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Recidivism: A Multi-Level Explanation

Brian Eric Oliver
University of Missouri-St. Louis, beock4@mail.umsl.edu

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By

Brian E. Oliver
Bachelor of Liberal Studies, University of Iowa, 2000
M.A., Criminology and Criminal Justice, University of Missouri – St. Louis, 2007

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<u>Advisory Committee</u>

Richard Rosenfeld, Ph.D.
Chairperson
Beth Huebner, Ph.D.
Andres Rengifo, Ph.D.
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Dissertation Abstract

Brian E. Oliver

Numerous studies have shown that several characteristics of offenders are related to their likelihood of recidivism after release from prison. Nearly all of these studies, however, have focused on offenders from just one state. Few studies have examined recidivism rates controlling for the characteristics of offenders from multiple states, and virtually none have examined recidivism rates controlling for characteristics of offenders from multiple states during different periods of time. Additionally, few studies have explored different types of recidivism across multiple jurisdictions to determine whether the same individual level factors explain variations in rearrest, reconviction, reimprisonment, and parole violations.

To address these shortcomings, this dissertation applied logistic regression models to data from the publicly available *Prisoners Released in 1994 dataset* to investigate the extent to which nine individual level factors explain variation in recidivism rates within three years of release from prison across 15 states. The nine factors are: 1) gender, 2) age at first arrest, 3) race, 4) age at release, 5) number of prior arrests, 6) type of current offense, 7) time served, 8) admission type and 9) release type. Eight forms of recidivism were examined: 1) rearrest for any offense, 2) rearrest for a new violent offense, 3) rearrest for a new property offense, 4) rearrest for a new drug offense, 5) rearrest for a new public order offense, 6) reconviction probability if rearrested, 7) reimprisonment probability if reconvicted, and 8) parole violations. The dissertation investigated differences in the effects of the individual level factors on each form of recidivism.

To investigate the effects of criminal justice policies and practices on state differences in recidivism rates, multilevel models were estimated that include three contextual variables, in addition to the nine individual factors. The state-level contextual variables are: 1) drug arrests per 100,000 residents, 2) police officers per 1,000 residents and 3) the arrest-offense ratio. In a final analysis, regression analyses were conducted to determine the extent to which the nine individual factors explain the increase in the three-year rearrest rates among persons released from prison in 1983 and 1994.

The findings reveal that differences in individual level characteristics help to explain the variation across states for some, but not all, forms of recidivism. The findings related to rearrest for a new violent offense, reconviction probability, and parole violations were not conclusive. Results from the multilevel models indicate that the contextual factor of police officers per 1,000 has a significant impact on property rearrests and a marginal impact on drug rearrests and reconviction probability. The analysis of rearrests during two separate time periods revealed that changes in contextual factors, as opposed to individual level characteristics, were responsible for the increase in rearrest rates which occurred between 1983 and 1994.

This study provides evidence that both individual level and contextual factors play a role in recidivism and need to be taken into consideration in implementing policy and designing programming. Two conclusions consistent with the findings are that treatment services need to be based on offender need and risk level and that states should consider reinstating discretionary parole. It would be beneficial for future research to examine the effect of additional individual and contextual variables on recidivism rates, particularly if a multi-state dataset, similar to the one used in this study, becomes available in which county of release is specified.

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The pages of this dissertation reflect the end of one journey and the beginning of another. They represent the culmination of six and a half years of change, a period filled with highs and lows, frustration and joy, and love and pain.

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CHAPTER 1 – INTRODUCTION

1.1: Introduction

Much attention has been drawn to the fact that the United States has the highest incarceration rate in the world. The prison and jail incarceration rate at yearend 2008 was 754 inmates per 100,000 U.S. residents (Sabol, West and Cooper, 2009). Although this represented a slight decline over the 2007 rate, it is nevertheless five to twelve times the average incarceration rate in most European countries (Tonry, 2004). Also, given that at least 95 percent of all U.S. prisoners will be released at some time (Hughes and Wilson, 2002), an unprecedented number of people are being released from prison in the United States. In 2008, 735,454 inmates were released to the community after serving time in prison (Sabol et al., 2009).

Unfortunately, many of the people who leave prison end up back in prison. Langan and Levin (2002) found that, within three years of their release, 67.5 percent of state prisoners released in 1994 were rearrested, 46.9 percent were reconvicted and 51.8 percent were back in prison, serving time for a new prison sentence or for a technical violation of the conditions of their release. Hughes and Wilson (2002) similarly found that 42 percent of those released on parole were returned to prison or jail and another nine percent absconded. What these numbers indicate is that less than half of the people released from prison are successfully reintegrated back into society. Meanwhile, the hundreds of thousands of offenders on parole or conditional release who return to prison each year end up costing states billions of dollars (Petersilia, 2001).

In light of the high level of recidivism in the United States, it is not surprising that much research has been done on why it occurs. The preponderance of the research over the past 25 years has focused on the effects that individual level characteristics, such as age, gender and race, have on recidivism. While such studies can be extremely enlightening in determining policies and programming, their ability to provide broadly applicable conclusions is limited in that very few address variations that exist either from state to state or during different periods of time. If offenders released from prison in Delaware have twice the rearrest rate as offenders released from prison in Michigan, for example, is this because the offenders in Delaware have a higher number of traits that are associated with reoffending, or does it have to do with differing state policies? Similarly, if national recidivism rates go up over a period of ten or eleven years, is it because the release cohorts are different – or is it because there have been changes in rehabilitative services offered to offenders released, because police have become more proactive in their response to crime or because of some other macro-level change?

Given the high human and monetary costs of recidivism and the complex interplay between state and federal systems, these are not idle questions. Even small statistical differences can tip decisions impacting thousands of lives and millions of dollars. Finding answers to these questions is, moreover, no easy task. A possible method, comparing recidivism rates across studies, may seem appealing, but would, unfortunately, not lead to scientifically valid results. Beck (2001) pointed out three major problems in this approach. One is that what is counted as recidivism in one jurisdiction or study may not be counted as recidivism in a second jurisdiction or study (some states include technical violators as recidivists while others don't). A second problem is that different jurisdictions and studies utilized different time frames. A third problem is that many studies do not include sufficient information to control for variables which would affect recidivism rates. These three problems make the idea of comparing recidivism rates across dissimilar studies an unwise proposition.

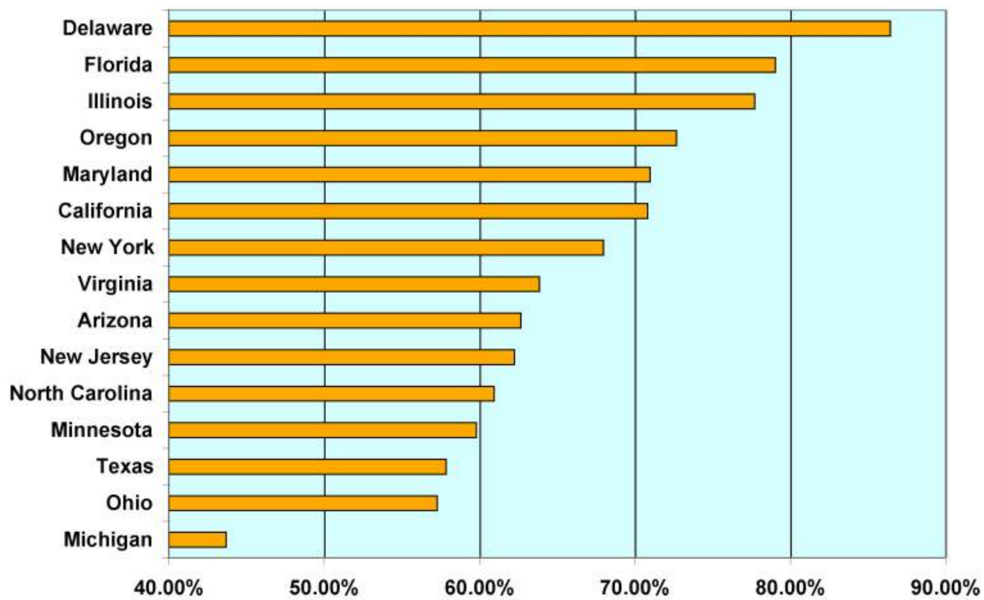
Instead of comparing previous studies, this dissertation draws its material on the effect of nine individual-level characteristics on recidivism directly from two multi-state data sets. Primary of these is the *Recidivism of Prisoners Released in 1994 dataset* (United States Department of Justice, 2009a), from which 262,529 of the 302,309 prisoners' cases were used. Data on 108,580 prisoners from the *Prisoners Released in 1983 dataset* (United States Department of Justice, 2004) are also brought into discussion of changes over time. From these two datasets, nine individual-level characteristics were extracted. These nine individual-level characteristics include gender, age at release, race, age at first arrest, number of prior arrests, current offense type, time served, type of admission, and type of release. These nine specific individual-level characteristics were chosen because data on these nine specific variables were included for all or most of the offenders in both the 1994 and 1983 Prisoners Released datasets. Although data was also included in both datasets regarding Hispanic origin, it was not included as an individual-level characteristic in this dissertation because of the large amount of missing data on this indicator (over 19 percent of cases from the 1994 dataset and over 33 percent of cases from the 1983 dataset).

