.126	0.136	0.054	0.082

Note: Reference categories are females, whites, under 25 years old at release, violent offenders, new court commitment admissions, first quintile of adjusted time served (shortest stays), and parole board releases.

[a] CA is reference category.

[b] NY is reference category.

[c] ID (individual demographics) - sex, race/ethnicity, age.

[d] CJD (criminal justice demographics) - offense, type of admission, and adjusted time served.

[e] CF (community factors) - legitimate opportunity and urbanization scales.

[f] PPC (public policy controls) - release type.

release evidently makes a difference in the probability of returning to prison (though this effect is relatively weak in the 3-state model for 1992). This may be a function of the type of inmate that is released in a particular way rather than the release mode itself; the multivariate models will separate these effects.

The criminal justice demographic (CJD) variable block has about half the predictive power of release type in the 4-state models. The diminishment of the criminal justice block in the 3-state models again indicate a California effect, perhaps that revocations are associated with specific types of offenders. Individual demographic (ID) characteristics of inmates trail criminal justice demographics in terms of predictive power in the single block 4-state models; but are more predictive in the 3-state models once California is removed, indicating that sex, age, race are better predictors of return than offense type in these jurisdictions. This is consistent with the bivariate distributions that states, and especially California, differed more in the criminal justice characteristics of the release cohorts and the effects of these characteristics on recidivism. Community factors appear to have a very limited effect on the probability of recidivism in the 4-state models and virtually no effect in the 3-state models.

When multiple blocks of variables are entered into the models simultaneously, we see that those variables that affect recidivism in the single block models generally retain independent predictive power. Adding blocks of variables increases the ability to predict recidivism indicating that the effects of the blocks are additive and independent. In the single block 4-state models in 1992, for example, individual characteristics account for 1.3% of the variance, criminal justice demographics 6.4% while the model including both blocks accounts for 7.8% of the variance.

The best fit model for the 4-state data includes the individual demographics block, the criminal justice demographics block, and the public policy block (the community factors don't add any power). The CJD block explains about the same amount of variance as the PPC block. This was determined by comparing the R^2 for the best fit model to the R^2 for the model excluding the other blocks one at a time. In the 1999 models the importance of public policy variables increased to become the most consequential (R^2=.077) followed by criminal justice variables (R^2=.037) and demographic variables (R^2=.021).

With the 3-state data, the best fit model includes the individual demographics block, the criminal justice demographics block, the public policy block and the state dummies, but the difference in the R squared between the model with and the model without the state dummies is not statistically significant. With California out of the analysis, the influence of public policy and criminal justice variables declines such that all three blocks of variables have about equal importance in predicting recidivism in the 1992 model (PPC=.013, ID=.023, CJD=.017). In the 1999 models, public policy variables are stronger predictors of recidivism (R^2=.047) than either criminal justice (R^2=.014) or individual demographics (R^2=.021).

Over time the models that exclude California are becoming more like the models using the 4-state data. This is consistent with the descriptive statistics that showed the other states adopting mandatory release and decreasing the use of discretionary parole between 1992 and 1999. Recall that Michigan, for example, went from 0% mandatory releases to 5% and from 93% parole board releases to 84%. New York went from 13% mandatory releases to 28% and from 84% parole board releases to 64%. The variance in release practices increased over time in New York, Michigan, and Pennsylvania and these practices may have affected the probability of recidivism.

The relative importance of release practices in predicting recidivism may reflect the selection of higher or lower risk inmates for release. Both parole boards and mandatory release practices subject inmates to some kind of risk assessment; the difference is that for parole boards this assessment affects whether a person is released while risk assessments in mandatory releases are most likely used to determine supervision level in the community. If the parole board assessment prior to release is a better predictor of risk, then recidivism should go up as the use of parole boards declines. The effects of release type could also reflect differences in supervision regimes for different classes of inmates. Those released through EOS, for example, may not recidivate because they are not supervised in the community – as a result their re-offending either may not be detected or they may not have specific conditions imposed on their behavior that leaves them vulnerable to revocation, such as regular drug use screenings. Presumably, the differential risk of persons released is mediated by including demographic and criminal justice demographics in the models which would suggest that different supervision regimes account for these effects.

The fact that state dummies added little or nothing to the explanatory power of the 3 or the 4 states models once release type was added to the model suggests that the effects of policy climate on the probability of recidivism are not great. In the aggregate the effects of policy climate may not occur in isolation, but in interaction with other factors affecting recidivism. These interactions will be assessed in the state-specific models.

The linear probability models served two purposes in the model-building process: to identify collinearity issues (resulting in the omission of the illegitimate opportunity scale and county arrest rate variable in later modeling) and to demonstrate that California is clearly different from the other states. Subsequent state models will identify if differences between the other three states are being obscured in the pooled 3-state models.

Logistic Regression Results

Binary logistic regressions were run for the 4-state and 3-state blocks to reinforce the results described above and yielded similar results with slightly higher predictive power across the various blocks (Appendix E). Logistic regressions were then run by state, variable block, and release cohort to identify a final model with which to compare recidivism by state. First, the Nagelkerke results, which are the functional equivalent of R^2 results for logistic regression, are presented for each state by variable block and release year. Then notable changes in the direction and magnitude of the coefficients and changes in the probability of recidivism given certain characteristics are summarized over the iterative models by state. Final models by state are compared later in the chapter.

Overall Variance Explained by Variable Block

The results of the variable blocks in the logistic regressions are consistent with the pooled state models, but there are also some notable differences that come to light by separating the analysis by state (Table 14). The best fit model in each state includes the public policy variables, the criminal justice demographics and the individual demographics. The contribution of the community scales varies somewhat across states but the contribution is slight in all cases. As before, the contribution of each block of variables is determined by the difference in pseudo R^2 between the best fit model and the model with the variable block in question removed.

In California in 1992 recidivism is related to method of release and criminal justice demographics in about equal measure (Psuedo R^2=.051 v .052) followed by individual demographics (.033). In the California model for 1999, the public policy variables account for 6.2% of the pseudo R^2, followed by individual demographics (5.8%) and criminal justice demographics (2.3). Overall, the pseudo R^2 is 13.7% and 14.8% in California in the 1992 and 1999 cohorts, respectively, in the best fit model.

In New York recidivism is most strongly predicted in 1992 by individual demographics (Psuedo R^2=3.1%) followed by criminal justice demographics (1.3%) and type of release (1.4%); once again virtually no impact from the social disorganization scales. In the 1999 model, the criminal justice demographic variables have the most predictive power (4.1%) followed by the public policy block (2.3%) and individual demographics (2.1%) which have essentially similar effects on recidivism. The importance of public policy variables increased over time. The

Table 14. Logistic Regression Nagelkerke R-Squares Results, by Release Year and State

Model number	Variable blocks entered	California		Michigan		New York		Pennsylvania	
		1992	1999	1992	1999	1992	1999	1992	1999
1	Individual demographics (ID)[a]	0.033	0.058	0.031	0.026	0.031	0.021	0.051	0.014
2	Criminal justice demographics (CJD)[b]	0.061	0.037	0.068	0.054	0.012	0.041	0.012	0.008
3	ID/CJD	0.085	0.083	0.098	0.077	0.043	0.062	0.060	0.022
4	Community factors (CF)[c]	0.001	0.003	0.008	0.019	0.001	0.000	0.004	0.001
5	Public policy control (PPC)[d]	0.043	0.057	0.006	0.041	0.013	0.011	0.058	0.235
6	ID/CJD/PPC	0.136	0.145	0.107	0.121	0.057	0.085	0.132	0.255
7	ID/CJD/PPC/CF	0.137	0.148	0.108	0.127	0.058	0.085	0.134	0.255

Note: Reference categories are females, whites, releases under 24 years old, violent offenders, new court commitment admissions, first quintile for adjusted time served (shortest stays), and parole board releases.

[a] ID (individual demographics) - sex, race/ethnicity, age.

[b] CJD (criminal justice demographics) - offense, type of admission, and adjusted time served.

[c] CF (community factors) - legitimate opportunity and urbanization scales.

[d] PPC (public policy controls) - release type.

full models were weakest in New York, accounting for only 5.8% of variance in 1992 and 8.5% in 1999. Results in California and New York are relatively consistent over both release cohorts.

Michigan and Pennsylvania, however, show a similar shift in the factors associated with recidivism between cohorts. For offenders release in 1992 in Michigan, criminal justice factors were the strongest predictors of return (6.7%), followed by individual demographics (3.1%). Social disorganization (at .1%) and release type (.9%) contributed very little to the model. By 1999, criminal, justice remained strong (5.1%) and the power of release type increased (4.3%), followed by individual demographics and social disorganization (2.6% and 1.9% respectively). There appears to a shift in policy between 1992 and 1999 in which recidivism became more closely tied with release policy. Overall, 10.8% of the difference in return to prison was explained in 1992 and 12.7% in 1999 for Michiganders.

Pennsylvania is a bit more difficult to interpret due to the omission of offense data in 1992 and the spike in time served in the 1999 cohort (see Table 8, previously). Release type, however, was a driving factor in the probability of return in both release cohorts, accounting for 7.2% of the variance in recidivism in 1992 and 23.3% in 1999 (we will attempt to address this disparity later). Individual demographics account for 5.1% of the variance in return in 1992 and 1.4% in 1999. Interestingly, criminal justice factors remained stable, despite the missing offense data in 1992 and the increase in average times served by the 1999 cohort. Social disorganization scales had a marginal impact (.9%) in 1992 and t in 1999 (.8%). Overall, the pseudo-R^2 for the Pennsylvania model in 1992 is 13.4% and 25.5% in 1999.

These results bring to light several points. First, policy variables in the form of release type appear to influence likelihood of return, but with different impacts across states and over time. Second, demographic and criminal justice factors have varying impacts across states.

Finally, social disorganization effects appear to be modest at best. We will now examine the individual state models in greater detail to better understand the relationships between variables. Unless otherwise stated, the statistical comparisons are made between the final models for each cohort year (Model 7).

California (See Appendices F-1 and F-2)

Overall, nearly all variables are significant in the California models, likely in part due to the sheer volume of cases. Individual and criminal justice demographics are consistent across models and within year, but there are some changes between exit cohorts. Hispanics were less likely than whites to return in both exit cohorts, with greater disparities in 1999 (Wald = 140 in the 1992 and Wald = 1,379 in 1999). Among offense types, effect was strongest for property offenders across both cohorts (Wald = 149 in 1992 and Wald = 154 in 1999), consistent with previous research. However, the impact of offense type on recidivism is small in comparison to individual demographics, and admission and release type. Time served had modest effects on return that changed over the two exit cohorts. Those serving more time were less likely to return compared to the short stays of quintile one releases in 1992, but more likely to return in 1999, though all time served effects were modest. Failing previously was the strongest predictor of subsequent failure in terms of the Wald statistic (Wald = 2,435 in 1992 and 1,288 in 1999), but mandatory releases had by far the largest impact in terms of the coefficient (5.1 in 1992 and 5.9 in 1999 compared to .861 and .580, respectively, for parole violators. While other factors, such as being Hispanic or a drug offender, may diminish this likelihood, a mandatory release, holding other factors constant, is in effect a temporary release. This is consistent with the general characterization of California as using a revolving door policy to manage the prison population.

The urbanization and legitimate opportunity scales had a small negative effect for both cohorts when modeled alone, diminishing further in the full model but nonetheless remaining significant for all but legitimate opportunity in 1992. More discussion of all outcomes is forthcoming in the final model comparisons.

Michigan (See Appendices G-1 and G-2)

Significance among variables in the Michigan models was less prevalent compared to California and outcomes in terms of coefficients and Wald statistics were less remarkable overall. Among individual demographics, being male or black increased the likelihood of recidivism, and Hispanics were less likely to return (although this effect is mild as indicated by the low Wald statistic in both years). The strongest predictor of success was for offenders older than 45 years at release. As in California, property offenders were more likely to return compared to violent offenders. Drug offenders were significantly less likely than violent offenders to return from the 1992 cohort, but slightly more likely in 1999 (though not significant). Parole violators were also more likely to return than new court commitments (Wald = 211 in 1992 and Wald = 140 in 1999), but coefficients were modest (.736 and .552). Those serving more time were slightly more likely to return than the short-stay offenders in both cohorts, but were of little note in 1992 and only statistically significant for quintiles 3 through 5 in 1999.

Persons released through EOS were significantly less likely than parole board releases to return among the 1992 cohort and 1999, with increasing effects over the cohorts (coefficient of -.0798 in 1992 and -1.39 in 1999 and similar increases in the Wald statistic). There were no mandatory releases among the 1992 cohort, but those released by mandatory statute in 1999 were more likely to return compared to those released by parole board, though differences in outcome were not statistically significant. Legitimate opportunity and urbanization scales were again mixed. Legitimate opportunity had a mild significant negative impact on recidivism on the 1992 exit cohort and was positive, but not significant on the 1999 cohort. The urbanization measure had a positive impact of recidivism for both cohorts, but was stronger in the 1999 cohort.