In addition, data on three state-level contextual variables – drug arrest rates, police per 1,000 residents and arrest-offense ratio – were gathered from several issues of *Crime in the United States* (Federal Bureau of Investigation, 1994, 1995, 1996, 1997, 1998), from the *Uniform Crime Reporting Program Data [United States]: 1975-1997* dataset (Federal Bureau of Investigation, 2000) and from information provided by the Florida Department of Law Enforcement, the Illinois Criminal Justice Information Authority and the Delaware State Police. It is noteworthy that very little past research has looked specifically at the role of contextual variables and recidivism (Fischer, 2007). In producing this dissertation, there were no problems locating published studies that explore the relationship between drug arrest rates and crime rates (e.g., Benson, Kim, Rasmussen, and Zuehlke, 1992; Benson, Rasmussen, and Sollars, 1995; Mendes, 2000; Shepard and Blackley, 2005). Also found were recent studies which explore the relationship between either police per capita or arrest-offense ratio and crime rates (Sampson and Cohen, 1988, Marvell and Moody, 1996; Weiss and Freels, 1996; Levitt, 1997; MacDonald, 2002). There were no published studies found, however, that looked directly at the relationship between these three contextual variables and any form of recidivism. This dissertation will thus provide information in an area which, to date, has been ignored by the research community.

Eight measures of recidivism are examined in this dissertation: 1) rearrest for any offense, 2) rearrest for a violent offense, 3) rearrest for a property offense, 4) rearrest for a drug offense, 5) rearrest for a public order offense (other than a parole violation), 6) reconviction following arrest for a new offense, 7) reimprisonment following conviction for a new offense, and 8) parole violations. Because parole violations result from either a new arrest or a technical violation without an accompanying arrest, a somewhat more detailed analysis of parole violations is undertaken. The use of multiple measures of recidivism allows for distinctions to be made regarding whether certain individual-level characteristics are equally effective in predicting variation in different measures of recidivism or if they have differing effects based on either the type of offense or the measure of recidivism used. All eight measures of recidivism came from variables included in the two datasets on prisoners released earlier described.

Three primary research questions are addressed in this dissertation: 1) To what extent can the variation in recidivism rates across space be explained by variations in the individual-level characteristics of offenders released from prison? 2) Can the addition of state-level contextual characteristics of police per 1,000 residents, arrest-offense ratio and state-level drug arrest rates help explain the variation in prevalence of recidivism across space that is not explained by the individual-level factors? 3) To what extent can the variation in rearrest rates over time be explained by variations in the individual-level characteristics of offenders released from prison and are there any state-level contextual variables which might help improve the explanation?

FIGURE 1: THREE YEAR REARREST RATES BY STATE



1.2: Research Question 1: To what extent can the variation in recidivism rates across space be explained by variations in the individual-level characteristics of offenders released from prison?

Although a widely cited statistic in the criminological literature is that, on average, two-thirds of offenders released from prison end up rearrested for a new crime (see, for example, Petersilia, 2001; Solomon, Johnson, Travis, and McBride, 2004), this is a national average that does not persist on a state-level basis. When three year state-level rearrest for a new offense percentages are computed for offenders released from prisons in 15 states in 1994, it is clear that there is a wide degree of variation – with a low of 43.7 percent reported for Michigan and a high of 86.2 percent reported for Delaware (see Figure 1). As is shown later in this dissertation, there is similarly a wide degree of variation between states in rearrest rates for drug and public order offenses and violations of parole, as well as a lesser degree of variation between states in rearrest rates for violent and property offenses. There is also a wide degree of variation between states in the reconviction rate of rearrested offenders and the reimprisonment rate of reconvicted offenders.

What this information does not reveal, however, and what the current research addresses, is to what extent the variation in prevalence of various forms of recidivism across states can be explained by differences in the individual-level characteristics of the state-level release cohorts. Knowing this will help in understanding the degree to which differences in recidivism are the result of variations in the characteristics of prisoner populations and the degree to which differences are related to variations in policy and programming in different states.

1.3: Research Question 2: Can the addition of state-level contextual characteristics of police per capita, arrest-offense ratio and state-level drug arrest rates help explain the variation in prevalence of recidivism across space that is not explained by the individual-level factors?

The second research question is geared towards identifying if and to what extent the addition of three contextual factors – police per capita, arrest-offense ratio, and state-level drug arrest rates – can be used to explain some of the remaining variation that exists in recidivism probabilities across space. While differences in the previously described individual-level characteristics may very well explain a great deal of variation, there are also other variables that may explain differences in recidivism probabilities. Although no research to date has directly examined the relationship that exists between either police-strength or arrest-offense ratio and recidivism, some prior research has found that crime rates may be influenced by police strength and arrest-offense ratio (Tittle and Rowe, 1974; Wilson and Boland, 1978; Sampson and Cohen, 1988, Marvell and Moody, 1996, Levitt, 1997, MacDonald, 2002 - although it should noted that some studies have found no relationship – i.e., see Decker and Kohlfield, 1985; Weiss and Freels, 1996). Therefore, it would seem useful to test if these contextual factors could help explain variation in recidivism rates across space. Additionally, it would help to examine if variations in state-level drug arrest rates help explain variation in recidivism across space. This is an important factor to look at because, although it has commonly been stated that America has been fighting a War on Drugs since at least the early 1980s, research has found that, during this time, some states were more aggressive than others in targeting drug offenders (Mast, Benson, and Rasmussen, 2000; Benson, 2009).

1.4: Research Question 3: To what extent can the variation in rearrest rates over time be explained by variations in the individual-level characteristics of offenders released from prison and are there any state-level contextual variables which might help improve the explanation?

The third research question is very much like the first. To what extent can individual-level factors help explain the difference in three-year prevalence of rearrest for a new offense between the 1983 cohort and the 1994 cohort? To answer this question, the analysis will compare the rearrest rates from the 1983 cohort with those from the 1994 cohort. This section will additionally explore possible changes in criminal justice policy that led to the changes in national rearrest rates. It should be noted that while the section exploring recidivism variation across space includes eight different measures of recidivism, for recidivism over time, the only measure of recidivism used is rearrest for a new offense. This measure was chosen for the temporal analysis because arrests initiate reconviction and reimprisonment. It's the first link in the recidivism chain.

1.5: Chapter Overview

Chapter Two discusses the data, measures and analytic strategy for the full dissertation. This includes reviewing the sources of the data and explaining how missing or improperly entered data is dealt with. The eight separate outcome measures are defined. A discussion also describes additional steps taken to formulate the reconviction and reimprisonment outcomes. The chapter then closes with a discussion of the three sets of analyses to be conducted in the dissertation.

Chapter Three provides a review of prior research findings related to the nine individual-level characteristics to be analyzed in the dissertation and summaries of the state averages for the 1994 dataset. Logistic regressions were also run for each individual level characteristics for the recidivism measures of rearrest for a new offense, rearrest for a violent offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense. Where possible, theoretical explanations were further given explaining why people with specific characteristics were at greater risk of offending than others.

Chapter Four explores whether the inclusion of the nine individual-level characteristics helps explain variation between states in the overall rearrest rates and rearrests for specific types of offenses. The offense types include violent offenses, property offenses, drug offenses and public order offenses (excluding parole violations). Along with the calculations, there is a discussion of the theoretical perspectives related to the findings.

Chapter Five examines the helpfulness of the nine individual-level characteristics in explaining variation between states for other forms of recidivism. These include reconviction probability, reimprisonment probability and parole violations. Parole violations are analyzed separately from public order offenses because they may result from either a criminal charge accompanied by an arrest or a non-criminal technical violation that does not involve an arrest.

Chapter Six uses Hierarchical Linear Modeling to explore whether three state-level criminal justice factors help improve on the explanation of variation in recidivism between states. Once again, a discussion of the theoretical perspectives related to the findings accompanies the results.

Chapter Seven looks at recidivism over time to see to what extent individual-level factors can help explain variations in the three-year prevalence of rearrest that exists between the 1983 cohort and the 1994 cohort. After this analysis, possible alternative explanations will be discussed, though formal tests of these alternative hypotheses will not be conducted.

Chapter Eight concludes with policy implications and suggestions that stem from the findings presented in the previous chapters and offers suggestions for future research.

CHAPTER 2 – DATA, MEASURES AND ANALYTIC STRATEGY

2.1: Introduction

This chapter first provides details about the primary sources of data used in analyses that seek to answer the three research questions that were raised in chapter one. It next explains how the constructs for both the individual-level (level-one) and state-level (level-two) variables were operationalized for use in several quantitative analyses. It concludes with a discussion of the three analytic strategies that were used to answer the three research questions previously raised.

2.2: Data

The first step in gathering data for the dissertation involved accessing two large Bureau of Justice Statistics datasets containing information on prisoners released from state prisons in 1983 and 1994 and determining which of the cases therein were usable. The data sets are available from the Interuniversity Consortium for Political and Social Research (ICPSR) website (http://www.icpsr.umich.edu/). The *Recidivism of Prisoners Released in 1994 dataset* consists of 38,624 cases representative of 302,309 offenders released from 15 states in 1994. The 15 states include Arizona, California, Delaware, Florida, Illinois, Maryland, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Texas and Virginia. In line with Langan and Levin's (2002) analysis of the 1994 dataset, offenders were not included in this dissertation unless 1) a RAP sheet on the prisoner was found in the State criminal history repository, 2) the released prisoner was alive through the three-year follow-up period, 3) the prisoner's sentence was one year or longer, and 4) the prisoner's release was not recorded as release to custody/detainer/warrant, absent without leave, escape, transfer, administrative release, or release on appeal (Langan and Levin, 2002). This left a total sample of 33,625 cases representative of 271,669 offenders released in 1994.

The *Recidivism of Prisoners Released in 1983 dataset* consists of 16,355 cases representative of 108,580 offenders released from California, Florida, Illinois, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon and Texas. The dataset is based on an original sample of 18,374 cases; however, 2,019 were not included in the final sample because their sentence was less than one year, they died during the follow-up period or their release was classified as administrative release, absent without leave (AWOL), escape, transfer, or release on appeal or death (Beck and Shipley, 1989).

The next step involved determining how to deal with missing, incorrectly entered or otherwise errant data in the analysis. Data were classified as errant under one of three scenarios: 1) the offender's date of birth and date of release from prison had him or her recorded as being released from prison prior to age 13 (see Beck and Shipley, 1989; Langan and Levin, 2002); 2) the record indicated that an offender was released from prison for the current offense prior to the date he or she entered prison for the current offense, or 3) the offender's date of birth and date of first arrest had his or her first arrest occurring prior to the age of ten. This last exclusion was taken because the youngest person charged as an adult in

America in recent history was nine-years-old (see Quindlen, 1990) and the 1983 and 1994 data files only contain arrest information of juveniles charged as adults (Beck and Shipley, 1989; Langan and Levin, 2002). Further, to deal with the issue of missing data, cases were also excluded 1) if the offender's gender was recorded as missing, 2) if the offender's age at first arrest was unknown (either because arrest cycle one was blank or because the offender had arrests recorded for all 99 arrest cycles, meaning he or she had over 99 arrests and making his or her first arrest date impossible to determine), 3) if the offender's race was classified as missing, 4) if the offender's age of release was unknown, 5) if the type of current offense was unknown, 6) if the amount of time served on the offender's current sentence was unknown or 7) if the offender's type of release was calculated as missing. Cases where the offender's type of admission was missing were kept in the dataset due to the relatively large number of cases that would have had to be eliminated if these cases were taken out. After these steps were taken, the 1994 dataset contained 32,732 cases representative of 262,530 offenders released from prison in 1994 and the 1983 dataset contained 15,223 cases representative of 99,681 offenders released from prison in 1983. The analysis of recidivism across space only involved offenders from this revised 1994 dataset.

A second file, merging prisoners released from the same 11 states in either 1983 or 1994, was then created to look at rearrest over time. Before this file was created, prisoners released in 1994 from Arizona, Delaware, Maryland and Virginia were eliminated, as data from these states were not also collected for 1983. Following this, the two datasets were merged. The merged file contained

42,301 cases representing 342,602 offenders released from 11 states in either 1983 or 1994. The analysis of recidivism over time proceeded from the merged dataset containing these cases.

The three state level contextual variables used in the examination of recidivism across space are: 1) police per 1,000 residents, 2) arrest-offense ratio and 3) rate of drug arrests per 100,000 people. Data on police per 1,000 residents for the years 1993 to 1996 came from issues of *Crime in the United States* (Federal Bureau of Investigation, 1994, 1995, 1996, 1997). Data on arrest-offense ratio for 13 of the 15 states came from the *Uniform Crime Reporting Program Data [United States]: 1975-1997 dataset* (Federal Bureau of Investigation, 2000). This data set is available from the Interuniversity Consortium for Political and Social Research (ICPSR) website (http://www.icpsr.umich.edu/). Because complete data was not available for this variable for two states, the Florida Department of Law Enforcement and the Illinois Criminal Justice Information Authority provided additional data for this variable for their respective states. Drug arrests per 100,000 residents for the years 1994 to 1997 came from issues of *Crime in the United States* (Federal Bureau of Investigation, 1995, 1996, 1997, 1998). Because complete data was not available for this variable for three states, the Delaware State Police, the Florida Department of Law Enforcement and the Illinois Criminal Justice Information Authority provided additional data for this variable for their respective states.

Before proceeding on to the next section, it is important to explain why data for police per 1,000 residents came from different volumes of *Crime in the*

United States than data on drug arrests per 100,000 residents. Some researchers have found that using police strength as a measurement of crime control is potentially problematic. Kane (2006) wrote “because increases in crime rates often lead to increases in police deployment, it is often difficult to determine whether police deployment reduces crime, or whether crime increases lead to elevated levels of police deployment” (pp. 191-192). Kovandzic and Sloan (2002) also stated that “it was unlikely that police levels and crime impacted each other simultaneously because it took time for governments to hire and train new officers when confronted with higher crime rates. It was also reasonable to assume that offenders did not immediately respond to increased levels and the potentially increased likelihood of apprehension, until word got out that more officers were on the street” (p. 70).

The number of law enforcement employees reported in *Crime in the United States* allows for a way to address this issue. For each year, a section of the report gives totals for the number of full time state and local law enforcement employees who were employed on October 31 of that year. Thus, for the *Crime in the United States, 1993* report (Federal Bureau of Investigation, 1994), the number of police employees calculated would be the number employed on October 31, 1993. Using this date as the first date where police size is measured thus produces a minimum two-month lag between when the police are on the street and when prisoners from the datasets are released in 1994. While most research studies use a one or two year lag between police levels and subsequent crime measurement (Kane, 2006), Chamlin, Grasmick, Bursik and Cochran

(1992) presented evidence that it may actually take much less time for changes in police levels or arrest rates to have a deterrent effect on would be criminals. They further argued that using one-year time lags might be too long to uncover deterrent effects. On this basis, it is felt that the two month lag between police levels that exist on October 31 and the release of prisoners starting on January 1 of the following year provides enough time to address the concerns raised by prior researchers. It is for this reason that data on police per 1,000 residents came from the 1993 to 1996 *Crime in the United States* reports (Federal Bureau of Investigation, 1994, 1995, 1996, 1997), while data on drug arrests per 100,000 residents came from the 1994 to 1997 *Crime in the United States* reports (Federal Bureau of Investigation, 1995, 1996, 1997, 1998).

2.3: Measures

There are a total of eight outcome measures used in this dissertation: 1) Rearrest for a New Offense, 2) Rearrest for a Violent Offense, 3) Rearrest for a Property Offense, 4) Rearrest for a Drug Offense, 5) Rearrest for a Public Order Offense (other than a Parole Violation), 6) Reconviction for a New Offense, 7) Reimprisonment for a New Offense and 8) Parole Violations. *Rearrest for a New Offense* is defined as whether an offender was arrested for any new offense within three years of his or her release from prison in either 1983 or 1994. *Rearrest for a Violent Offense* is defined as whether an offender was arrested for a new violent offense within three years of his or her release from prison in either 1983 or 1994. *Rearrest for a Property Offense* is defined as whether an offender was arrested for a new property offense within three years of his or her release from prison in either 1983 or 1994. *Rearrest for a Drug Offense* is defined as whether an offender was arrested for a new drug offense within three years of his or her release from prison in either 1983 or 1994. *Rearrest for a Public Order Offense (other than a Parole Violation)* is defined as whether an offender was arrested for a public order offense, other than a parole violation, within three years of his or her release from prison in either 1983 or 1994. *Parole Violations* were defined and analyzed in two separate manners. The first involved analyzing all the offenders who were rearrested on a new charge of violating parole within three years of their release from prison along with those sent back to prison within three years of their release on a technical violation of parole. The second involved analyzing those resentenced to prison on a new conviction for a criminal charge of parole violation along with those sent back to prison within three years of their release on a technical violation of parole. This two-phase analysis helps in differentiating the use of parole violations by parole officers compared to prosecuting attorneys.

The regression equations used in this dissertation all include individual level variables that have consistently been shown to be associated with offender recidivism. These variables include gender, age at release, race, age at first arrest, number of prior arrests, time served, current offense type, type of admission and type of release. For the first two regression models, state of release is also included in the regression equation. For the third regression model, police per 1,000 residents, arrest-offense ratio and drug arrests per 100,000 residents are entered separately into the regression equation. For the fourth regression model, state of release and year of release are both included in the regression equation

Modifications were made to the model structure for reconvictions and reimprisonment for a new offense. The problem that existed with using the same formula for reconvictions and reimprisonment as had been used for rearrest has to do with the relationship that exists between rearrest for a new offense, reconviction for a new offense and reimprisonment for a new offense. Because a prerequisite of being reconvicted of a new offense is that one must first be rearrested for a new offense and because a prerequisite of being reimprisoned for a new conviction is that one must be reconvicted for a new offense, classes of offenders with higher rearrest rates will, by default, have higher reconviction rates because a prerequisite of being reconvicted is that one must first be rearrested. Similarly, classes of offenders with higher reconviction rates will, by default, have higher reimprisonment rates because a prerequisite of being reimprisoned for a new offense is that one must first be reconvicted for a new offense. Therefore, as males, blacks and younger offenders are rearrested at higher rates than females, non-blacks and older offenders, these groups would almost certainly have higher reconviction rates and higher reimprisonment rates. This would create a problem in that the results of the regression model would be biased by arrest rates and conviction rates.

To control for this potential problem, the samples for two of the analyses include offenders only if they met specific conditions. First, the between state reconviction analyses were limited exclusively to offenders who had been rearrested. Second, the between state reimprisonment for a new offense analyses were limited exclusively to offenders who had been reconvicted. Limiting the offenders in this way produced reconviction and reimprisonment probability results that were more meaningful. The two research questions these areas address are, specifically: 1) For rearrested offenders, what is the probability of being reconvicted for a new offense and what individual and contextual level factors are related to this probability? 2) For reconvicted offenders, what is the probability of being reimprisoned for the new conviction and what individual and contextual level factors are related to this probability?