New York (See Appendices H-1 and H-2)

Males were consistently more likely to return to prison than females across cohorts. Blacks were more likely to return than whites in both release cohorts, but effects decreased over time (coefficient went from 0.5 in 1992 to .094 in 1999). The effect of ethnicity on likelihood of return changed between the 1992 and 1999 cohorts. Hispanics were significantly more likely to return in 1992, but less likely in 1999 (but 1999 effect was not significant). Older offenders were less likely than younger offenders to return, with the coefficient and Wald gaining strength as inmates aged. Once again property offenders were more likely to return that other violent offenders in both cohorts. Parole violator admission status was not available for the 1992 cohort, but was significant in 1999 and had the strongest Wald statistic among all variables (647). Time served was also missing in 1992, but inmates serving more time appear to be less likely to return than short stay inmates, with marginal significance.

Those released by EOS were significantly less likely than those released by parole board to return over both cohorts, with greater effects of magnitude in the 1999 cohort (coefficient of -.0161 compared to -1.137, respectively). Mandatory releases were slightly more likely than parole board releases to return in 1992 (not statistically significant) and slightly less likely than parole board releases to return in 1999 (again, not significant). Overall, being older than 45 years of age and EOS release were the strongest predictors of success for both release cohorts, with EOS surpassing the age effect in 1999. Both the legitimate opportunity and urbanization scales were significant in 1992 when modeled alone, but effects disappeared in the fully-loaded model. Neither scale was significant in 1999.

Pennsylvania (see Appendices I-1 and I-2)

As discussed earlier, Pennsylvania is an anomaly compared to the other states for several reasons. Offense type was not available for the 1992 cohort. Individual demographics were consistent across models within year, though gender and race had a slightly greater impact in 1992, even when run without other variable blocks (see Model 1 for each cohort year). Age effects were greatest for the 45 and older releases, but the magnitude declined by half for the 1999 cohort (a coefficient effect of -1.293 in 1992 and -.0591 in 1999). Of offense data available in 1999, only property offenders were significantly more likely to return than violent offenders. Time served had a significant effect for quintiles 3 and 4 in 1992 but were not significant for the 1999 cohort.

Public policy measures were far stronger than in Michigan or New York in terms of magnitude. Releases through EOS were significantly more likely to return than parole board releases in the 1992 cohort (an effect size of -2.407) and even more pronounced for the 1999 cohort (-3.425). There were no releases by mandatory statute in 1992 or 1999. Legitimate opportunity has a mild significant negative effect in 1992, but didn't test in 1999. Urbanization was significant in both cohort years when run alone, but failed to reach significance in the full models for either cohort year.

Comparing Final Models

Results for final models are discussed in terms of variable blocks in the order listed in Table 15. Notable differences within and between states are highlighted, as well as possible explanations for some of these differences.

Individual Factors

The directionality among gender and race characteristics was consistent across state and over time, but significance and magnitude varied. Males were more likely than females to return, blacks more likely than whites. Hispanic origin, however, had different predictive effects across states and cohorts. Hispanics were less likely to return than whites with strong effects in California that increase between cohorts. This finding could be an artifact stemming from the possibility that Hispanics are more likely to be non-citizens than whites and may either be deported or leave the state or country of their own accord. In New York Hispanics were significantly more likely than white to return in 1992, but less likely (though not significant) in 1999. Meanwhile, Hispanic origin had no significant impact on recidivism for those released in Michigan and Pennsylvania. There was also a lot of missing data for the Hispanic variable in Michigan and Pennsylvania; it is possible a similar effect would have been found in these states been able to differentiate Hispanic releases from white and black releases.

Age at time of release had significant negative effects in all states, but not for all age categories and magnitude and strength varied widely. Overall, releases 45 years and older were less likely to return than released younger than 25 years old. Magnitude effects were greatest in the 1992 Michigan and Pennsylvania cohorts (coefficient of -1.020 and -1.293, respectively), but even the smallest coefficient (-0.511 in the 1999 Michigan cohort) was notable. Age effects for the 25-34 age categories were not significant in the Michigan cohorts or the 1999 Pennsylvania cohort and 35-44 age categories were not significant in either these states in the cohorts. Generally, however, the assumption that older persons are less likely to return holds true across these results.

Table 15. Comparing Final Logistic Regression Models, by Release Year and State

	California								Michigan							
	1992				1999				1992				1999			
Variable	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald
Constant	−4.961		0.230	466.984	−5.400		0.027	341.437	−1.523		0.118	166.557	−1.438		0.112	165.511
Individual demographics[a]																
Male	0.423	***	0.028	225.903	0.432	***	0.023	341.437	0.484	***	0.089	29.333	0.392	***	0.081	23.286
Black	0.292	***	0.021	192.152	0.294	***	0.018	268.287	0.381	***	0.051	55.144	0.334	***	0.050	45.140
Hispanic	−0.242	***	0.020	140.000	−0.717	***	0.019	1379.641	0.208		0.208	1.003	−0.247		0.167	2.183
Other	0.020		0.088	0.049	0.084		0.065	1.668	0.020		0.375	0.003	−0.018		0.309	0.003
Age at release (years)																
25−34	−0.268	***	0.023	132.635	−0.445	***	0.025	322.734	−0.094		0.056	2.835	−0.057		0.062	0.837
35−44	−0.432	***	0.026	281.092	−0.524	***	0.025	425.384	−0.266	***	0.064	17.130	−0.045		0.065	0.477
45+	−0.868	***	0.035	607.668	−0.829	***	0.029	798.144	−1.020	***	0.117	75.563	−0.511	***	0.081	39.646
Criminal history[b]																
Offense																
Property offense	0.271	***	0.022	149.194	0.250	***	0.020	154.707	0.472	***	0.058	65.385	0.621	***	0.057	120.470
Drug offense	−0.098	***	0.022	20.419	−0.022		0.019	1.390	−0.206	**	0.068	9.177	0.017		0.064	0.072
Public order offense	−0.220	***	0.031	48.985	0.019		0.030	0.405	0.145		0.096	2.281	0.091		0.076	1.436
Other offense	0.315	***	0.047	44.931	−0.265	**	0.090	8.587	−1.769		1.045	2.865	−0.427		0.594	0.516
Parole violator admission	0.861	***	0.017	2435.472	0.580	***	0.016	1288.267	0.736	***	0.051	211.088	0.552	***	0.047	140.450
Time served (quintiles)																
2	−0.041		0.022	3.509	0.110	***	0.020	30.298	0.048		0.082	0.348	0.155		0.087	3.198
3	−0.076	*	0.034	5.138	0.177	***	0.027	44.836	0.198		0.162	1.502	0.359	**	0.125	8.290
4	−0.156	***	0.022	49.345	0.061	**	0.021	8.041	0.038		0.062	0.373	0.174	**	0.064	7.522
5	−0.123	***	0.026	22.334	0.079	***	0.023	11.292	0.080		0.058	1.901	0.120	*	0.056	4.625
Public policy controls[c]																
Mandatory release	5.108	***	0.226	511.224	5.907	***	0.269	483.790					0.051		0.102	0.253
Expiration of sentence release									−0.798	***	0.102	61.258	−1.369	***	0.081	289.029
Community factors																
Legitimate opportunity	−0.004		0.010	0.162	−0.028	***	0.006	20.070	−0.055	*	0.028	3.894	0.096	***	0.029	10.880
Urbanization	−0.098	***	0.009	111.258	−0.121	***	0.010	145.068	0.140	**	0.047	8.858	0.315	***	0.043	52.539
Model fit																
Hosmer and Lemeshow	139.703	***			97.845	***			17.346	*			5.528			
Nagelkerke R2	0.135				0.146				0.108				0.127			
Log likelihood	91918.7				113121				11584.11				12899.54			

Table 15 (continued)

	New York								Pennsylvania							
	1992				1999				1992				1999			
Variable	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald
Constant	−1.148		0.075	234.080	−1.118		0.077	209.750	−1.343		0.141	91.027	−1.122		0.145	59.965
Individual demographics[a]																
Male	0.477	***	0.054	78.848	0.407	***	0.053	57.898	0.644	***	0.118	31.145	0.570	***	0.111	26.259
Black	0.500	***	0.045	121.992	0.294	***	0.044	56.556	0.511	***	0.065	61.092	0.278	***		
Hispanic	0.271	***	0.051	28.192	−0.086		0.050	2.916	−0.091		0.106	0.733	−0.032		0.094	0.113
Other	0.187		0.217	0.746	−0.246		0.193	1.626	−0.698		0.787	0.786	−0.573		0.391	2.151
Age at release (years)																
25−34	−0.228	***	0.033	47.213	−0.219	***	0.039	31.292	−0.231	**	0.075	9.510	−0.044		0.077	0.323
35−44	−0.510	***	0.045	149.297	−0.291	***	0.041	49.942	−0.566	***	0.084	45.043	−0.141		0.081	3.057
45+	−0.947	***	0.072	174.651	−0.697	***	0.055	161.058	−1.293	***	0.113	105.637	−0.591	***	0.098	36.742
Criminal history[b]																
Offense	0.396	***	0.039	100.437	0.344	***	0.043	64.779	—				0.343	***	0.067	25.875
Property offense	−0.118	***	0.034	12.018	−0.081	*	0.037	4.780	—				−0.043		0.063	0.469
Drug offense	−0.349	***	0.067	26.800	−0.360	***	0.063	32.803	—				0.075		0.131	0.326
Public order offense	−1.636	***	0.470	12.121	−0.885	***	0.260	11.536	—				0.257		0.155	2.749
Other offense	—				0.763	***	0.030	647.047	0.554	***	0.062	78.575	0.148	**	0.055	7.082
Parole violator admission	0.396	***	0.039	100.437	0.344	***	0.043	64.779	—				0.343	***	0.067	25.875
Time served (quintiles)																
2	—				0.109	*	0.046	5.581	0.078		0.093	0.708	−0.027		0.112	0.057
3	—				0.142	*	0.063	5.120	0.300	*	0.123	5.897	−0.208		0.232	0.803
4	—				0.162	***	0.040	16.187	0.203	**	0.075	7.312	0.072		0.083	0.742
5	—				0.081	*	0.037	4.841	0.099		0.073	1.860	0.094		0.063	2.249
Public policy controls[c]																
Mandatory release	0.052		0.041	1.627	−0.050		0.035	1.961								
Expiration of sentence release	−0.161	***	0.123	170.148	−1.137	***	0.058	382.079	−2.407	***	0.162	220.194	−3.425	***	0.132	671.094
Community factors																
Legitimate opportunity	−0.002		0.013	0.320	0.016		0.010	2.880	−0.087	*	0.038	5.332	−0.013		0.035	0.132
Urbanization	0.015		0.008	2.943	0.005		0.008	0.404	0.024		0.039	0.393	0.023		0.047	0.237

Table 15 (continued)

	New York						Pennsylvania					
	1992			1999			1992			1999		
Variable	Coefficient	*SE*	Wald	Coefficient	*SE*	Wald	Coefficient	*SE*	Wald	Coefficient	*SE*	Wald
Model fit												
Hosmer and Lemeshow	12.338			27.550 ***			11.455			5.083		
Nagelkerke R2	0.058			0.085			0.134			0.255		
Log likelihood	30164.1			31248.62			8104.491			9653.898		

Note: Dash indicates that data were not available.

[a] Comparison groups are females, whites, and releases under 25 years old.

[b] Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c] Comparison group is expiration of sentence release for California and parole board release for other states.

*** significant at < .001 level. ** significant at < .01 level. * significant at < .05 level.

Criminal Justice Factors

In terms of criminal offense, property offenders were significantly more likely than violent offenders to return to prison. This is consistent with previous research that property offenders are more active and more likely to return than other criminal types (Spellman, 1994; Langan and Levin, 2002). Drug offenders are also generally less likely than violent offenders to return (with the exception of those in the 1999 Michigan cohort), but effects are not significant across states and cohorts. Recidivism of drug offenders is likely tied more directly to post-release conditions and revocation thresholds, both of which may vary by state (and even by parole office within state).

A significant predictor of recidivism is a previous failure. Parole violators subsequently released had consistent positive effects on recidivism across states and cohorts, although magnitude varied. The smallest effect was in the 1999 Pennsylvania cohort, perhaps because parole violators were more likely to be released mainly by expiration of sentence, which has a significantly negative impact on likelihood of return.

Time served effects varied by state and each cohort. In California persons serving more time were less likely to return in 1992, but effects were modest compared to most other variables. By 1999 persons serving longer terms than the short-stay inmates were more likely to return, perhaps a result of supervision practices. For example, perhaps the threshold for revocation rose over time due to limited incarceration bed space. Persons serving the least time may have fewer priors and thus more chances to err on parole compared to inmates with longer sentences, who may pose a greater public safety risk due to their priors or offense. Time served had positive effects in both Michigan cohorts, though only significant effects in 1999. Similar positive effects were seen in New York and the 1992 Pennsylvania cohorts. In the 1999

Pennsylvania cohort, however, quintiles 2 and 3 were less likely to return than short-stay inmates and quintiles 3 and 4 were more likely to return (although none of these variables were significant).