The predictor of primary interest for the first two research questions, which deal with recidivism across space, is *State of Release* – defined as being Arizona, California, Delaware, Florida, Illinois, Maryland, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Texas and Virginia. For the research question dealing with recidivism over space and whether individual level characteristics help explain variations in recidivism across space, there were two separate sets of logistic regression models used. One of these models compared each state with a single contrast – an approach commonly referred to as a "fixed effects" approach (details of this approach are provided in Chapter 4). In this model, the state with the lowest recidivism rate for the recidivism measure under consideration served as the reference category (except for the recidivism measure of reimprisonment probability, which used the state with second lowest recidivism rate) and the predictor of *State of Release* was entered into the analysis as a series of dichotomous variables. The second model involved a series of state-by-state comparisons. For the research question dealing with recidivism over space and whether the addition of contextual variables helped explain variations above and beyond individual level characteristics, the predictor of *State of Release* was entered into the analysis as a series of dichotomous variables with the state with the lowest recidivism rate for the recidivism measure under consideration serving as the reference category (except for the recidivism measure of reimprisonment probability, which used the state with second lowest recidivism rate). For the research question dealing with recidivism over time, a second predictor of primary interest is *Year of Release* – 1983 or 1994. This variable was binary coded with 1983 as the omitted contrast. For the combined dataset containing 1983 and 1994 data, *State of Release* was further modified with Arizona, Delaware, Maryland and Virginia removed.

This analysis also includes important individual-level predictors of recidivism. For the purpose of analysis the variables were coded in the following manner. *Gender* was coded as one for males and zero for females. *Age at Release* is the age of the prisoner at the time of release from confinement and is coded as a continuous measure. *Race* consists of three categories: white, black and other. *Race* was entered into the models as a series of dichotomous variables with "white" serving as the reference category.

Age at First Arrest reflects the age of the offender at the time of his or her first arrest and was coded as a continuous measure. *Number of Prior Arrests* reflects each released prisoner's arrest history, not including the arrest leading to the current incarceration, and was coded as a continuous measure. *Current Offense Type* consists of five categories of offenders: violent, property, drugs, public order or other. *Current Offense Type* was entered into the models as a series of dichotomous variables with “property offense” serving as the reference category. *Time Served* was coded as a continuous variable representing the number of months served in prison during the current incarceration. *Type of Admission* consists of five categories: new court commitment, parole revocation, probation revocation, other, and unknown. *Type of Admission* was entered into the models as a series of dichotomous variables with “new court commitment” serving as the reference category. *Type of Release* consists of four categories: discretionary parole, mandatory supervised release, expiration of sentence, and other. *Type of Release* was entered into the models as a series of dichotomous variables with “discretionary parole” serving as the reference category. A detailed description of how each of these measures was created from the merged data is described in the Appendix A.

The state level variables used in this dissertation were entered into equations known as multilevel models. Multilevel models are statistical models that are structured with variables measured at two or more levels. In such models variables in one level are nested within another level. Examples of multilevel models include: students nested within classes, patients nested within hospitals and, in the current analysis, individuals released from prison nested within individual states. In the current model, the impact of the state-level variables is tempered by the effect of the individual-level variables. In such situations the latter variables are referred to as level-one variables and they are nested in larger groups referred to as level-two variables (Raudensush and Bryk, 2002).

To estimate the effect of the state level variables on various forms of recidivism, three multilevel models were created. In each of these models, the level-one data consisted of the nine individual level variables previously described. The state level variable of *Police per 1,000 Residents* was entered into the first multilevel model as a rate per capita derived by taking the 1993 to 1996 average for the number of law enforcement personnel employed by a state divided by the four year average of each state's population for the same time period and multiplying this result by 1,000. The state level variable of *Arrest-Offense Ratio* was entered into a separate multilevel model as a proportion derived by taking the 1994 to 1997 year average of arrests for Index I crimes (murder, rape, robbery, aggravated assault, burglary, larceny and motor vehicle theft) for each state divided by the four year average of Index I crimes for each state for the same time period. The state level variable of *Drug Arrests per 100,000 Residents* was entered into a third multilevel model as a rate per capita derived by taking the 1994 to 1997 year average of the number of drug arrests in a state divided by the four year average of each state's population for the same time period and multiplying this result by 100,000.

2.4: Analytic Strategy

As the outcome measures are all dichotomous (rearrested/not rearrested, reconvicted/not reconvicted, etc.), logistic regressions were used in each of the multivariate analyses. In the dissertation, there are three separate sets of analyses. The first set of analyses explores the differences in recidivism probabilities that exist between individual states for the 1994 cohort and the extent to which the inclusion of individual level characteristics helps explain these differences. The second set of analyses uses Hierarchical Linear Modeling to help determine if and to what degree the addition of the three state level contextual factors to the models of individual level factors helps explain differences across states in various forms of recidivism. The third set of analyses explores the differences in rearrest probabilities that exist over time (between the 1983 and 1994 cohorts) and to what extent the inclusion of individual level characteristics helps explain these differences. The first and third sets of models in this dissertation were estimated using STATA, version 10.0 (StataCorp, 2007) or 11.0 (StataCorp, 2009) and the second set of models was estimated using HLM 6.0 (Raudenbush, Bryk and Congdon, 2004).

In the first set of analyses, logistic regressions were run for each combination of states from the 1994 cohort. These involved two separate sets of analysis. The first involved a model with a single contrast state omitted. The second involved a series of state-by-state logistic regressions comparing the recidivism probabilities of those released, for example, from California in 1994 with those released from Florida in 1994. For the second model, this process was repeated until every possible state by state combination had been estimated. After these initial regressions were computed, a second set of models was run which added the nine individual level characteristics to the models. Both models were repeated for 1) rearrest for any offense, 2) rearrest for a violent offense, 3) rearrest for a property offense, 4) rearrest for a drug offense, 5) rearrest for a public order offense (other than a parole violation), 6) reconviction for a new offense for rearrested offenders, 7) reimprisonment following conviction for a new offense, and 8) violation of parole. The results present preliminary evidence as to what extent individual level characteristics help explain variation in rearrest, reconviction, reimprisonment and parole violation probabilities across space.

In the second set of analyses, Hierarchical Linear Modeling was conducted, with the individual level factors entered in as Level 1 predictors and the state level contextual factors entered in as Level 2 predictors This process was repeated for 1) rearrest for a new offense, 2) rearrest for a violent offense, 3) rearrest for a property offense, 4) rearrest for a drug offense, 5) rearrest for a public order offense (other than a parole violation), 6) reconviction for a new offense for rearrested offenders and 7) reimprisonment following conviction for a new offense. Because of the limited degrees of freedom that resulted from the sample consisting of only 15 states, models were constructed using only one of the three contextual variables at a time. The results of these models indicate if the three contextual variables help explain variation in recidivism across space.

In the third set of analyses, a preliminary regression was first run with year of release the only variable entered into the model. Following this, a second regression was run adding all of the individual level characteristics to the first model. The resulting coefficients and odds ratios present preliminary evidence as to what extent individual level characteristics help explain variation in rearrest probabilities over time. A final regression was then run with state of release added to the equation. The third set of analyses concludes with a discussion of contextual factors that may have contributed to the findings.

CHAPTER 3

EXPLORING THE IMPACT OF INDIVIDUAL LEVEL COVARIATES

3.1: Introduction

To accurately compare prevalence of recidivism over time and across space, it is first necessary to control for individual-level variables that have been shown to have an influence on both the likelihood of offending and likelihood of recidivism. Research has found that certain groups of individuals are more likely to be involved in crime than others and, to accurately compare recidivism rates between different groups, these differences need to be taken into account. For the purpose of this research, nine individual-level factors are examined: 1) gender, 2) age at release, 3) race, 4) age at first arrest, 5) number of prior arrests, 6) current offense type, 7) time served, 8) type of admission, and 9) type of release.

To provide a better understanding of why these nine variables were chosen for use in this research and why they might be expected to have an influence on prevalence of rearrest, what follows is a review of the literature for each variable. When possible, this review also includes theoretical explanations about why each variable might have the effect it does on recidivism. Following each review, logistic regressions testing for significance are run on 32,732 cases representing 262,530 offenders from the *Prisoners Released in 1994 dataset*. These logistic regressions include models for overall rearrests, violent rearrests, property rearrests, drug rearrests and public order rearrests.

Models are not estimated for reconvictions or reimprisonments in this chapter because those analyses must await the results of the rearrest models. Because certain groups of offenders are more likely to be rearrested than others, this fact will, by default, make certain types of offenders more likely to reconvicted and reimprisoned simply because they are more likely to be rearrested. The appropriate line of questioning for reconviction is: What are the chances of a certain group being reconvicted provided the analysis consists solely of those who have been rearrested? Similarly, a more appropriate line of questioning for reimprisonment is: What are the chances of a certain group being reimprisoned provided the analysis consists solely of those who have been reconvicted. Because the dataset must be modified to correctly conduct these analyses, these outcomes are addressed in chapter 5.

These regressions allow tests for statistical significance to be conducted for each of the individual level variables, both individually and when all nine variables are included in the model. Table 1 at the end of the chapter lists the models for the outcomes of rearrest for any offense, rearrest for a violent offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense with all the individual level characteristics entered into the models. The measures reported for each outcome include the odds ratio, standard error and level of significance for each variable in each of the five models. The end of the chapter also includes a discussion of a correlation matrix of the nine predictors to help detect for potential problems with multicollinearity.