Public Policy Factors

Parole board release was the reference category for all states but California, which had fewer than 100 such releases in 1992 and 1999. Thus, EOS was used as the reference category in California; however, this is still problematic since there were no EOS returns from either cohort (note that only 2%, approximately 3,700 inmates, were released through EOS in California in 1992 and 1999). So while it is not surprising that mandatory release is significant in California since it is practically the only method of release, this does not explain the finding that the mandatory release variable trumps every other variable in terms the impact on the coefficient. It appears that the release and revocation policy in California is the driving force behind its recidivism rate even holding constant other factors.

The difference in recidivism by release type was more distinct in the other states. EOS releases were consistently less likely to return than parole board releases, ranging in effect size from -0.161 in the 1992 New York cohort to -3.425 in the 1999 Pennsylvania cohort. “Let them out and let them be” seems to be a solid strategy to trim recidivism rates. While the effect of mandatory releases is clear in California, the policy had mixed results compared to parole board releases in other states. For instance, mandatory parole releases were more likely than parole board releases to return in the 1992 New York cohort and less likely in the 1999 cohort, but neither was significant. Mandatory releases in the 1999 Michigan were also more likely to return than parole board releases, but results again were not significant.

The consistently negative effect of EOS release on recidivism begs the question whether persons released by EOS are somehow different that those released by mandatory release or parole board. Are those released without supervision offender types with a lower risk to recidivism? Table 16 indicates that the offense profiles of inmates released by EOS do not support this contention. The largest offense group released under EOS did vary somewhat by state – drug offenders in California and New York, property offenders in Michigan, and "other" offenders in Pennsylvania – but it is evident that EOS was utilized for all offender types among the states.[23] It is possible a key factor to explain these differences is not accounted for in the models, but based on these results the best way to reduce return is to release offenders without supervision.

Table 16. Offenders Released, by Offense Type, Release Type, and State (Cohorts Combined)

	California		Michigan		New York		Pennsylvania	
	EOS	Other release	EOS	Other release	EOS	Other release	EOS	Other release
Total	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Violent	24.3	36.8	25.3	37.0	27.1	36.4	20.1	31.9
Property	30.6	29.3	40.2	37.4	19.7	24.7	12.1	21.5
Drug	35.0	23.3	24.4	10.0	46.7	32.7	16.7	19.3
Public order	8.2	7.2	10.0	15.2	6.0	6.1	2.2	5.8
Other *	1.9	3.4	0.1	0.4	0.5	0.1	48.9	21.5

Note: EOS = expiration of sentence.

* Includes missing offense for 1992 in Pennsylvania.

Community Factors

Legitimate opportunity has a negative influence on recidivism in California, the 1992 cohort in Michigan, and the 1992 cohort in Pennsylvania that is statistically significant (as

23. For a more detailed breakout of offenses see Appendix table J.

opportunity goes up, recidivism goes down), but the mean score value for both is less than 1 unit, limiting its impact. Urbanization has a negative impact on recidivism in California (with a mean value of less than 2 units and a maximum of 4 units) and a positive one in Michigan (with a mean value of less than 1 unit and a maximum of 1.5 units). The more urban the area in California, the lower the likelihood of a return to prison; the more urban the area in Michigan, the higher the likelihood of return. This could be due to a number of factors including law enforcement resources (police, probation, and parole officers) and priorities, styles of supervision, revocation thresholds, and differences in criminal activity and policy reaction between large cities such as Los Angeles and Detroit.

Overall, the effects of predictive variables across states are both similar and different. The effects of demographic variables on recidivism are largely similar across state. Men recidivate more than women; blacks return at higher rates than other races; and younger releases more than older ones. The effect of Hispanic origin differs across states with this ethnic status being negatively related to recidivism in California but not elsewhere. This could be due to the proximity of California to the Mexican border and the possibility that some released inmates choose to return to Mexico, thereby avoiding return to prison.

There is somewhat less consistency across states in the effects of criminal justice variables across states. Offense and admissions type have similar effects across states. Property offenders recidivate at higher rates than violent offenders everywhere, and other types of offenders recidivate less than violent offenders, although not uniformly across states. Released inmates who failed on supervision previously are always and everywhere more likely to recidivate. Finally, the effect of time served on recidivism varies in magnitude and direction across states and time, with more time served associated with lower likelihood of return only in

California for the 1992 cohort and the 2nd and 3rd quintiles of the 1999 Pennsylvania cohort; otherwise effects of additional time served increase likelihood of return (though not always significantly).

The effects of policy variables vary significantly across states largely because these variables vary considerably across states. The effects of mandatory release, for example, are strong and positive only in California where almost all releases are of this type. Rather than being the effect of the selectivity with which inmates are assigned this form of release, this seeks to be the result of the community supervision regime practiced in California. In contrast, release through EOS has a strong negative effect on recidivism in all states.

Overall, the models demonstrate that recidivism profiles differ across states and within states over time. Recidivism is not a consequence of a short list of factors that can consistently predict who will come back across places. Rather, it is a complex phenomenon that is influenced by individual characteristics, criminal justice demographics, public policy control decisions, and community factors. Even controlling for all of these things, there are many predictors missing, as evidenced by the low Nagelkerke results. One of the missing factors in these models is time. Table 17 shows pooled cohort models by state to isolate the effect of time on recidivism while controlling for the other variables. While this technique obscures changes in variable blocks between years, it highlights that persons released in 1992 were significantly less likely to return than those released in 1999 in California and Michigan, and significantly less likely to return in New York, even after controlling for the other blocks. This indicates that the goal of reducing

Table 17. Pooled Year Models by State

	California				Michigan				New York				Pennsylvania			
Variable	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald	Coefficient		*SE*	Wald
Constant	−5.385		.175	949.044	−1.532		.081	359.489	−.991		.052	365.408	−1.232		.099	155.839
Year dummy (1992)[a]	.089	***		64.974	.211	***	.032	43.653	−.213	***	.031	45.983	.081		.051	2.559
Individual demographics[b]																
Male	.413	***	0.018	532.188	.443	***	.060	55.114	.430	***	.038	129.565	.605	***	.080	56.500
Black	.221	***	0.013	291.595	.443	***	.033	181.637	.425	***	.030	206.402	.388	***	.041	90.844
Hispanic	−.519	***	0.014	1458.534	−.046		.129	.126	.137	***	.032	18.069	−.042		.068	.383
Other	.089		0.052	2.886	−.014		.239	.003	−.033		.144	.052	−.543		.349	2.421
Age at release (years)																
25−34	−.341	***	0.017	408.473	−.062		.041	2.232	−.222	***	.025	77.203	−.130	*	.053	5.959
35−44	−.454	***	0.018	645.821	−.122	**	.045	7.318	−.379	***	.029	175.112	−.330	***	.058	32.556
45+	−.795	***	0.022	1319.714	−.638	***	.063	101.330	−.787	***	.042	347.362	−.863	***	.075	131.943
Criminal history[c]																
Offense																
Property offense	.271	***	0.015	332.559	.519	***	.040	167.625	.360	***	.029	157.558	.336	***	.065	26.457
Drug offense	−.054	***	0.014	14.522	−.119	**	.046	6.629	−.103	***	.025	17.166	−.068		.061	1.227
Public order offense	−.085	***	0.021	15.892	.078		.059	1.771	−.362	***	.046	62.310	.089		.129	.476
Other offense	.236	***	0.041	33.370	−.961		.501	3.683	−1.145	***	.225	25.905	.250		.154	2.642
Parole violator admission	.724	***	0.012	3806.013	.681	***	.034	405.849	.785	***	.029	709.987	.337	***	.041	68.091
Time served (quintiles)																
2	.032	*	0.015	4.886	.106		.059	3.184	.115	*	.046	6.218	.044		.071	.385
3	.057	**	0.021	7.794	.293	**	.098	8.883	.139	*	.063	4.923	.266	*	.105	6.443
4	−.047	**	0.015	9.164	.091	*	.044	4.227	.158	***	.040	15.783	.143	**	.055	6.692
5	−.026		0.017	2.305	.093	*	.040	5.357	.066		.036	3.418	.073		.047	2.445
Public policy controls[d]																
Mandatory release	5.506	***	0.173	1016.425	.000		.098	.000	−.014		.026	.306				
Expiration of sentence release					−1.191	***	.063	359.312	−1.234	***	.052	570.045	−3.139	***	.102	942.106
Model fit																
Hosmer and Lemeshow	229.204				27.144				47.457				23.759			
Nagelkerke R2	0.134				0.111				0.07				0.2			
Log likelihood	206027.7				24653.19				61504.19				17863.78			

[a] Comparison group is 1992 release cohort.

[b] Comparison groups are females, whites, and releases under 25 years old.

[c] Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[d] Comparison group is parole board release.

*** significant at <.001 level. ** significant at <.01 level. * significant at <.05 level.

recidivism through increased sanctions over the 1990s was ineffective in at least two states in the study, at least in the context of variables included in the model. This is likely at least in part due to other policy changes that are unmeasured in the models, such as changes in law enforcement, prosecution, sentencing practices, or supervision and revocation policies over the decade.

Hypotheses Outcomes

We are now able to address the hypotheses stated at the outset of this research. Each of the hypotheses outcomes is detailed in Table 18 by individual and criminal justice factors, community factors, and state and public policy factors, , and. Individual and criminal justice demographics impact recidivism inconsistently across states (Hypotheses 1 and 2). Whites, males, and older inmates were less likely to return than blacks, females, and younger inmates. But, unexpectedly, Hispanics were less likely than whites to return in California and New York, resulting in a failure to fully accept the null hypothesis. Consistent with previous research, property offenders are the most likely to return compared to other offender types. Drug offenders were less likely than violent offenders to return in most cases, though the magnitude of these effects diminished in later part of the decade, particularly in California and Michigan. Public order and other offenses also had mixed results.

Previous failure is indeed predictive of subsequent failure. Parole violator releases were consistently and significantly more likely to return to prison, even after holding other factors constant (Hypothesis 3). The assumption that increased time served would be correlated with lower rates of recidivism (Hypothesis 4) was inconsistent in its effects. In the 1992 California cohort it had a negative effect (more time served correlated with lower recidivism), but nearly everywhere else (but for a subset of the 1999 Pennsylvania cohort) more time served was associated with slightly higher rates of recidivism, with varying levels of significance.

Table 18. Hypotheses Outcomes

	Hypothesis	Outcome	Null
Individual and criminal justice factors			
1	Males, minorities, and younger released will have significantly higher rates of recidivism compared to females, whites, and older release inmates.	Sex and age variables test (males and younger inmates more likely to return), but race does not. Mixed results for Hispanics.	Mixed
2	Property offenders will have significantly higher rates of return than other offender types.	Property offenders had the highest probability of return	Accept
3	Previous failure is correlated with subsequent failure.	Parole violators were consistently more likely to return than new court admissions.	Accept
4	Greater time served will result in lower probability of return.	Time served was inconsistent in its relationship with recidivism.	Mixed
Community factors			
5	The more legitimate opportunities in the community, the lower the rate of recidivism.	Small negative and positive effects across cohorts	Mixed
6	The more illegitimate opportunities in the community, the higher the rate of recidivism.	Not included in final model (NA)	NA
7			Mixed
State and public policy factors			
8	Type of release (i.e., discretionary parole, mandatory release, EOS) will have no significant impact on rates of recidivism.	Type of release had significant impact on recidivism, with EOS correlated with lower rates of return and mandatory release associated with higher rates of return.	Reject
9	State will have no significant impact on recidivism.	Aggregate results indicate that state does matter.	Reject
10	Recidivism will decrease between the 1992 and 1999 cohorts for all states.	Recidivism increased between the two cohort periods.	Reject

Social disorganization scales as measured here have marginal and inconsistent effects (Hypotheses 5 and 7; 6 is no longer testable since the illegitimate opportunity scale was dropped). Both the legitimate and urbanization scales had different effects across states, and effects were mostly underwhelming. It is possible these would be more pronounced had the scales been based on neighborhood or census tract level measures.

Regarding public policy measures, release type has a significant impact on the likelihood of return (Hypothesis 8), and the null is clearly rejected. If we are to reduce the prison population by minimizing the recidivism rate, increasing EOS releases is the most promising strategy, followed by a return to parole board releases; mandatory statute release is the least successful type of release. The role of state also matters in predicting recidivism (Hypothesis 9). Even after controlling for all other factors, there are underlying causal influences unaccounted for between states that affect recidivism. This is mostly clearly demonstrated in the difference between the 4-state and 3-state models in the linear and logistic regression results. Finally, despite all the measures taken to reduce crime in the 1990s, the policies have resulted in an overall increase in recidivism (Hypothesis 10). The implications of these findings are discussed more fully in the following chapter.

CHAPTER 5

DISCUSSION AND CONCLUSION

The objective of this study was to inform efforts to reduce the prison population by identifying factors that contribute to recidivism. By expanding the range of factors we think of when measuring recidivism, we can better understand why people come back and adapt policies to address some of these factors. Recall the initial research questions at the outset of this study –

1. Is recidivism the product of persons, places, or policies, or some combination thereof?
2. How does the impact of individual, community, and public policy characteristics on recidivism differ when modeled in isolation by block and when modeled together?
3. Does the strength and significance of the effects of individual attributes accounting for recidivism differ depending upon the policy context and location?
4. How do these findings inform the debate over how to reduce the size of the prison population within states and as a nation?
5. Can recidivism be reduced with policy changes as opposed to the more difficult task of changing individuals?

Findings will be summarized in accordance with the first three research questions in the discussion of findings. The fourth and fifth questions are addressed in the next section on the impact of findings on policy reforms. Finally, recommendations for further study are discussed.

Discussion of Findings

Overall, the individual, community, and public policy blocks of variables each affected recidivism, there was variation across place and over time, and effects changed as different variables were introduced. This demonstrates that recidivism is about more than just criminal behavior and reinforces the fact that it is inappropriate to compare recidivism rates between groups without controlling for some basic variables correlated with the likelihood of return. There are 51 different prison systems including the Federal Bureau of Prisons; this study only included 4 and found variations in why people come back. It is likely that a more comprehensive study with additional states and predictor variables would yield further variations.

Overall, the individual, criminal justice, and public policy variables all offer context as to why people come back, both when modeled isolation and together, indicating independent effects. The community variables show relative little effect on recidivism. The main overlap in the full models run on the aggregated state data occurs with the state and type of release dummies, indicating that much of the difference between states is due to the difference in release policies. The relatively modest contributions of the state dummies over and above what release practices explains suggest that there is no policy climate effect, at least as it measured here, on recidivism. The fact that state dummies had more power in the 4-state models indicate that there may residual policy effects at work in California, but we are unable to determine this due to collinearity.

Generally, and consistent with previous research, returns to prison were more likely male than female, black than white, younger than older, and property offenders rather than violent offenders. Being male and age at time of release were the most powerful and consistent individual correlates of subsequent recidivism (males are more likely to return; older releases were less likely to return). A previous failure was predictive of a subsequent failure, and there was no consistent effect of time served. Based on the aggregate Nagelkerke results, the impact of individual characteristics and criminal justice characteristics were additive, but explained only a portion of recidivism. Such traits may be useful in characterizing the population and assessing risk in conjunction with other variables, but are a weak foundation upon which to base policy in isolation. Further, most of these are not characteristics we can directly impact to reduce recidivism.

The social disorganization of the residential community to which the inmate is released had little effect on recidivism. Legitimate opportunity and urbanization varied in significance, and had modest overall value in predicting recidivism compared to the other variables. This may be because the scales of legitimate opportunity and urbanization were insufficiently specified to capture environmental effects. Measures of social disorganization more directly tied to the individual, such as legitimate opportunities and urbanization at the neighborhood or Census tract level may prove to be more effective in predicting recidivism.

Policy variables were significant across places, but for mandatory releases in the 1992 New York and 1999 Michigan cohorts. Mandatory releases were the least successful and EOS releases were the most successful in terms of recidivism, net of individual and community effects. This is likely tied not just to whether to a person was subject to post-custody supervision, but the degree of supervision and the threshold for revocation. As already stated, there appears to be a residual effect of the policy climate in California when compared to the other states – this could be related to a significant difference in post-release supervision practices. Release mechanism has the greatest effect in California as indicated by the fact that state dummies and release type have much greater effects on recidivism when California is in the model than when it is not. Mandatory release subjects all released inmates to a period of supervision without using a parole board or other entity to determine who should be released. This is used universally in California and evidently has a substantial effect on recidivism. The effects of mandatory release are neither as strong nor in the same direction for the other states in the analysis, suggesting there is something unique about the supervision policies in California that increase the probability of recidivism.

When inmates are released by EOS they are not subject to post release supervision. In each state but California, being released by EOS significantly reduces the likelihood of returning to prison. This may be due to the fact that subsequent offending by EOS releases is less likely to be detected and result in a return to prison. It could also be that the conditions of supervision are the drivers in returns to prison. Because the data do not allow us to separate out technical violators from other admission types, this cannot be addressed with this data. However, it does raise the question as to whether increasing the numbers of persons under supervision will reduce the prison population in the longer term.

Recidivism rates are differentially dependent on who you are, what you did, how much time you served, type of release, and the state and county in which you reside. Traditional thinking on criminal behavior and recidivism assumes a) characteristics of the individuals are the driving factors behind why people return to prison and; b) length of incarceration and post-custody supervision should result in cessation of subsequent criminal behavior. The fact that the probability of recidivism is tied to type of release even when other attributes are held constant defies the conventional assumption that people are in prison simply because they are bad people.

In terms of interactions, many of the effects of individual characteristics are constant across states while others vary. For instance, sex, race, and age predicted probability of return in New York and Michigan slightly better in 1992 compared to 1999; drug offenders released from Michigan prisons in 1992 were significantly less likely than violent offenders to return, but slightly more likely (though not significantly) than violent offenders to return when released in 1999. Hispanic origin decreased likelihood of return in both California and New York (it is unknown if similar effects would have resulted had the Hispanic information in the Michigan and Pennsylvania data been better).

Increased length of time served had varying impacts on likelihood of return, even within state. The strength of the time served variables was also systematically weaker than the sex, age, race, and release type dummies. The most powerful predictor of return was the presence or absence of post-custody supervision. Mandatory statute release in California was overwhelmingly correlated with a return to prison after holding all other factors constant.[24] Conversely, EOS was strongly correlated with decreased likelihood of return.

Unexpectedly, results from the New York model in 1999 indicated that parole board releases were less successful than mandatory releases (though not statistically significant). While the level of post-custody supervision unknown, it is clear that any type of supervision is more likely to result in revocation than no supervision and we suspect the rate of return can be exacerbated by harsher supervision policies. Additional research is necessary to follow up on this result.

Findings also indicate that county level measures of legitimate opportunity and urbanization are modest as well as inconsistent in significance and directional influence. For example, legitimate opportunity had a significant and negative impact in Michigan in 1992, but a positive significant impact in 1999. The urbanization scale had a negative impact in California counties both years, but a positive effect in Michigan. Reasons behind these discrepancies are challenging to identify without improved measurement scales and a county by county analysis. Preliminary analysis on models using county dummies showed some significant differences between counties, particularly in California. This finding is supported by Ball (2011), who posits

24. Recent modifications to California policy issued in the "realignment" guidelines may result in various outcomes, potentially positive and negative – some of these will be discussed in the next section.

that different counties deal with crime in different ways, and that incarceration is not driven by crime, but by policies that vary by offense, county, and criminal justice response. Overall, the legitimate opportunity and urbanization scales were disappointing, but it must be restated that the specified measures may be insufficient due the county unit of measurement, available data used to create the scales, or both. Recommendations for improvement on these measures for future research are discussed shortly.

Application of Findings

At the outset of this study, it was argued that a reduction in the prison population can be achieved through decreased recidivism, but in order to do so the factors contributing to recidivism must be better identified and applied to policy. In addressing the fourth and fifth questions, applications of the findings will be discussed in terms of policy changes both under review and underway; specific examples of changes in effect or proposed in the individual states included in the study will also be highlighted.

Some states were making small changes to sentencing policies prior to the national financial crisis, mostly pertaining to drug offenders (King, 2007; Greene and Mauer, 2010). However, the recession that began in late 2007 contributed to the fiscal instability in most state budgets leading legislators to seek cuts each subsequent fiscal year. In 2008, 26 of the 37 states for which numbers were reported showed a decrease in corrections spending, which resulted in cuts to healthcare services and offender programs, delayed construction or expansion of facilities, closings of prison wings and facilities, and reduced staff, salaries, and benefits (Scott-Hayward, 2009). States are coping with the budget crisis in two main ways – first, by cutting costs short-term through reduced staffing, programming, and facility construction and expansion, and second, by reviewing and revising sentencing and release policies to reduce the number incarcerated persons.

Thirteen states have commissioned task forces to review sentencing and release policies (National Conference of State Legislators, 2010), but many are not waiting for the results of these reviews to act – several have already taken actions such as increasing thresholds for theft-related crime, relaxing mandatory drug sentences, expanding good time, instituting early probation and parole release, expanding parole eligibility, easing technical violator thresholds, using intermediate sanctions, and targeting high-risk offenders for supervision (National Conference of State Legislators, 2009, 2010; Scott-Hayward, 2009; King 2010; Austin, 2010).

These changes are being characterized by supporters as a shift from being *tough on crime* to *smart on crime* with a focus on evidence-based practices, with the prison industry, unions, and a residual fear of being “soft on crime” being blamed as the main obstacles to reforms (Mauer, 2011). However, it must be noted that the “evidence” cited is selective and inconsistent, such as the claim that less time served will not affect recidivism or the mixed results reported for post-custody supervision as either increasing or decreasing recidivism rates. The results presented in the previous section, for example, suggest that reducing sentence length could increase the risk of recidivism in some places. In addition, there are also preliminary stirrings of concern that some of these sweeping reforms may compromise public safety (Davey, 2010). A handful of high-profile incidents that involve a violent crime committed by a “low-level” offender released early could result in public pressure to abandon the reforms, when perhaps only modification is required. The opinion of one prosecutor in Michigan reflects the fear that some reforms are endangering public safety: “they’re making [policy] mistakes left, right, and sideways” (Davey, 2010). It is imperative that these policies are truly based on research and applied to the appropriate populations if they are to survive the media scrutiny of the inevitable anecdotal examples of policy failure.

The implications of this research for policy reforms will be discussed in terms of changes in sentencing policy (including diversion and treatment) and changes in release policies. California will be discussed separately since the changes associated with the realignment plans resulting from the Supreme Court order to reduce their prison population have many wide-reaching implications.

Changes in Sentencing Policies and Treatment Alternatives

The main revisions to existing law within the last decade or so occurred in relation to drug offenses. Drug laws have been revised in several states shortly before or since 1999, the last release cohort in the study. In Michigan, for example, the 650 lifer law that automatically sentenced someone convicted with more than 650 grams of cocaine or heroin to life was repealed in 1998 and mandatory minimums for many other drug offenses were revised in 2002 (Greene and Mauer, 2010). Similarly, New York modified the Rockefeller Drug Laws, which, in conjunction with other reforms and a general decline in crime is credited with reducing the prison population by 20% between 1999 and 2009 (Greene and Mauer, 2010) and resulting in the closing of seven prison facilities (Kaplan, 2011). Decriminalizing drug possession as well as providing treatment for those with drug problems may keep a subset of offenders out of prison, but these efforts are not enough to reduce a national prison population that is largely made up of other offender types. And, as indicated by the results in the logistical regressions, drug offenders are already less likely to return than violent or property offenders.

Mandatory treatment or other diversion for drug offenders will also likely have similar modest impacts on the overall prison population; success of such programs on reducing the prison population is contingent on the volume of persons served, the quality of treatment, program completion, and the thresholds at which additional sanctions kick in. For instance, California's Proposition 36 diverts first and second time possession offenders to treatment rather than incarceration. While there is some research proclaiming its success in terms of cost savings and lowered recidivism (Uranda et al., 2008; Ehlers and Ziedenburg, 2006), success in the latter is mainly achieved by those who complete treatment, which is accomplished in about a third of cases. There is also no information on outcomes for alternatives such as small fines or no formal action at all (if such programs treat low-level first time offenders who may – or may not – have a substance abuse problem, but were unlikely to reoffend regardless of abuse issues, it may be even cheaper to do nothing). This is not to say such approaches are not effective, but that our hopes of reducing the prison as a whole should not be reliant on treatment policies for drug offenders. First, drug offenders are often serving time for trafficking, and a subset of those serving time for possession plead their charge down – dealing drugs does not mean one is a drug addict. Second, previous research has indicated that substance abuse problems are correlated not just with drug offending, but with other criminal behavior as well (Benda, Corwyn, and Toombs, 2001; DeJong, 1997) – to reduce the prison population offenders with a drug problem should be treated regardless of their charge.

There is also a movement toward using suspended sentences or community supervision in conjunction with "low-level" or "non-violent" offenders. This could be effective, but we must consider that we have already increased the number of persons on probation by over 3.5 times between 1980 and 2010, from 1.1 million to 4.1 million and that nearly 6 in 10 persons under any type of correctional supervision are on probation (Snell, 1995; Glaze, 2011). In addition, nearly one-quarter (24%) of persons in state prison in 2004 were on probation when arrested for the offense that resulted in their current incarceration; another fifth (19%) were on parole (BJS, 2009). The models indicate that post release supervision increases the chance of recidivism and, if we can extend this to probation, this will mean that increasing the probation population will increase the pool of persons with a higher probability of being admitted to prison by supervision revocation. For this reason, increased use of probation may not bring the reductions in the prison population that is predicted. Probation supervision, while cheaper than incarceration, also costs money, and examples abound of probation offices that are already short-staffed and experiencing cuts (Duran, 2011; Poinski, 2011; Spagenthal-Lee, 2011). However, if these shortages lead to a decline in the actual supervision of offenders (that is, they only come to the attention of the office if a new crime is committed), perhaps increased community supervision could result in lower recidivism, as observed among EOS releases.