3.2: Gender

One universally accepted fact in criminology is that males are more likely than females to commit acts which are defined as criminal and subject to imprisonment. This is evident in government reports highlighting that over 90 percent of people in prison in the United States are male (Sabol et al., 2009), that over 70 percent of people on probation in the United States are male (Glaze and Bonczar, 2009) and that over 70 percent of people arrested in the United States are male (Federal Bureau of Investigation, 2009). It is also evident in several self-report studies in which males admit to higher rates of criminal behavior than females (Graham and Bowling, 1995; Flood-Page, Campbell, Harrington, and Miller, 2000; Ferguson and Horwood, 2002) as well as in the National Crime Victimization Survey (Bureau of Justice Statistics, 2008) in which the majority of crime victims report that the perpetrator was male.

Another widely reported fact is that for males and females who have begun engaging in criminal behavior, males are statistically more likely to continue offending, even if they have been caught and subject to sanctions. This was the finding in reports by Beck and Shipley (1989) (which analyzed data from the *Prisoners Released in 1983 dataset*), by Langan and Levin (2002) and Rosenfeld et al. (2005) (both which analyzed data from the *Prisoners Released in 1994 dataset*) and by a meta-analysis of 131 studies by Gendreau, Little and Goggin (1996). While the vast majority of evidence has found that males are more likely to recidivate than females, a few studies have found that no sex difference in the likelihood of reoffending. One such finding came from a report issued by

Harer (1994). Examining the recidivism rates of offenders released from federal prisons in 1987 (with recidivism being defined as being rearrested for a new offense or having parole revoked), Harer found that there was no statistical difference in the recidivism rates of male (40.9 percent) and female (39.7 percent) offenders. Unfortunately, Harer was unable to provide any explanation for why, unlike other studies, gender was not a significant predictor of recidivism in his research.

One theoretical explanation of why males have higher recidivism rates than females is differential association (Sutherland, 1947). This theory locates the source of criminal behavior as existing within the intimate social networks of individuals and further states that those who are exposed to social networks that include delinquent associates are themselves likely to become delinquent. In support of this theoretical explanation, Steffensmeier (1983) pointed out that the criminal underworld is a highly segregated arena, which is almost exclusively controlled by men and largely excludes women. In her study of male and female heroin users, Covington (1985) found that while female users were often shunned by male criminals and were more likely to commit offenses such as prostitution, drug dealing or theft independent of other people, male users who were differentially associated with other criminals tended to have higher crime rates. Steffensmeier and Allan (1996) additionally pointed out that case studies and interviews of female offenders reveal that, even among serious female offenders, there exists no strong commitment to criminal behavior. “This,” they added, "stands in sharp contrast to the commitment and self-identification with crime and the criminal lifestyle that is often found among male offenders" (p. 464).

Logistic regressions confirm that male offenders in the sample have statistically higher prevalence of rearrest than female offenders. While 68.70 percent of male offenders released in 1994 were rearrested for a new crime within three years of their release, only 57.53 percent of female offenders were rearrested. This difference is statistically significant both alone (O.R.=1.620, $p<.001$) and when the other eight individual level characteristics are included in the model (O.R.=1.601, $p<.001$).

Interestingly, however, while male offenders in the sample are significantly more likely to be rearrested for a violent offense (O.R.=2.474, $p<.001$), a property offense (O.R.=1.183, $p<.05$) and a public order offense (O.R.=1.389, $p<.001$), they are not more likely to be rearrested for a drug offense (O.R.=1.121, n.s.). This would appear to offer some support to the ideas that police efforts to crack down on drug offenses in the mid 1990s were gender neutral and that, unlike other crimes, female offenders were more likely to become involved in either possession or sales of drugs. When the other eight individual level characteristics are included in the model, however, while males remain significantly more likely to be rearrested for a violent offense (O.R.=2.170, $p<.001$), a property offense (O.R.=1.189, $p<.05$) and a public order offense (O.R.=1.290, $p<.01$), they also become significantly more likely to be rearrested for a drug offense (O.R.=1.196, $p<.05$). This significant finding (with the other eight characteristics held constant) may be because female offenders, as a whole, possess fewer characteristics associated with increased odds of recidivism than male offenders.

It is also worth noting that the odds ratio is quite a bit larger for violent rearrests than for other types of rearrests when comparing male and female offenders. This finding is in line with previous research, which has found that female offenders' contribution to violent crime is minor compared to males (Steffensmeier and Allan, 1996; Chesney-Lind and Pasko, 2004).

3.3: Age at First Arrest

A second variable which research has found to be related to recidivism risk is age at first arrest, with offenders who experience their first arrest at a younger age more at risk for future offending than those who are first arrested at an older age. In a review of seventy-one studies involving 177 independent samples of offenders, Pritchard (1979) found that offenders who had a first arrest prior to age 18 had an increased risk of recidivism and those whose first arrest didn't occur until at least age 22 were consistently found to have a decreased risk of recidivism. Similarly, in Beck and Shipley's (1989) report on prisoners released in 1983, they found that the "age at which a released prisoner was first arrested and charged as an adult was inversely related to recidivism: the younger the age at first arrest, the higher the rate of recidivism" (p. 8, Table 15).

Theoretically, there are several possible explanations for why age at first arrest would be a risk factor for future criminal behavior. One set of theories is the "state dependence interpretation" which states that "past criminal involvement reduces internal inhibitions or external constraints to future crime or increases the motivation to commit crime" (Nagino and Farrington, 1992, p. 503). This explanation is consistent with social learning (Akers, 1985), social bonding and control (Hirschi, 1969) and differential association (Sutherland, 1947) theories. Such theories hold that some children learn to engage in delinquent behavior because of their early relationships with family members who are involved in crime. Under these theories, if such learning takes place at a very young age (i.e., prior to age ten), such behavior is more likely to persist because there exist few learned inhibitions or constraints to prevent future involvement in crime. A second theory that can be used is that put forth by Gottfredson and Hirschi (1990) that postulates that early onset of criminal behavioral is the result of low self-control, which develops in some children at an early age and persists into adulthood.

In the present analysis, age at first arrest is found to be a significant predictor of rearrest for any offense by itself (O.R.=0.935, $p<.001$) as well as a significant predictor of rearrest for a violent offense (O.R.=0.919, $p<.001$), rearrest for a property offense (O.R.=0.950, $p<.001$), rearrest for a drug offense (O.R.=0.960, $p<.001$) and rearrest for a public order offense (O.R.=0.943, $p<.001$). When the other eight individual level factors are included in the model, it is no longer a significant predictor for rearrest for any offense (O.R.=1.006, n.s.), rearrest for a property offense (O.R.=1.003, n.s.), rearrest for a drug offense (O.R.=1.000, n.s.) and rearrest for a public order offense (O.R.=0.991, n.s.), although it remains a significant predictor for violent rearrest (O.R.=0.965, p<.001).

It is also worth noting that the odds ratio is quite a bit smaller for violent rearrests than for other types of rearrests when looking at the age of first arrest. This finding suggests that violent offenders begin engaging in criminal behavior that results in adult arrests at a younger age than other types of offenders. There are at least two possible explanations for this finding. The first is that since society views violent crime as more serious than non-violent crime, those who have a history of committing violent offenses will be handled by the adult court system at a younger age, even though there is no actual age difference between when violent and non-violent offenders first begin offending. The second possible explanation is that violent offenders begin their criminal careers at a younger age than non-violent offenders.

3.4: Race

A third common finding in criminology in the United States is that African Americans are more likely to be involved as defendants in the criminal justice system than whites. While the actual number of white inmates is nearly identical to the number of inmates who are African American, the rate of incarceration is six and a half times greater for African American males compared to white males and three times greater for African American females compared to white females (Sabol et al., 2009). Similarly, while whites represented 56 percent of probationers in 2008, compared with 29 percent for African Americans (Glaze and Bonzcar, 2009), the 2000 Census reported that 75.1 percent of the U.S. population was white while only 12.3 percent was black (United States Census Bureau, 2000). This indicates that blacks are also overrepresented compared to whites among those found guilty of committing crimes and sentenced to probation. In addition to their being overrepresented in the criminal justice system, the evidence is consistent in finding that African Americans have higher recidivism rates than whites (Beck and Shipley, 1989; Gendreau et al., 1996; Harer, 1994; Kubrin and Stewart, 2006; Langan and Levin, 2002; Rosenfeld et al., 2005).

One theory that may be able to explain why African Americans have higher recidivism rates than whites is the social disorganization theory first proposed by Shaw and McKay (1969 [1942]) and later modified by Kornhauser (1978), Stark (1987), Bursik (1988), Sampson and Groves (1989), and Bursik and Grasmick (1993). Research by Harer (1994) found that poverty is associated with recidivism and more recent research by Kubrin and Stewart (2006) found that individuals "who return to disadvantaged neighborhoods recidivate at a greater rate while those who return to resource rich or affluent communities recidivate at a lesser rate" (p. 165). As the United States Census Bureau (n.d.) reports that U.S. citizens who are African American have much higher poverty rates than whites, it is quite plausible that one reason why African Americans recidivate at higher rates than whites has to do with the poverty levels and lack of resources in communities to which African American offenders released from prison return.

In the present analysis, African American offenders had a three-year prevalence of rearrest for any offense (73.04%) that was 10.24 percentage points higher than that of white offenders (62.80%). Logistic regressions performed on the dataset reveal that, when no other characteristics are included in the model, African Americans have a significantly higher prevalence of rearrest than whites for all offenses (O.R.=1.605, $p<.001$), for violent offenses (O.R.=1.664, $p<.001$), for property offenses (O.R.=1.248, $p<.001$) and for drug offenses (O.R.=1.454, $p<.001$) but not for public order offenses (O.R.=1.065, n.s.). When the other eight individual level characteristics are included in the model, African Americans continue to exhibit a significantly higher prevalence of rearrest than whites for all offenses (O.R.=1.657, $p<.001$), for violent offenses (O.R.=1.678, $p<.001$), for property offenses (O.R.=1.346, $p<.001$) and for drug offenses (O.R.=1.364, $p<.001$) but the difference remains non-significant for public order offenses (O.R.=1.008, n.s.).

3.5: Age at Release

A fourth common finding of criminology is that street crime is a young person's activity and that, following adolescence, the older a person gets, the less likely he or she is to be involved in crime. While there have been many who have agreed with this assessment wholeheartedly (Hirschi and Gottfredson, 1983; Gove, 1985), others have pointed out that the age-crime curve is not necessarily as invariant as once thought, as criminals who get older may become involved in different types of crime that are less likely to be reported to the authorities (Cline, 1980; Steffensmeier, Allan, Harer, and Streifal, 1989).

Despite the debate over whether offenders desist as they age or simply change the crimes they commit, studies reflecting crime and recidivism are unanimous that the older an offender is when released from prison, the less likely he or she is to be rearrested (Beck and Shipley, 1989; Gendreau et al., 1996; Harer, 1994; Langan and Levin, 2002; Rosenfeld et al., 2005). Farrington (1986) points out that a variety of theoretical perspectives help explain the relationship between age and crime. One theoretical explanation is biological in nature with offending related to physical factors, such as the levels of testosterone in males and physical agility for both males and females (both of which peak during adolescence and decline with age). A second set of theories which help explain the age crime curve are differential association (Sutherland, 1947) and social bonding and control (Hirschi, 1969). Under the theory of differential association, adolescents become involved in offending (and continue offending during their teen years) because they break away from the protective influence of parents and begin bonding, instead, with delinquent peers. As a person reaches his or her 20s and 30s, however, offending declines as the bonding shifts away from peers and is replaced by family (or, more specifically, spouses and/or children). Another important social bond in the desistance process that occurs when a person reaches adulthood is steady employment.

Logistic regressions performed on the dataset confirm that age at release is one of the strongest predictors of recidivism, and that the younger an offender is when released, the more likely he or she is to be rearrested. Age at release is a highly significant predictor of rearrest for any offense by itself (O.R.=0.959, $p<.001$) as well as a significant predictor of rearrest for a violent offense (O.R.=0.959, $p<.001$), rearrest for a property offense (O.R.=0.981, $p<.001$), rearrest for a drug offense (O.R.=0.982, $p<.001$) and rearrest for a public order offense (O.R.=0.964, $p<.001$). When the other eight individual level characteristics are included in the model, age at release remains a highly significant predictor of rearrest for any offense (O.R.=0.938, $p<.001$) as well as a significant predictor of rearrest for a violent offense (O.R.=0.957, $p<.001$), rearrest for a property offense (O.R.=0.961, $p<.001$), rearrest for a drug offense (O.R.=0.964, $p<.001$) and rearrest for a public order offense (O.R.=0.950, $p<.001$).

3.6: Number of Prior Arrests

One of the strongest predictors of future criminal behavior is past criminal behavior. In other words, a person who has been arrested more frequently in the past is more likely to be arrested again in the future. This result was found in research conducted by Beck and Shipley (1989), Gendreau et al. (1996), Kubrin and Stewart (2006), Langan and Levin (2002) and Rosenfeld et al. (2005).

Theoretically, two reasons that might help explain why those with more prior arrests are more likely to be rearrested are differential association (Sutherland, 1947) – defined previously in the discussion on gender – and social learning theory (Akers, 1985). Social learning theory assumes that criminal behavior is a learned behavior with some people learning how to be delinquent by associating with and imitating the actions of the peers they associate with. Under these theories, offenders with more prior arrests would be more likely to revert back to crime because, by being deeply involved within antisocial groups, this association would increase the likelihood of returning to crime. Similarly, since offenders with many prior arrests may only know how to survive financially through criminal behavior and may, in fact, have developed a form of self-identification related to crime (Steffensmeier and Allan, 1996), they are much more likely to return to crime than those with few arrests.

Logistic regressions performed on the dataset confirm that the number of prior arrests is one of the strongest predictors of recidivism, and that offenders with more prior arrests are more likely to be rearrested. Number of prior arrests is a highly significant predictor of rearrest for any offense by itself (O.R.=1.075, $p<.001$) as well as a significant predictor of rearrest for a violent offense (O.R.=1.023, $p<.001$), rearrest for a property offense (O.R.=1.052, $p<.001$), rearrest for a drug offense (O.R.=1.044, $p<.001$) and rearrest for a public order offense (O.R.=1.028, $p<.001$). When the other eight individual level characteristics are included in the model, number of prior arrests remains a highly significant predictor of rearrest for any offense (O.R.=1.086, $p<.001$) as well as a significant predictor of rearrest for a violent offense (O.R.=1.028, $p<.001$), rearrest for a property offense (O.R.=1.058, $p<.001$), rearrest for a drug offense (O.R.=1.051, $p<.001$) and rearrest for a public order offense (O.R.=1.041, $p<.001$).

It is also worth noting that the odds ratio is quite a bit smaller for violent rearrests than for other types of rearrests when looking at the number of prior arrests. There are two plausible explanations for this finding. The first explanation is that the finding may indicate that violent recidivism is less likely than other forms of crime for offenders who have heavy previous involvement in the criminal justice system because chronic offenders are rational beings (Cornish and Clarke, 1986) who realize the risks inherent in engaging in acts of criminal violence. The second explanation is that chronic offenders who are prone to use violence are better screened for release and more closely monitored after release than chronic offenders who are not prone to use violence.

3.7: Current Offense Type

Both Beck and Shipley (1989) and Langan and Levin (2002) found that property offenders were more likely to be rearrested for a new crime within three years of their release from prison than violent offenders, drug offenders and public order offenders. In the present analysis, property offenders had a three-year prevalence of rearrest (74.04%) that was at least seven percentage points higher than that of drug offenders (66.77%), violent offenders (62.12%) and public order offenders (62.15%).

Logistic regressions on the dataset confirm that violent offenders (O.R.=0.616, $p<.001$), drug offenders (O.R.=0.734, $p<.001$) and public order offenders (O.R.=0.572, $p<.001$) all had significantly lower prevalence of rearrest than property offenders when type of offense was examined individually. When the other eight individual level characteristics were controlled, violent offenders (O.R.=0.710, $p<.001$), drug offenders (O.R.=0.751, $p<.001$) and public order offenders (O.R.=0.762, $p<.001$) remained significantly less likely to be rearrested when compared to property offenders.

This finding did not persist when examining arrests for specific offenses, however. Based on the idea of offense specialization – namely that an offender who commits one type of offense is more likely to be rearrested for that same type of offense than is one who has committed a different type of offense – the standard regression model with property offenders serving as the omitted contrast variable were not run. Instead, the omitted contrast used in the model matched the rearrest offense type under examination. For rearrests for violent offenses, the omitted contrast was violent offender; for rearrests for property offenses, the omitted contrast was property offender; for rearrests for drug offenses, the omitted contrast was drug offender; and for rearrests for public order offenses, the omitted contrast was public order offender. This method allowed the models to clearly show if offenders who had been released for a specific offense type were more likely to be rearrested for the same offense type than other types of offenders.

The results of these regressions reveal evidence in support of offense specialization. These equations revealed that violent offenders were significantly more likely to be rearrested for a violent offense than property offenders (O.R.=0.723, $p<.001$), drug offenders (O.R.=0.585, $p<.001$) or public order offenders (O.R.=0.585, $p<.001$); that property offenders were significantly more likely to be rearrested for a property offense than violent offenders (O.R.=0.398, p<.001), drug offenders (O.R.=0.363, p<.001) or public order offenders (O.R.=0.345, p<.001); that drug offenders were significantly more likely to be rearrested for a drug offense than violent offenders (O.R.=0.420, p<.001), property offenders (O.R.=0.535, p<.001) or public order offenders (O.R.=0.405, p<.001); and that public order offenders were significantly more likely to be rearrested for a public order offense than either violent offenders (O.R.=0.810, p<.01) or drug offenders (O.R.=0.826, p<.001). The only non-significant finding is that public order offenders were not significantly more likely to be rearrested for a public order offense than property offenders (O.R.=0.885, n.s.).

When the other eight individual level characteristics are included in the model, violent offenders remained significantly more likely to be rearrested for a violent offense than property offenders (O.R.=0.658, p<.001), drug offenders (O.R.=0.543, p<.001) and public order offenders (O.R.=0.636, p<.001); property offenders remained significantly more likely to be rearrested for a property offense than violent offenders (O.R.=0.460, p<.001), drug offenders (O.R.=0.366, p<.001) and public order offenders (O.R.=0.396, p<.001); drug offenders remained significantly more likely to be rearrested for a drug offense than violent offenders (O.R.=0.459, p<.001), property offenders (O.R.=0.481, p<.001) and public order offenders (O.R.=0.441, p<.001); and public order offenders remained significantly more likely to be rearrested for a public order offense than either violent offenders (O.R.=0.750, p<.001) or drug offenders (O.R.=0.736, p<.001). Additionally, with the other variables entered into the model public order offenders became significantly more likely to be rearrested for a public order offense than property offenders (O.R.=0.720, $p<.001$).