Changes in Release Policies

The reinstitution of good time, expanded parole eligibility, and early release to probation and parole and are the main approaches being implemented directly and immediately to reduce prison populations. Given the mixed findings on the impact of time served on recidivism, it is likely that good time credits, which can reduce sentences by half in a two-for-one credit (two days credit for each one served), will have little impact on the recidivism of released offenders as a whole. Still, a merit program implemented in New York released 24,000 inmates early from 1997 to 2006 and found a lower recidivism rate (31%) for the early release compared to the full-termers (39%) (National Conference of State Legislatures, 2009). It is not specified if there was a difference in characteristics between those released early and the general population. If they were older drug offenders released with limited post-custody supervision, for example, this could explain the difference in recidivism. The level of post-custody supervision, conditions, and revocation practices may also contribute to these results.

Regarding post-custody supervision, it is neither the early release nor the expanded eligibility that cause concern, but rather the type of supervision and the types of offenders being considered for such community supervision. As noted previously, results of the study indicate that those released *without* supervision are most successful; yet, states are touting early release of non-serious (usually meaning non-violent) offenders as the answer to reducing the prison population. Our models suggest that this will not work, particularly with property offenders, unless the nature of supervision fundamentally changes as well, depending on the nature of the post-custody supervision. It may work with drug offenders who are less likely to re-offend after release and who have minimal conditions and requirements.

While there is evidence that some jurisdictions are simultaneously implementing policies such as easing revocation thresholds, shortening time on supervision, utilizing intermediate sanctions, and applying other measures to boost success on parole, these approaches must be adopted widely and consistently to have an impact. Further, when studies of recidivism of these parolees are conducted, the details of parole supervision policies and practice should be a core element in the assessment. A number of states, for example, are easing technical violator thresholds (King, 2010). A rigorous pre and post treatment study should be conducted to discern both the effect of these policy changes and a profile of parolees for whom the policy changes were most effective. Finally, the increased use of both probation and parole assume that the budgets will allocate the needed funds to support additional officers.

The California Experiment

This study highlights the several ways that California corrections have operated differently than other states. Additional changes underway in the California penal system are setting the stage for an experimental study assessing the impact on policy on recidivism. The state is in the process of rolling out its realignment plan, designed in response to the U.S. Supreme Court requirement that they reduce their prison population to 137.5% of design capacity by May of 2013, which equates to some 37,000 inmates within 2 years (Brown vs. Plata, 2011). The plan includes diverting "non-violent," "non-serious," and "non-sex offenders" to county jails and releases similar offender types to probation (county supervision) rather than state parole supervision; any revocation time will be served in the county jail or using some alternative sanction such as electronic monitoring or home detention (California Department of Corrections and Rehabilitation Fact Sheet, 2012). Funding of $354 million was allocated among the counties to support increasing local jail capacity to receive these inmates (CDCR, 2012). Local officials have expressed serious concerns about their capacity to deal with these additional offenders with current probation staffing levels and existing bed space in local jails, as well as concerns about public safety if resources prove to be insufficient (Krisberg and Taylor-Nicholson, 2011). Ad hoc fixes to the plan continue to be passed to address loopholes and unanticipated issues, and there are surely more to come.

The main concern stemming from the findings in this study is that California has previously established a system in which offenders serve short terms, go to community supervision, and are revoked back to incarceration at very high rates. There is no evidence that shifting the responsibility of non-violent offenders to the county level will result in a reduction in recidivism or that there are consistent and widespread efforts to revise revocation thresholds or improve services. There *is* evidence that community supervision offices are already struggling

(Duran, 2011; Poinski, 2011l; Spagenthal-Lee, 2011) and the fact that some California jails were already crowded prior to the implementation of the realignment: of the top 50 largest jails in the nation in 2010, nine were located in California; six of these were over-capacity one or more years between 2008 and 2010 (Minton, 2011). While the system may succeed in meeting the letter of the law to reduce the prison population, the method will likely unleash a slew of fresh problems. The mandate is already being blamed for a spike in violent crime rates (Solis, 2012) and increased violence in jails (Alexander, 2012).

Reforms must be based on careful research and presented not just in terms of cost savings but also contextually, by acknowledging that there will be some cases where persons diverted or released as a result of some of these reforms will subsequently commit undesirable acts, setting the stage for reactionary policy reform. We cannot afford to continue to modify policy based on an immediate crisis or anecdotal events. As Mauer (2011) notes, we needn't strive for perfect set of policies, but simply policies that yield better outcomes than those in the past. Time will tell if California earns the dubious distinction of what *not* to do when attempting to reduce the prison population.

Recommendations for Future Study

There are two main ways to further expand upon we know about recidivism. While this research included factors beyond the individual, the results were mixed. The community scales were largely inconclusive and while release type was significant, it is not clear specifically why. In addition, there are other dependent variables that would be useful to adopt in refining our understanding of recidivism beyond the binary 3-year marker. It is recommended that further research is conducted before drawing conclusions about how policies could be adapted to reduce recidivism.

Enhancing the Model

The results thus far indicate that we could achieve reductions in recidivism may by better identifying reasons offenders return. There are several ways to enhance the models presented here to better specify and expand upon these factors. Consistent with the discussion of findings, these will be presented in terms of individual and criminal justice characteristics, community measures, and public policy variables. It has been acknowledged that while age, race, or offense can be included in risk assessments prior to release, there is nothing we can do about these static factors to influence recidivism rates. There are other similar variables that could be included for the purposes of risk assessment such as marital status, presence of children, the strength of these relationships, living situations prior to incarceration, and frequency of contact while incarcerated. Families of the incarcerated could well have positive effects in reducing recidivism and these impacts could be bolstered with community and prison programs that support such relationships (Bayse , Allgood, Van Wyk, 1991; Bobbitt and Nelson, 2004; Cornille, Barlow, and Cleveland, 2005; Dunn and Arbuckle, 2002).

Other individual factors not included in this study, but believed to impact recidivism, include education, employment, income level, mental health and substance abuse status and treatment, and participation in inmate programs such as life skills and anger management, to name a few. While we cannot change static variables such as age, race, or sex, it may be possible to produce incremental impacts on recidivism by influencing criminogenic factors through increased education and employment opportunities, mental health diagnosis and treatment, and using programs to address other challenges to success on the outside, such as substance abuse treatment, anger management, and interviewing skills. There have been some small scale studies that indicate such programs may be worthwhile, such as the finding that employed parolees in Pennsylvania are three times more likely to remain arrest-free (Meredith, Speir, and Johnson

2007) and a decline by half in recidivism among released offenders receiving aid to obtain entitlement benefits and mental health treatment in the community (Yamatani, 2008). However, there were no identified studies found that include the individual, community, and policy variables in addition to these other criminogenic factors in assessing recidivism.

Community factors used here were at the county level and were approximate to the year of release using decennial information (1990 for the 1992 cohort and 2000 for the 1999 cohort). Similar measures (household income, unemployment, high school degree, violent crime rate, unmarried males, to name a few) may have greater impact at the neighborhood or Census tract level and some may be available at time periods that coincide more closely with time of release. Including monthly employment data as Sabol (2007) did in studying the relationship between pre-incarceration employment, prison releases and subsequent employment could also be illuminating. In addition, other factors that serve as indicators of community support networks, such as social service assistance programs, after school programs, time in residence, law enforcement hotspots, relationships with local law enforcement, and loss of social capital (as it correlates with high-levels of incarceration at the neighborhood level, see Braman 2004), could also be useful in refining the influence of community on recidivism. It is unlikely such variables could be included in large-scale studies over multiple states, but perhaps there are administrative systems that would share such data for a series of state-specific studies.

Release type was identified as having a significant impact on likelihood of return to prison, but with different magnitudes and mixed results for parole board releases. These effects can be further unpacked by incorporating measures that classify levels of post-custody supervision (low, medium high, maximum, for example), staff workloads, and general threshold guidelines for parole revocation (such as a failed drug test, a missed appointment, or a new arrest). We know these vary by state, but may also vary significant by county (Ball, 2011). Other public policy factors that could be included in expanded predictive models include more extensive criminal history information (previous offenses, previous participation in diversion programs, treatment, etc.) and subsequent admission type (including for technical violations, a measure not available in NCRP) which may involve permission to access and merge multiple administrative datasets.

Expanding the Dependent Variable

The binary dependent variable used in this study was useful in measuring a baseline for recidivism, but many researchers argue that a simple binary measure is simply not sufficient when studying recidivism (Blumstein et al. 1986; Maltz 1984). Schmidt and Witte (1988:152) further specify:

> It is now widely recognized that the length of time until recidivism is a much more useful variable than the simpler yes/no measure of recidivism for some fixed time after release, and there are two reasons for this. First, the timing of recidivism contains useful information; from a statistical point of view, it is inefficient to ignore this. Second, once we have estimated the distribution of time until recidivism, we can make predictions of the rate of recidivism for any period of time after release, not just for the particular follow-up period found in the data used to estimate the model.

Frequency of return was assessed because parsing out number of times returned was necessary to build the dataset. Still, it is apparent that states vary in how often inmates are returned (Appendix table 1); these differences merit additional research. Neither was time to first return used a dependent variable in the study, but Table 6 indicates that this, too, varies by jurisdiction, and could be partially explained with the inclusion of some additional post-custody supervision measures. As noted earlier, the ability to differentiate reliably between technical violators and new offenses would also help in assessing how recidivism outcomes and how we might change policy without increased risk to public safety. Additional work to further refine the effects of individual and criminal justice characteristics, community effects, and type of release on time to return and number of times returned will be pursued in future work.

Conclusion

The research presented here is a first step in expanded how we think about recidivism. The results indicate that there are many factors behind a return to prison. Recidivism is not solely linked to the characteristics of the individual, the community from which they come, or how they are released, but rather a complex combination of these factors. Even after controlling for these effects, state and time also impacted rates of recidivism. The influence of individual factors in risk to return was confirmed, the effects of community were weaker than anticipated, and the policy effects were much stronger than anticipated. The variation between states reinforces that we refrain from comparing the success rates of one state to another unless similar methodology and definitions are applied. Data enhancements, such as consistent definitions and reporting on admission types, in particular parsing out technical violations from general parole revocations, would be helpful in further refining the story of why people come back.

If there is one conclusion from this research it is that there is no simple answer to the problem of recidivism. As much as we like to pin our hopes of solving the revolving door problem with a risk-assessment tool, a model treatment or work program, or cutting edge technology such as GPS systems to prevent returns to prison, there is no such magical solution. We would be wise to approach policy changes with great care and be prepared to vigorously assess the impact of such changes. Such caution is unlikely in the current quest to cut costs by any means necessary, but we can learn by closely studying the short and long term outcomes of such policy changes and perhaps learn from the mistakes that we are inevitably currently making. If increased community supervision proves to be one of the main policy reforms in this decade, we must better define the elements of that supervision and the subsequent effects on recidivism.

APPENDIX A

MAXIMUM NUMBER OF RETURNS EACH COHORT YEAR BY STATE

	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
1992	5		2		5		2	
1993	6		4		5		2	
1994	6		4		4		2	
1995	5		3		6		2	
1996	5		2		3		2	
1997	5		3		4		2	
1998	5		3		4		2	
1999	6	6	3	3	4	4	2	2
2000	5	5	3	3	4	4	2	2
2001	6	6	2	2	5	4	3	3
2002	5	5	2	2	5	5	2	3

APPENDIX B

COUNTIES EXCLUDED FROM ONE OR BOTH COHORTS

	California	Michigan		New York	Pennsylvania
Total counties	57	83		57	66
Excluded counties	6	48		18	26
	Alpine	Alcona	Lake	Allegany [a]	Armstrong [a]
	Mariposa [a]	Alger	Leelanau	Chenango	Bedford
	Mono	Alpena	Luce	Cortland [a]	Cameron
	Plumas [a]	Antrim [a]	Mackinac	Delaware [a]	Carbon
	Sierra	Arenac	Manistee [a]	Essex	Clarion
	Trinity [a]	Baraga	Marquette	Franklin [a]	Clinton [a]
		Benzie	Menominee	Greene [a]	Columbia
		Charlevoix	Missaukee	Hamilton	Elk
		Cheboygan	Montcalm [a]	Lewis	Forest
		Chippewa	Montmorency	Madison [a]	Fulton
		Clare	Oceana	Otsego [a]	Huntingdon
		Clinton [a]	Ogemaw	Schoharie [a]	Juniata
		Crawford	Ontonagon	Schuyler	McKean
		Delta	Osceola [a]	Seneca	Mifflin
		Dickinson	Oscoda	St. Lawrence [a]	Montour
		Emmet	Otsego [a]	Washington [a]	Perry [a]
		Gladwin [a]	Presque Isle	Wyoming	Philadelphia
		Gogebic	Roscommon [a]	Yates	Pike
		Gratiot [a]	Sanilac [a]		Potter
		Houghton	Schoolcraft		Schuylkill
		Huron	Wexford [a]		Somerset [a]
		Ionia [a]			Sullivan
		Iosco [a]			Susquehanna
		Iron			Tioga [a]
		Isabella*			Union
		Kalkaska			Wyoming
		Keweenaw			

[a] Excluded from 1992 and 1999 cohorts.