3.8: Time Served

The findings regarding whether or not the amount of time an offender serves in prison affects recidivism are mixed. In one study, Gendreau, Goggin and Cullen (1999) looked at 50 studies to see if prison vs. probation and if more time vs. less time increased or decreased recidivism rates. Among the studies analyzed, 23 studies involving 68,248 offenders looked at whether people who spent more time or less time in prison had higher recidivism rates. They found that offenders who spent more time in prison had the equivalent of a three percent increase in recidivism and they stated that on "the basis of the results, we can put forth one conclusion with a good deal of confidence. None of the analyses conducted produced any evidence that prison sentences reduce recidivism" (p. 18).

Evidence by Beck and Shipley (1989) and by Langan and Levin (2002) does not support the conclusion of Gendreau et al. (1999). Instead, both studies found that the amount of time served was not associated with an increased rate of recidivism for offenders who served 60 months or less in prison. Additionally, both studies found that offenders who served 61 months or more had significantly lower recidivism rates than those who served 60 months or less.

While it is beyond the scope of this dissertation to do a detailed analysis exploring the differences in findings, there is one highly plausible explanation for the differences in findings between Gendreau et al.'s (1999) study and the others.

This difference relates to the time period when the offenders involved in the studies were released from prison. While Beck and Shipley's (1989) study related to prisoners released in 1983 and Langan and Levin's (2002) study related to prisoners released in the 1994, Gendreau et al. (1999) noted that 86 percent of the studies they analyzed (related to the effect the amount of time spent in prison had on recidivism) were conducted in the 1970s. The differences in what time period the offenders served their sentences may have had an impact on what the characteristics of inmates who served longer sentences were like. This is particularly relevant given the implementation of many tough-on-crime policies in America that took place in the 1980s and 1990s. With both parole board and judicial discretion more widely used in the 1970s than in the 1980s or 1990s, it is quite likely that these factors allowed lower risk offenders to be released more quickly in the 1970s than in the 1980s or 1990s. If this was, in fact, the case -- and it again needs to be emphasized that it is beyond the scope of this dissertation to do an in depth analysis of the validity of this hypothesis -- then this could very well explain the conflicting findings.

Theoretically, the finding that increased prison length is associated with lower recidivism rates is rooted in the simple specific deterrence theory (Andenaes, 1968). This theory holds that, in most cases, when individuals experience a more severe sanction, they are more likely to have a future reduction in criminal activity. The reasoning behind this is that as punishment increases, the costs associated with crime increase and a rational being would be less likely to repeat the behavior that led to the unpleasant result.

According to Gendreau et al. (1999) the belief that incarceration is related to higher recidivism rates (the belief that prisons are "schools of crime") also has theoretical support. Two theoretical rationales that can be used to explain this result are differential association (Sutherland, 1947) and social learning theory (Akers, 1985). These theories state that if an offender is given a longer sentence he would end up associating with a group of fellow criminals for a longer period of time and would be more likely to learn criminal behavior from his peers, thereby strengthening criminal tendencies.

Logistic regressions performed on the dataset present some findings that contrast with the prior research by Gendreau et al. (1999). More specifically, these results indicate that those who serve longer terms in prison have a significantly lower prevalence of rearrest for any offense (O.R.=0.993, $p<.001$) as well as a significantly lower prevalence of rearrest for a property offense (O.R.=0.995, $p<.001$), rearrest for a drug offense (O.R.=0.991, $p<.001$) and rearrest for a public order offense (O.R.=0.996, $p<.001$). While time served is also related to a lower prevalence of rearrest for a violent offense, this result is not statistically significant (O.R.=0.999, n.s.).

When the other eight individual level characteristics are included in the models, those who serve longer terms in prison continue to exhibit a significantly lower prevalence of rearrest for any offense (O.R.=0.998, $p<.01$) as well as a significantly a lower prevalence of rearrest for a property offense (O.R.=0.998, $p<.05$) and rearrest for a drug offense (O.R.=0.996, $p<.001$). Interestingly, when the eight other characteristics are added to the model, the result related to a lower prevalence of rearrest for a violent offense becomes statistically significant (O.R.=0.998, $p<.05$) while the result related to a lower prevalence of rearrest for a public order offense becomes non-significant (O.R.=0.999, n.s.).

3.9: Type of Admission

Recent research has found that the type of admission to prison is related to the risk that an individual will reoffend. Specifically, Rosenfeld et al. (2005) found that individuals who had entered prison as the result of parole violation were more likely to be rearrested than those who entered as the result of a new court commitment. They pointed out that this finding was somewhat interesting in that it persisted even controlling for age and prior arrests.

Recent research has found partial support that parole failure may be related to recidivism via the theory of low self-control as postulated by Gottfredson and Hirschi (1990). Langton (2006) followed 4,116 juvenile offenders paroled by the California Youth Authority in 1964 and 1965 and found that low self-control was significantly and positively related to parole failure controlling for both static (e.g., offender's age at time of sentencing, race, offense type) and dynamic factors (e.g., alcohol use, drug use, delinquent associates). This finding provides evidence that offenders who have previously failed parole would be more likely to either fail again or commit a new crime because of their overall lower levels of self-control.

In the present analysis, those who entered prison on a parole revocation had a three-year prevalence of rearrest (76.07%) that was 11.78 percentage points higher than those who entered prison as a new court commitment (64.28%). Logistic regressions performed on the dataset reveal that this finding is significant both alone (O.R.=1.691, $p<.001$) and when the other eight individual level characteristics are included in the model (O.R.=1.457, $p<.001$). The models further reveal that, when admission type is entered into the model by itself, those who entered prison on a parole revocation are significantly more likely than those admitted via a new court commitment to be rearrested for a violent offense (O.R.=1.340, $p<.001$), for a property offense (O.R.=1.478, $p<.001$) and for a drug offense (O.R.=1.483, $p<.001$), but not for a public order offense (O.R.=1.051, n.s.). When the other eight individual level characteristics are included in the models, the findings remain the same: those admitted via parole violation remain more likely to be rearrested for a violent offense (O.R.=1.306, $p<.001$), for a property offense (O.R.=1.213, $p<.001$) or for a drug offense (O.R.=1.253, $p<.001$), but not for a public order offense (O.R.=1.091, n.s.).

3.10: Type of Release

The few studies that have looked into whether type of release from prison is significantly related to recidivism have produced mixed findings. Solomon, Kachnowski and Bhati (2005) conducted an analysis of the *Prisoners Released in 1994 dataset* and found no differences in the two-year prevalence of rearrest of those released unconditionally and those released via mandatory supervised release. Additionally, although those released via discretionary parole had prevalence of rearrest four percentage points lower than the other types of offenders, the authors deemed that this was not a very significant finding and wrote, “while post prison supervision may have modest effects on recidivism in some cases, it does not appear to improve prevalence of rearrest for the largest subsets of released prisoners.” (p. 15)

These findings stand in contrast to a book chapter written by Rosenfeld et al. (2005). While their findings were similar to Solomon et al.’s (2005) in that they did not find statistically significant lower prevalence of rearrest when comparing those released via mandatory supervised release and those released unconditionally, their findings regarding those released on discretionary parole were markedly different. They wrote: “Discretionary parole release has a consistent and strong effect on the incidence of rearrest in our sample, especially for violent and property offenses. Prisoners released on discretionary parole accumulate 36% fewer arrests for violent crime than those released unconditionally with no supervision in the community (the contrast category)” (pp. 95-96).

Few other studies have looked at type of release. Schlager and Robins (2008) published the only other study located for use in this dissertation. They utilized a random sample of 500 inmates taken from the 14,780 offenders released from prison in New Jersey in the 2001 calendar year. They compared the recidivism rates of those released by discretionary parole versus those released unconditionally. Their findings were in line with those of Rosenfeld et al. (2005). “Overall, offenders who maxed out were rearrested and reconvicted at statistically significant rates greater than parolees. Seventy percent of max outs were rearrested, and 44% of max outs were reconvicted compared with 60% of parolees who were rearrested and 34% who were reconvicted up to 4 years after release" (p. 242).

In the present analysis, those released via discretionary parole had a three-year prevalence of rearrest (59.65%) that is at least ten percentage points less than those who were released via mandatory supervised release (70.14%) and expiration of sentence (71.11%). Logistic regressions performed on the dataset reveal that offenders released via mandatory supervised release have higher recidivism rates than those released via discretionary parole and that this finding is significant both alone (O.R.=1.589, p<.001) and when the other eight individual level characteristics are included in the model (O.R.=1.364, p<.001). Those released via mandatory supervised release further are significantly more likely to be rearrested for a violent offense (O.R.=1.391, p<.001), for a property offense (O.R.=1.295, p<.001), for a drug offense (O.R.=1.518, p<.001) and for a public order offense (O.R.=1.306, p<.001). When the eight other individual level factors are added to the models, those released via mandatory supervised release remain significantly more likely to be rearrested for a violent offense (O.R.=1.313, p<.001), for a drug offense (O.R.=1.314, p<.001) and for a public order offense (O.R.=1.162, p<.01). The difference in the likelihood of being rearrested for a property offense, however, becomes non-significant when other factors are added to the model (O.R.=1.078. n.s.).

Similar significant findings result when comparing those released via expiration of sentence with those released via discretionary parole. This finding is significant both alone (O.R.=1.665, p<.001) and when the eight individual level characteristics are included in the model (O.R.=1.527, p<.001). Those released via expiration of sentence are also significantly more likely to be rearrested for a violent offense (O.R.=2.037, p<.001), for a property offense (O.R.=1.463, p<.001), for a drug offense (O.R.=1.380, p<.001) and for a public order offense (O.R.=1.875, p<.001). When the eight other individual level factors are added to the models, those released via expiration of sentence remain significantly more likely to be rearrested for a violent offense (O.R.=1.937, p<.001), for a property offense (O.R.=1.346, p<.001), for a drug offense (O.R.=1.282, p<.01) and for a public order offense (O.R.=1.777, p<.01).