APPENDIX C

NUMBER AND PERCENT OF MISSING CASES, BY STATE AND COHORT YEAR

	California		Michigan		New York		Pennsylvania	
	1992	1999	1992	1999	1992	1999	1992	1999
Race	2,687/3.5	17,430/15.6	32/.3	11/.1	8,035/33.2	289/1.2	4/.1	6/.1
Hispanic origin	1,845/2.4	2,179/2	9,623 /98.7	10,413/98	164/.7	83/.3	5,896/80.8	6,637/68.7
Education	77,231/100	111,471/100	176/1.8	84/.8	589/2.4	1,152/4.6	7,301/100	9,662/100
Offense	145/.2	69/.1	0	0	39/.2	0	7,301/100	2/0

APPENDIX D

VARIABLES ENTERED IN FACTOR ANALYSIS MODELING

Legitimate opportunity	Illegitimate opportunity
Median household income Percent of unemployed adults Percent employed outside county of residence Percent using public transportation to work Percent of households on public assistance Percent households on SSI Percent of young adult drop-outs Percent high school or higher Percent less than 9th grade Percent below poverty level Percent white population Average household size	Violent crime rate per 1,000 residents Property crime rate per 1,000 residents Percent unmarried males Number males 16-24 Percent young adult drop-outs Percent high school or higher Percent less than 9th grade Percent black males unemployed Rate of prison releases per 10,000 county residents Percent single moms Percent renters
Urbanization	**Law Enforcement**
Vacant housing units Occupied housing units Percent renters Same house as 5 years prior Same county as 5 years prior Housing units per square mile Percent black Percent foreign born Percent English in home Population per square mile Percent single moms Percent using public transportation to work	Total Part 1 crime rate per 1,000 residents Violent crime rate per 1,000 residents Property crime rate per 1,000 residents Total arrest rate per 1,000 residents Public order arrests as percent of total arrests Drug arrest rate per 1,000 residents

APPENDIX E

NAGELKERKE R-SQUARES FOR LOGISTIC REGRESSION MODELS FOR AGGREGATES STATES, BY RELEASE YEAR

Model number	Variable blocks entered	R^2 for 3-year return: CA, MI, NY, PA[a] 1992	CA, MI, NY, PA[a] 1999	MI, NY, PA[b] 1992	MI, NY, PA[b] 1999
1	State	0.068	0.075	0.001	0.008
2	Individual demographics (ID)[c]	0.018	0.028	0.032	0.019
3	Criminal justice demographics (CJD)[d]	0.085	0.056	0.022	0.029
4	ID/CJD	0.103	0.077	0.055	0.048
5	Community factors (CF)[e]	0.006	0.006	0.000	0.001
6	Public policy control (PPC)[f]	0.089	0.105	0.016	0.056
7	State/PPC	0.094	0.117	0.017	0.059
8	State/ID/CJD/CF	0.170	0.190	0.077	0.118
9	ID/CJD/PPC	0.168	0.181	0.076	0.117
10	ID/CJD/PPC/CF	0.168	0.182	0.077	0.117

Note: Reference categories are females, whites, under 24 years old at release, violent offenders, new court commitment admissions, first quintile of adjusted time served (shortest stays), and parole board releases.

[a] CA is reference category.

[b] NY is reference category.

[c] ID (individual demographics) **-** sex, race/ethnicity, age.

[d] CJD (criminal justice demographics) **-** offense, type of admission, and adjusted time served.

[e] CF (community factors) **-** legitimate opportunity and urbanization scales.

[f] PPC (public policy controls) **-** release type.

APPENDIX F-1

CALIFORNIA LOGISTIC REGRESSION MODELS FOR 1992 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	0.226	0.034	43.94	0.013	0.020	0.42	-0.035	0.039	0.78	-4.121	0.215	367.70
Individual demographics[a]												
Male	0.437 ***	0.027	264.21				0.405 ***	0.028	213.45			
Black	0.287 ***	0.019	229.12				0.233 ***	0.020	139.01			
Hispanic	-0.311 ***	0.019	263.78				-0.260 ***	0.020	173.21			
Other	-0.052	0.085	0.38				0.037	0.087	0.18			
Age at release (years)												
25-34	-0.116 ***	0.022	27.72				-0.285 ***	0.023	154.06			
35-44	-0.252 ***	0.024	105.90				-0.439 ***	0.025	300.02			
45+	-0.759 ***	0.034	509.16				-0.876 ***	0.035	639.30			
Criminal history[b]												
Offense												
Property offense				0.248 ***	0.021	140.93	0.307 ***	0.022	200.31			
Drug offense				-0.092 ***	0.020	20.05	-0.046 *	0.021	4.69			
Public order offense				-0.250 ***	0.030	70.63	-0.146 ***	0.031	22.33			
Other offense				0.325 ***	0.045	53.01	0.356 ***	0.046	60.28			
Parole violator admission				0.806 ***	0.016	2458.14	0.770 ***	0.017	2031.74			
Time served (quintiles)												
2				-0.047 *	0.021	50.68	-0.048 *	0.021	5.10			
3				-0.084 **	0.031	7.21	-0.089 **	0.032	7.57			
4				-0.097 ***	0.021	20.81	-0.117 ***	0.022	28.51			
5				-0.088 ***	0.025	12.84	-0.055 *	0.026	4.64			
Public policy controls[c]												
Mandatory release										4.584 ***	0.215	454.39
Expiration of sentence release												
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	59.943***			187.537***			144.046***			0		
Nagelkerke R2	0.033			0.061			0.085			0.04		
Log likelihood	97904			100126			94899			101341		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is expiration of sentence release.

Variable	Model 5 Coefficient		SE	Wald	Model 6 Coefficient		SE	Wald	Model 7 Coefficient		SE	Wald
Constant	-5.088		0.229	492.57	0.485		0.017	842.37	-4.961		0.230	466.98
Individual demographics[a]												
Male	0.420	***	0.028	223.07					0.423	***	0.028	225.90
Black	0.229	***	0.020	129.04					0.292	***	0.021	192.15
Hispanic	-0.280	***	0.020	195.16					-0.242	***	0.020	140.00
Other	0.034		0.088	0.15					0.020		0.088	0.05
Age at release (years)												
25-34	-0.263	***	0.023	128.08					-0.268	***	0.023	132.64
35-44	-0.424	***	0.026	272.45					-0.432	***	0.026	281.09
45+	-0.862	***	0.035	601.48					-0.868	***	0.035	607.67
Criminal history[b]												
Offense												
Property offense	0.273	***	0.022	151.56					0.271	***	0.022	149.19
Drug offense	-0.105	***	0.022	23.26					-0.098	***	0.022	20.42
Public order offense	-0.206	***	0.031	43.24					-0.220	***	0.031	48.99
Other offense	0.324	***	0.047	47.69					0.315	***	0.047	44.93
Parole violator admission	0.856	***	0.017	2411.06					0.861	***	0.017	2435.47
Time served (quintiles)												
2	-0.036		0.022	2.76					-0.041		0.022	3.51
3	-0.071	*	0.034	4.43					-0.076	*	0.034	5.14
4	-0.150	***	0.022	45.49					-0.156	***	0.022	49.35
5	-0.118	***	0.026	20.64					-0.123	***	0.026	22.33
Public policy controls[c]												
Mandatory release	5.091	***	0.226	507.87					5.108	***	0.226	511.22
Expiration of sentence release												
Community factors												
Legitimate opportunity					-0.033	***	0.009	13.61	-0.004		0.010	0.16
Urbanization					-0.039	***	0.008	22.52	-0.098	***	0.009	111.26
Model fit												
Hosmer and Lemeshow	144.360***				457.979***				139.703***			
Nagelkerke R2	0.133				0.001				0.135			
Log likelihood	92030.640				103641				91918.703			

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is expiration of sentence release.

APPENDIX F-2

CALIFORNIA LOGISTIC REGRESSION MODELS FOR 1999 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	0.657	0.031	439.52	0.055	0.017	10.22	0.309	0.036	75.89	-4.869	0.237	423.52
Individual demographics[a]												
Male	0.456 ***	0.022	411.61				0.403 ***	0.023	308.18			
Black	0.216 ***	0.016	176.41				0.199 ***	0.016	145.35			
Hispanic	-0.859 ***	0.018	2239.48				-0.749 ***	0.019	1624.84			
Other	0.091	0.063	2.04				0.121	0.064	3.56			
Age at release (years)												
25-34	-0.355 ***	0.024	222.44				-0.478 ***	0.024	383.73			
35-44	-0.42 ***	0.024	297.74				-0.554 ***	0.025	490.94			
45+	-0.73 ***	0.028	670.65				-0.849 ***	0.029	867.05			
Criminal history[b]												
Offense												
Property offense				0.216 ***	0.017	224.43	0.296 ***	0.02	230.74			
Drug offense				-0.058 ***	0.016	12.46	0.037 *	0.018	4.18			
Public order offense				-0.015	0.025	0.34	0.071 *	0.029	6.05			
Other offense				-0.327 ***	0.076	18.63	-0.318 ***	0.086	13.86			
Parole violator admission				0.586 ***	0.014	1766.74	0.486 ***	0.016	942.56			
Time served (quintiles)												
2				0.11 ***	0.018	38.35	0.121 ***	0.02	37.91			
3				0.16 ***	0.023	49.25	0.182 ***	0.025	51.36			
4				0.079 ***	0.019	17.74	0.089 ***	0.021	17.80			
5				0.085 ***	0.021	16.92	0.155 ***	0.023	45.08			
Public policy controls[c]												
Mandatory release										5.463 ***	0.237	532.63
Expiration of sentence release												
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	130.603***			184.799***			60.656***			0		
Nagelkerke R2	0.058			0.037			0.083			0.055		
Log likelihood	119621			143726			117822			142248		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is expiration of sentence release.

Variable	Model 5 Coefficient	SE	Wald	Model 6 Coefficient	SE	Wald	Model 7 Coefficient	SE	Wald
Constant	-5.573	0.271	423.01	0.73	0.015	2315.58	-5.400	.027	341.437
Individual demographics[a]									
Male	0.437 ***	0.023					.432 ***	.023	341.437
Black	0.222 ***	0.017					.294 ***	.018	268.287
Hispanic	-0.771 ***	0.019					-.717 ***	.019	1379.641
Other	0.105	0.065					.084	.065	1.668
Age at release (years)									
25-34	-0.444 ***	0.025					-.445 ***	.025	322.734
35-44	-0.526 ***	0.025					-.524 ***	.025	425.384
45+	-0.833 ***	0.029					-.829 ***	.029	798.144
Criminal history[b]									
Offense									
Property offense	0.245 ***	0.02					.250 ***	.020	154.707
Drug offense	-0.031	0.019					-.022	.019	1.390
Public order offense	0.028	0.029					.019	.030	.405
Other offense	-0.269 **	0.09					-.265 **	.090	8.587
Parole violator admission	0.582 ***	0.016					.580 ***	.016	1288.267
Time served (quintiles)									
2	0.117 ***	0.02					.110 ***	.020	30.298
3	0.177 ***	0.026					.177 ***	.027	44.836
4	0.06 **	0.021					.061 **	.021	8.041
5	0.074 ***	0.023					.079 ***	.023	11.292
Public policy controls[c]									
Mandatory release	5.899 ***	0.269	482.45				5.907 ***	.269	483.790
Expiration of sentence release									
Community factors									
Legitimate opportunity				-0.048 ***	0.005	79.51	-.028 ***	.006	20.070
Urbanization				-0.098 ***	0.008	141.57	-.121 ***	.010	145.068
Model fit									
Hosmer and Lemeshow	89.289***			690.839***			97.845***		
Nagelkerke R2	0.144			0.003			0.146		
Log likelihood	113297			146567.5			113121		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is expiration of sentence release.

APPENDIX G-1

MICHIGAN LOGISTIC REGRESSION MODELS FOR 1992 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.165	0.098	142.06	-0.920	0.063	213.38	-1.483	0.116	163.37	-0.456	0.022	433.84
Individual demographics[a]												
Male	0.526 ***	0.086	37.36				0.484 ***	0.089	29.73			
Black	0.357 ***	0.045	62.81				0.416 ***	0.048	76.49			
Hispanic	0.040	0.199	0.04				0.213	0.205	1.08			
Other	-0.086	0.365	0.06				-0.013	0.373	0.00			
Age at release (years)												
25-34	0.087	0.053	2.68				-0.085	0.055	2.35			
35-44	-0.055	0.060	0.83				-0.266 ***	0.064	17.34			
45+	-0.959 ***	0.114	71.41				-1.026 ***	0.117	77.18			
Criminal history[b]												
Offense												
Property offense				0.428 ***	0.057	57.16	0.466 ***	0.058	65.40			
Drug offense				-0.113	0.066	2.92	-0.183 **	0.068	7.35			
Public order offense				0.022	0.093	0.06	0.083	0.095	0.77			
Other offense				-1.775	1.043	2.90	-1.827	1.043	3.07			
Parole violator admission				0.074 ***	0.048	239.19	0.714 ***	0.050	207.25			
Time served (quintiles)												
2				0.033	0.081	0.16	0.039	0.082	0.23			
3				0.074	0.157	0.22	0.130	0.160	0.66			
4				-0.022	0.061	0.13	0.001	0.062	0.00			
5				0.004	0.056	0.01	0.041	0.058	0.52			
Public policy controls[c]												
Mandatory release												
Expiration of sentence release										-0.577 ***	0.097	35.391
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	0.384			23.121**			12.088			0.000		
Nagelkerke R2	0.031			0.068			0.098			0.006		
Log likelihood	12183.556			11953.287			11699.866			12397.268		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

Variable	Model 5 Coefficient	SE	Wald	Model 6 Coefficient	SE	Wald	Model 7 Coefficient	SE	Wald
Constant	-1.474	0.116	160.54	-0.659	0.033	404.43	-1.523	0.118	166.56
Individual demographics[a]									
Male	0.483 ***	0.089	29.48				0.484 ***	0.089	29.33
Black	0.424 ***	0.048	78.64				0.381 ***	0.051	55.14
Hispanic	0.216	0.206	1.10				0.208	0.208	1.00
Other	-0.005	0.375	0.00				0.020	0.375	0.00
Age at release (years)									
25-34	-0.085	0.056	2.36				-0.094	0.056	2.84
35-44	-0.255 ***	0.064	15.84				-0.266 ***	0.064	17.13
45+	-1.012 ***	0.117	74.67				-1.020 ***	0.117	75.56
Criminal history[b]									
Offense									
Property offense	0.459 ***	0.058	62.86				0.472 ***	0.058	65.39
Drug offense	-0.213 **	0.068	9.83				-0.206 **	0.068	9.18
Public order offense	0.134	0.096	1.95				0.145	0.096	2.28
Other offense	-1.810	1.045	3.00				-1.769	1.045	2.87
Parole violator admission	0.758 ***	0.050	228.27				0.736 ***	0.051	211.09
Time served (quintiles)									
2	0.045	0.082	0.31				0.048	0.082	0.35
3	0.192	0.162	1.41				0.198	0.162	1.50
4	0.030	0.062	0.23				0.038	0.062	0.37
5	0.078	0.058	1.81				0.080	0.058	1.90
Public policy controls[c]									
Mandatory release									
Expiration of sentence release	-0.810 ***	0.102	63.264				-0.798 ***	0.102	61.258
Community factors									
Legitimate opportunity				-0.075 **	0.027	7.92	-0.055 *	0.028	3.89
Urbanization				0.287 ***	0.043	43.61	0.140 **	0.047	8.86
Model fit									
Hosmer and Lemeshow	5.792			15.089*			17.346*		
Nagelkerke R2	0.107			0.008			0.108		
Log likelihood	11631.104			12336.791			11584.111		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is parole board release.

APPENDIX G-2

MICHIGAN LOGISTIC REGRESSION MODELS FOR 1999 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-0.905	0.092	96.44	-0.85	0.058	213.47	-1.403	0.107	172.52	-0.234	0.022	115.34
Individual demographics[a]												
Male	0.317 ***	0.078	16.55				0.379 ***	0.08	22.36			
Black	0.417 ***	0.042	100.74				0.436 ***	0.045	95.51			
Hispanic	-0.415 **	0.161	6.62				-0.229	0.164	1.94			
Other	-0.005	0.296	0.00				0.04	0.304	0.02			
Age at release (years)												
25-34	0.066	0.058	1.30				-0.005	0.061	0.01			
35-44	0.132 *	0.06	4.85				0.009	0.063	0.02			
45+	-0.386 ***	0.075	26.42				-0.464 ***	0.079	34.92			
Criminal history[b]												
Offense												
Property offense				0.524 ***	0.053	95.81	0.599 ***	0.055	120.42			
Drug offense				0.132 *	0.061	4.72	0.074	0.062	1.41			
Public order offense				-0.086	0.073	1.40	0.018	0.074	0.06			
Other offense				-0.542	0.577	0.88	-0.603	0.585	1.06			
Parole violator admission				0.55 ***	0.043	162.40	0.493	0.045	121.72			
Time served (quintiles)												
2				0.104	0.084	1.54	0.127 ***	0.085	2.24			
3				0.209	0.119	3.07	0.236	0.121	3.82			
4				0.062	0.06	1.62	0.096	0.061	2.46			
5				-0.024	0.052	0.22	-0.004	0.053	0.01			
Public policy controls[c]												
Mandatory release										-0.233 *	0.093	6.32
Expiration of sentence release										-1.243 ***	0.077	261.69
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	6.42			35.480***			14.263			0		
Nagelkerke R2	0.026			0.054			0.077			0.041		
Log likelihood	13721			13508			13316			13613		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

Variable	Model 5 Coefficient		SE	Wald	Model 6 Coefficient		SE	Wald	Model 7 Coefficient		SE	Wald
Constant	-1.381		0.11	156.62	-0.586		0.029	412.07	-1.438		0.112	165.51
Individual demographics[a]												
Male	0.411	***	0.081	25.73					0.392	***	0.081	23.29
Black	0.461	***	0.046	102.47					0.334	***	0.05	45.14
Hispanic	-0.216		0.166	1.69					-0.247		0.167	2.18
Other	-0.033		0.309	0.00					-0.018		0.309	0.00
Age at release (years)												
25-34	-0.037		0.062	0.35					-0.057		0.062	0.84
35-44	-0.007		0.065	0.01					-0.045		0.065	0.48
45+	-0.461	***	0.081	32.69					-0.511	***	0.081	39.65
Criminal history[b]												
Offense												
Property offense	0.572	***	0.056	105.23					0.621	***	0.057	120.47
Drug offense	-0.022		0.063	0.12					0.017		0.064	0.07
Public order offense	0.043		0.076	0.32					0.091		0.076	1.44
Other offense	-0.49		0.595	0.68					-0.427		0.594	0.52
Parole violator admission	0.587	***	0.046	161.14					0.552	***	0.047	140.45
Time served (quintiles)												
2	0.168		0.087	3.76					0.155		0.087	3.20
3	0.377	**	0.125	9.15					0.359	**	0.125	8.29
4	0.169	**	0.063	7.10					0.174	**	0.064	7.52
5	0.125	*	0.056	4.96					0.12	*	0.056	4.63
Public policy controls[c]												
Mandatory release	0.015		0.102	0.02					0.051		0.102	0.25
Expiration of sentence release	-1.39	***	0.08	300.979					-1.369	***	0.081	289.029
Community factors												
Legitimate opportunity					-0.14	***	0.028	25.53	0.096	***	0.029	10.88
Urbanization					0.444	***	0.039	129.62	0.315	***	0.043	52.54
Model fit												
Hosmer and Lemeshow	12.022				22.140**				5.528			
Nagelkerke R2	0.121				0.019				0.127			
Log likelihood	12955.4				13782.32				12899.54			

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

APPENDIX H-1

NEW YORK LOGISTIC REGRESSION MODELS FOR 1992 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.059	0.067	250.98	-0.527	0.025	459.30	-1.656	0.47	12.43	-0.547	0.015	1395.68
Individual demographics[a]												
Male	0.518 ***	0.053	96.08				0.482 ***	0.053	81.24			
Black	0.406 ***	0.041	98.22				0.521 ***	0.043	149.43			
Hispanic	0.171 ***	0.044	15.40				0.319 ***	0.046	48.17			
Other	0.18	0.214	0.70				0.222	0.216	1.06			
Age at release (years)												
25-34	-0.218 ***	0.033	44.22				-0.227 ***	0.033	47.26			
35-44	-0.503 ***	0.041	149.57				-0.503 ***	0.041	147.82			
45+	-0.979 ***	0.071	190.92				-0.941 ***	0.071	174.58			
Criminal history[b]												
Offense												
Property offense				0.253 ***	0.037	45.61	0.354 ***	0.039	83.34			
Drug offense				-0.174 ***	0.032	29.25	-0.116 ***	0.033	11.94			
Public order offense				-0.421 ***	0.066	40.68	-0.356 ***	0.067	28.13			
Other offense				-1.906 ***	0.467	16.66	-1.656 ***	0.47	12.43			
Parole violator admission				--			--					
Time served (quintiles)												
2				--			--					
3				--			--					
4				--			--					
5				--			--					
Public policy controls[c]												
Mandatory release										0.056	0.039	2.08
Expiration of sentence release										-1.5 ***	0.121	153.08
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	13.75			0			8.596			0		
Nagelkerke R2	0.031			0.12			0.043			0.013		
Log likelihood	30641			31174			30420			31170		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is parole board release.

	Model 5			Model 6			Model 7		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.116	0.072	238.98	-0.658	0.032	434.33	-1.148	0.075	234.08
Individual demographics[a]									
Male	0.474 ***	0.054	78.10				0.477 ***	0.054	78.85
Black	0.531 ***	0.043	154.04				0.5 ***	0.045	121.99
Hispanic	0.318 ***	0.046	47.27				0.271 ***	0.051	28.19
Other	0.202	0.217	0.87				0.187	0.217	0.75
Age at release (years)									
25-34	-0.224 ***	0.033	45.48				-0.228 ***	0.033	47.21
35-44	-0.505 ***	0.042	146.64				-0.51 ***	0.0452	149.30
45+	-0.942 ***	0.072	173.30				-0.947 ***	0.072	174.65
Criminal history[b]									
Offense									
Property offense	0.386 ***	0.039	97.11				0.396 ***	0.039	100.44
Drug offense	-0.123 ***	0.034	13.17				-0.118 ***	0.034	12.02
Public order offense	-0.352 ***	0.067	27.26				-0.349 ***	0.067	26.80
Other offense	-1.653 ***	0.47	12.37				-1.636 ***	0.47	12.12
Parole violator admission	--						--		
Time served (quintiles)									
2	--						--		
3	--						--		
4	--						--		
5	--						--		
Public policy controls[c]									
Mandatory release	0.05	0.041	1.53				0.052	0.041	1.63
Expiration of sentence release	-1.616 ***	0.123	172.07				-0.1608 ***	0.123	170.148
Community factors									
Legitimate opportunity				-0.028 *	0.013	4.91	-0.002	0.013	0.32
Urbanization				0.024 **	0.008	9.58	0.015	0.008	2.94
Model fit									
Hosmer and Lemeshow	15.729*			24.507***			12.338		
Nagelkerke R2	0.057			0.001			0.058		
Log likelihood	30169			31382			30164		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

APPENDIX H-2

NEW YORK LOGISTIC REGRESSION MODELS FOR 1999 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-0.946	0.067	201.28	-0.865	0.038	512.60	-1.217	0.075	264.14	-0.408	0.016	632.41
Individual demographics[a]												
Male	0.465 ***	0.052	80.36				0.387 ***	0.053	53.00			
Black	0.297 ***	0.038	60.18				0.318 ***	0.041	61.34			
Hispanic	-0.088 *	0.042	4.49				-0.032	0.045	0.52			
Other	-0.265	0.188	1.99				-0.192	0.191	1.01			
Age at release (years)												
25-34	-0.053	0.037	2.04				-0.221 ***	0.039	32.48			
35-44	-0.069	0.039	3.18				-0.281 ***	0.041	48.15			
45+	-0.504 ***	0.053	92.07				-0.682 ***	0.054	158.71			
Criminal history[b]												
Offense												
Property offense				0.32 ***	0.04	63.14	0.397 ***	0.041	91.90			
Drug offense				-0.063	0.033	3.64	0.015	0.034	0.19			
Public order offense				-0.346 ***	0.061	31.97	-0.322 ***	0.062	26.83			
Other offense				-0.869 ***	0.257	11.44	-0.768 *	0.26	8.74			
Parole violator admission				0.624 ***	0.028	494.28	0.643 ***	0.029	485.57			
Time served (quintiles)												
2				0.05	0.045	1.23	0.057	0.046	1.55			
3				0.108	0.061	3.18	0.107	0.061	3.03			
4				0.178 ***	0.039	21.01	0.217 ***	0.039	30.21			
5				0.106 **	0.035	9.47	0.152 ***	0.036	18.38			
Public policy controls[c]												
Mandatory release										-0.077 **	0.029	6.92
Expiration of sentence release										-0.732 ***	0.055	178.875
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	14.23			30.689***			44.200***			0		
Nagelkerke R2	0.021			0.041			0.062			0.011		
Log likelihood	32449			32357			31687			32932		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is parole board release.

Variable	Model 5 Coefficient	SE	Wald	Model 6 Coefficient	SE	Wald	Model 7 Coefficient	SE	Wald
Constant	-1.108	0.077	209.57	-0.507	0.026	392.31	-1.118	0.077	209.75
Individual demographics[a]									
Male	0.404 ***	0.053	57.21				0.407 ***	0.053	57.90
Black	0.32 ***	0.041	60.74				0.294 ***	0.044	45.56
Hispanic	-0.038	0.045	0.70				-0.086	0.05	2.92
Other	-0.228	0.193	1.41				-0.246	0.193	1.63
Age at release (years)									
25-34	-0.218 ***	0.039	30.98				-0.219 ***	0.039	31.29
35-44	-0.286 ***	0.041	48.82				-0.291 ***	0.041	49.94
45+	-0.691 ***	0.055	160.03				-0.697 ***	0.055	161.06
Criminal history[b]									
Offense									
Property offense	0.333 ***	0.043	61.32				0.344 ***	0.043	64.78
Drug offense	-0.81 *	0.037	4.79				-0.081 *	0.037	4.78
Public order offense	-0.365 ***	0.063	33.84				-0.36 ***	0.063	32.80
Other offense	-0.895 ***	0.26	11.80				-0.885 ***	0.26	11.54
Parole violator admission	0.766 ***	0.03	653.52				0.763 ***	0.03	647.05
Time served (quintiles)									
2	0.109 *	0.046	5.59				0.109 *	0.046	5.58
3	0.143 *	0.063	5.18				0.142 *	0.063	5.12
4	0.164 ***	0.04	16.61				0.162 ***	0.04	16.19
5	0.08 *	0.037	4.71				0.081 *	0.037	4.84
Public policy controls[c]									
Mandatory release	-0.048	0.035	1.89				-0.0498	0.035	1.96
Expiration of sentence release	-1.136 ***	0.058	381.31				-1.137 ***	0.058	382.079
Community factors									
Legitimate opportunity				-0.008	0.009	0.83	0.016	0.01	2.88
Urbanization				0.008	0.007	1.59	0.005	0.008	0.40
Model fit									
Hosmer and Lemeshow	28.776***			57.512 ***			27.550***		
Nagelkerke R2	0.085			0			0.085		
Log likelihood	31255.6			33125.97			31248.62		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is parole board release.

APPENDIX I-1

PENNSYLVANIA LOGISTIC REGRESSION MODELS FOR 1992 RELEASE COHORT

	Model 1			Model 2			Model 3			Model 4		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.253	0.133	89.31	-0.777	0.054	209.10	-1.308	0.137	90.53	-0.505	0.026	374.47
Individual demographics[a]												
Male	0.684 ***	0.115	35.18				0.641 ***	0.116	30.36			
Black	0.449 ***	0.056	63.35				0.419 ***	0.057	54.48			
Hispanic	-0.154	0.101	2.31				-0.141	0.102	1.93			
Other	-0.99	0.769	1.66				-0.966	0.771	1.57			
Age at release (years)												
25-34	-0.127	0.071	3.18				-0.173 *	0.073	5.67			
35-44	-0.402 ***	0.079	25.73				-0.475 ***	0.082	33.69			
45+	-1.126 ***	0.121	86.54				-1.175 ***	0.123	90.99			
Criminal history[b]												
Offense												
Property offense				--			--					
Drug offense				--			--					
Public order offense				--			--					
Other offense				--			--					
Parole violator admission				0.291 ***	0.057	26.20	0.285 ***	0.059	23.11			
Time served (quintiles)												
2				0.045	0.089	0.26	0.028	0.09	0.09			
3				0.315 **	0.116	7.38	0.328 **	0.118	7.70			
4				0.16 *	0.072	4.95	0.145 *	0.073	3.90			
5				-0.067	0.068	0.97	-0.024	0.071	0.11			
Public policy controls[c]												
Mandatory release												
Expiration of sentence release										-2.075 ***	0.159	171.36
Community factors												
Legitimate opportunity												
Urbanization												
Model fit												
Hosmer and Lemeshow	8.034			10.408			12.273			0		
Nagelkerke R2	0.051			0.012			0.06			0.058		
Log likelihood	8544.9			8745.9			8495.1			8511.6		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level

[a]Comparison groups are females, whites, and releases under 25 years old.

[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).

[c]Comparison group is parole board release.

	Model 5			Model 6			Model 7		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.3	0.14	86.73	-0.766	0.041	347.30	-1.343	0.141	91.03
Individual demographics[a]									
Male	0.643 ***	0.118	29.77				0.644 ***	0.118	31.15
Black	0.48 ***	0.058	68.39				0.511 ***	0.065	61.09
Hispanic	-0.108	0.103	1.09				-0.091	0.106	0.73
Other	-0.702	0.786	0.80				-0.698	0.787	0.79
Age at release (years)									
25-34	-0.224 **	0.075	8.95				-0.231 **	0.075	9.51
35-44	-0.552 ***	0.084	43.14				-0.566 ***	0.084	45.04
45+	-1.284 ***	0.126	104.38				-1.293 ***	0.1126	105.64
Criminal history[b]									
Offense									
Property offense	--						--		
Drug offense	--						--		
Public order offense	--						--		
Other offense	--						--		
Parole violator admission	0.547 ***	0.062	77.18				0.554 ***	0.062	78.58
Time served (quintiles)									
2	0.08	0.092	0.75				0.078	0.093	0.71
3	0.303 *	0.123	6.03				0.3 *	0.123	5.90
4	0.201 **	0.075	7.17				0.203 **	0.075	7.31
5	0.101	0.072	1.95				0.099	0.073	1.86
Public policy controls[c]									
Mandatory release									
Expiration of sentence release	-2.409 ***	0.162	220.78				-2.407 ***	0.162	220.194
Community factors									
Legitimate opportunity				-0.118 ***	0.036	10.96	-0.087 *	0.038	5.33
Urbanization				0.149 ***	0.034	19.15	0.024	0.039	0.39
Model fit									
Hosmer and Lemeshow	18.835*			14.645*			11.455		
Nagelkerke R2	0.132			0.004			0.134		
Log likelihood	8113.5			8785.1			8104.5		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

APPENDIX I-2

PENNSYLVANIA LOGISTIC REGRESSION MODELS FOR 1999 RELEASE COHORT

	Model 1			Model 2			Model 3		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.116	0.122	83.13	-0.697	0.06	133.13	-1.116	0.137	66.77
Individual demographics[a]									
Male	0.347 ***	0.106	10.82				0.419 ***	0.107	15.42
Black	0.204 ***	0.05	161.46				0.242 ***	0.053	20.97
Hispanic	-0.057	0.081	0.49				-0.29	0.085	0.12
Other	-0.37	0.379	0.95				-0.335	0.38	0.77
Age at release (years)									
25-34	-0.066 *	0.07	0.90				-0.025	0.071	0.12
35-44	-0.177 ***	0.073	5.89				-0.125	0.075	2.75
45+	-0.556 ***	0.09	38.57				-0.499 ***	0.091	29.79
Criminal history[b]									
Offense									
Property offense				0.145 *	0.059	6.02	0.205 ***	0.06	11.50
Drug offense				0.026	0.056	0.21	0.02	0.058	0.11
Public order offense				-0.352 **	0.117	9.11	-0.258 *	0.118	4.77
Other offense				0.194	0.142	1.88	0.22	0.143	2.37
Parole violator admission				-0.17 ***	0.049	11.82	-0.187 ***	0.05	13.74
Time served (quintiles)									
2				-0.027	0.105	0.06	-0.036	0.106	0.12
3				-0.629 **	0.205	9.39	-0.63 **	0.206	9.34
4				-0.118	0.078	2.30	-0.141	0.078	3.24
5				-0.134 *	0.058	5.34	-0.145 *	0.059	6.12
Public policy controls[c]									
Mandatory release									
Expiration of sentence release									
Community factors									
Legitimate opportunity									
Urbanization									
Model fit									
Hosmer and Lemeshow	2.602			20.111**			14.657		
Nagelkerke R2	0.014			0.008			0.022		
Log likelihood	11431			11478			11375		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

	Model 5			Model 6			Model 7		
Variable	Coefficient	SE	Wald	Coefficient	SE	Wald	Coefficient	SE	Wald
Constant	-1.114	0.144	60.01	-0.909	0.037	601.58	-1.122	0.145	59.97
Individual demographics[a]									
Male	0.573 ***	0.111	26.73				0.57 ***	0.111	26.26
Black	0.291 ***	0.058	25.64				0.278 ***	0.064	19.10
Hispanic	-0.021	0.091	0.06				-0.032	0.094	0.11
Other	-0.567	0.391	2.11				-0.573	0.391	2.15
Age at release (years)									
25-34	-0.042	0.077	0.31				-0.044	0.077	0.32
35-44	-0.141	0.081	3.03				-0.141	0.081	3.06
45+	-0.591 ***	0.098	36.66				-0.591 ***	0.098	36.74
Criminal history[b]									
Offense									
Property offense	0.339 ***	0.067	25.82				0.343 ***	0.067	25.88
Drug offense	-0.047	0.062	0.57				-0.043	0.063	0.47
Public order offense	-0.068	0.131	0.27				0.075	0.131	0.33
Other offense	0.255	0.154	2.72				0.257	0.155	2.75
Parole violator admission	0.149 **	0.055	7.20				0.148 **	0.055	7.08
Time served (quintiles)									
2	-0.029	0.112	0.07				-0.027	0.112	0.06
3	-0.209	0.232	0.81				-0.208	0.232	0.80
4	0.071	0.083	0.73				0.072	0.083	0.74
5	0.094	0.063	2.25				0.094	0.063	2.25
Public policy controls[c]									
Mandatory release									
Expiration of sentence release	-3.425 ***	0.132	671.245				-3.425 ***	0.132	671.094
Community factors									
Legitimate opportunity				-0.05	0.032	2.40	-0.013	0.035	0.13
Urbanization				0.094 *	0.04	5.53	0.023	0.047	0.24
Model fit									
Hosmer and Lemeshow	5.903			19.741***			5.083		
Nagelkerke R2	0.255			0.001			0.255		
Log likelihood	9654.154			11522.61			9653.898		

***Significant at <.001 level; **significant at <.01 level; *significant at <.05 level
[a]Comparison groups are females, whites, and releases under 25 years old.
[b]Comparison group are violent offenders, new court commitment admissions, and first quintile for adjusted time served (shortest stays).
[c]Comparison group is parole board release.

APPENDIX J

OFFENDERS RELEASED BY STATE, OFFENSE AND RELEASE TYPE, COHORTS COMBINED

	California		Michigan		New York		Pennsylvania[a]	
	EOS	Other release	EOS	Other release	EOS	Other release	EOS	Other release
Violent	36.8 %	24.3 %	37.5	42.8 %	36.4 %	27.2 %	40.2 %	38.3 %
Murder[b]	3.0	1.3	0.4 %	1.2	0.6	1.9	1.7	4.5
Negligent manslaughter	0.5	0.5	1.1	1.4	0.6	0.5	1.5	1.9
Kidnapping	1.8	0.9	1.4	0.7	2.7	1.2	4.9	2.5
Rape	0.6	0.3	14.2	4.4	1.4	0.6	5.6	2.0
Other sex assault	3.9	2.5	5.7	11.7	3.0	0.8	14.7	17.2
Robbery	15.0	9.0	13.5	6.0	22.4	17.5	9.8	8.9
Assault	10.7	8.3	1.2	0.6	5.3	4.0	2.2	1.3
Other violent offense	1.4	1.5	0	16.9	0.5	0.6	0	0
Property	29.3 %	30.6 %	36.1 %	26.3 %	24.7 %	19.7 %	27.8 %	25.5 %
Burglary	14.6	13.1	8.1	8.3	14.4	10.9	10.9	11.2
Larceny	7.5	9.0	14.1	3.1	3.3	2.9	4.7	3.9
Car theft	4.2	4.5	4.7	0.9	1.2	1.1	0.3	0.3
Arson	0.5	0.3	0.8	5.7	0.5	0.5	0.9	0.8
Fraud	1.8	2.1	2.5	3.0	1.5	1.5	5.3	5.2
Stolen property	0.6	1.6	4.0	0.8	3.4	2.6	3.9	2.9
Other property offense	0.0	0.1	2.0	4.4	0.5	0.3	1.7	1.2
Drug	23.3 %	35.0 %	10.1 %	23.4 %	32.7 %	46.7 %	22.2 %	29.1 %
Possession	3.0	5.5	5.3	20.2	7.4	12.1	1.8	4.8
Trafficking	13.6	19.1	4.7	0.2	25.0	34.3	0.3	0.7
Other drug offense	6.7	10.4	0.2	3.0	0.3	0.3	20.1	23.6
Public order	7.2 %	8.2 %	15.9 %	7.5 %	6.1 %	6.0 %	7.2 %	4.5 %
Weapons	3.8	3.3	7.9	4.4	4.8	4.0	1.5	0.7
DWI	2.0	3.4	3.0	3.0	0.9	1.3	1.3	1.7
Other public order offense	1.4	1.4	5.0	0.1	0.4	0.8	4.5	2.1
Other offense	3.4 %	1.9 %	0.4 %	0.0 %	0.1 %	0.4 %	2.6 %	2.7 %

EOS = Expiration of sentence.

[a]Includes offenses for 1999 only.

[b]Includes non-negligent manslaughter.

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