It is also worth noting that the odds ratio is quite a bit higher for those released via expiration of sentence for both violent rearrests and public order rearrests than for those released via discretionary parole. A possible explanation for this finding is that those who have problems with either violence or obeying the rules of public order were made to serve their entire sentence as a result of institutional behavior involving these types of misconduct. As a result, since offenders who are prone to these types of behavioral problems are more likely to serve their full prison sentences, without parole or supervised release, such offenders are also more likely to be rearrested for these types of offenses.

3.11: Relationships among the Individual Predictors

Tables 2a and 2b provide a correlation matrix of the individual level variables. Based on Cohen's (1988) interpretation of effect sizes, this matrix reveals that the only variables that have a strong relationship between each other are age at first arrest and age at release with an effect size of .527. While Cohen determined that a correlation of at least .300 but less than .500 was required to have a moderate relationship, and while no other relationships reach this threshold, it is nevertheless noteworthy to point out that there are four additional correlations greater than .250. The correlation between age at first arrest and number of prior arrests is -.264; the correlation between age at release and number of prior arrests is .256; the correlation between serving time for a violent offense and time served is .277; and the correlation between being admitted for a parole violation and being released via mandatory supervised release is .283.

Although there were an additional 27 comparisons with small relationships (that is, a correlation of at least .100 but no greater than .250), it is important to take into consideration that there were a total of 202 comparisons in the correlations. This means that only approximately 0.5 percent of the comparisons had a strong relationship, only approximately 2.0 percent had close to a moderate relationship and only approximately 13.5 percent had a small relationship. What this says is that not only does there exist no association between predictors in approximately 84 percent of comparisons, but there further only exists a moderate to strong relationship in 2.5 percent of comparisons. These results indicate that the independent effects of the predictors entered into the model are not unduly influenced by correlations with other variables.

3.12: Discussion

While the preceding sections helped highlight the findings of prior research in relation to the nine individual-level recidivism predictors to be included in the upcoming chapters, the preliminary logistic regressions revealed some interesting findings and how they relate to rearrest risks for specific offenses. One finding of interest concerns offense specialization. In all but one of the comparisons, an offender released from prison for a specific offense category was statistically more likely to be rearrested for the same type of crime when compared to other offense categories. Another notable finding is how several of the factors had a noticeably different impact on rearrest for a violent offense as opposed to overall risk for rearrest for any offense. The odds ratios were noticeably different in relation to gender, age at first arrest, number of prior arrests, and release via expiration of sentence for those rearrested for a violent rearrest compared to those rearrested for any offense. These findings suggest that the predictors for violent offending may be somewhat different than the predictors of non-violent offending. Specifically, gender is a more influential predictor of violent recidivism than non-violent recidivism, people who enter the adult criminal justice system at a younger age are at an increased risk of violent recidivism, and offenders who max-out their sentences are at an increased risk of violent recidivism. The findings also suggest that having a lengthy criminal record does not increase the risk of future violent offending. These findings are important from a policy perspective as they suggest that males who enter the adult criminal justice at a young age and who have behavior problems while incarcerated, and therefore serve their entire sentence in prison, are at an increased risk of violent recidivism. As such, it would appear that society would benefit if such offenders were more closely monitored upon their release (i.e., intensive parole supervision). Officials also should consider providing such inmates more intensive end-of-sentence programming to reduce their risk of violent recidivism.

Overall, the findings indicate that the nine individual-level predictors help to explain variation in recidivism. But how useful are they in explaining differences in rearrest rates across the states? In other words, does one state have a higher recidivism rate than another solely because it has a more “recidivism prone” population of released prisoners? And are the nine individual-level predictors equally effective at predicting differences in rearrests for specific forms of crime – violent, property, drug and public order offenses – or are the predictors better able to explain variations in certain types of offending compared to others?

These questions are explored in more detail in the next chapter. The forms of recidivism to be addressed are rearrest for any offense, rearrest for a violent offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense other than a parole violation (additional forms of recidivism will be examined in Chapter 5). The findings presented in the next chapter show that the nine individual-level predictors help explain some of the variation across states for rearrest for any offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense. The findings regarding rearrest for violent offending, however, are mixed.

Table 1: Logistic Regression Models for All Individual Level Characteristics					
	Any Offense	Violent	Property	Drug	Public Order
	Odds Ratio Std. Err.	Odds Ratio Std. Err.	Odds Ratio Std. Err.	Odds Ratio Std. Err.	Odds Ratio Std. Err.
Gender	1.601*** *0.121*	2.170*** *0.237*	1.189* *0.100*	1.196* *0.100*	1.290** *0.109*
Age at First Arrest	1.006 *0.005*	0.965*** *0.007*	1.003 *0.006*	1.000 *0.006*	0.991 *0.006*
Black	1.657*** *0.070*	1.678*** *0.082*	1.346*** *0.06*	1.364*** *0.062*	1.008 *0.044*
Other Race	0.672* *0.134*	1.293 *0.268*	0.801 *0.158*	0.586* *0.138*	0.970 *0.188*
Age at Release	0.938*** *0.003*	0.957*** *0.004*	0.961*** *0.004*	0.964*** *0.004*	0.950*** *0.004*
Prior Arrests	1.086** *0.006*	1.028*** *0.004*	1.058*** *0.004*	1.051*** *0.004*	1.041*** *0.003*
Violent Offense	*0.710**** *0.038*	Omitted	0.460*** *0.024*	0.459*** *0.026*	0.750*** *0.057*
Property Offense	Omitted	0.658*** *0.038*	Omitted	0.481*** *0.027*	0.720*** *0.054*
Drug Offense	0.751*** *0.042*	0.543*** *0.034*	0.366*** *0.02*	Omitted	0.736*** *0.057*
Public Order Offense	0.762*** *0.057*	0.636*** *0.055*	0.396*** *0.031*	0.441*** *0.037*	Omitted
Other Offense	0.690*** *0.176*	0.568 *0.186*	0.549* *0.158*	0.662 *0.163*	0.483* *0.148*
Time Served	0.998** *0.001*	0.998* *0.001*	0.998* *0.001*	0.996*** *0.001*	0.999 *0.001*
Parole Violation	1.457*** *0.083*	1.306*** *0.076*	1.213*** *0.066*	1.253*** *0.069*	1.091 *0.06*
Probation Violation	1.386** *0.147*	1.443** *0.154*	1.673*** *0.167*	1.096 *0.122*	2.307*** *0.22*
Other Admission Type	0.810 *0.124*	0.741 *0.139*	0.940 *0.147*	0.694 *0.134*	0.806 *0.136*
Unknown Admission Type	0.509*** *0.067*	0.451 *0.067*	0.559*** *0.073*	0.554*** *0.082*	0.240*** *0.034*
Mandatory Supervised Release	1.364*** *0.063*	1.313*** *0.072*	1.078 *0.052*	1.314*** *0.067*	1.162** *0.06*
Expiration of Sentence	1.528*** *0.12*	1.937*** *0.162*	1.346*** *0.105*	1.282** *0.105*	1.777*** *0.137*
Other Release Type	1.497*** *1.497*	1.353*** *0.095*	0.924 *0.059*	0.900 *0.06*	2.214*** *0.133*
Model Statistics					
Observations	*32,732*	*32,732*	*32.732*	*32,732*	*32.732*
Pseudo R^2	*0.1100*	*0.0692*	*0.0863*	*0.0745*	*0.0553*
Log Pseudolikelihood	*-146985.23*	*-127522*	*-150385.06*	*-149246.06*	*-146070.57*
* p<.05 , ** p <.01, *** p<.001					

Table 2A: Correlation Matrix of Individual Level Characteristics (Part 1)											
	1	2	3	4	5	6	7	8	9	10	11
1	1	-.097**	.011**	-.011**	0	-.037**	-.007**	.072**	-.018**	-.067**	.039**
2	-.097**	1	.079**	-.078**	-.006**	.527**	-.264**	-0.003	-.079**	.043**	.053**
3	.011**	.079**	1	-.980**	-.102**	.048**	-.053**	-.026**	.087**	-.121**	.065**
4	-.011**	-.078**	-.980**	1	-.099**	-.042**	.057**	.022**	-.088**	.127**	-.069**
5	0	-.006**	-.102**	-.099**	1	-.027**	-.018**	.018**	.005*	-.032**	.020**
6	-.037**	.527**	.048**	-.042**	-.027**	1	.256**	-.010**	-.025**	-.004*	.057**
7	-.007**	-.264**	-.053**	.057**	-.018**	.256**	1	-.118**	.132**	-.016**	-.028**
8	.072**	-0.003	-.026**	.022**	.018**	-.010**	-.118**	1	-.384**	-.370**	-.176**
9	-.018**	-.079**	.087**	-.088**	.005*	-.025**	.132**	-.384**	1	-.494**	-.235**
10	-.067**	.043**	-.121**	.127**	-.032**	-.004*	-.016**	-.370**	-.494**	1	-.226**
11	.039**	.053**	.065**	-.069**	.020**	.057**	-.028**	-.176**	-.235**	-.226**	1
12	-.013**	.023**	.050**	-.049**	-.005**	.008**	.022**	-.073**	-.097**	-.094**	-.045**
13	.076**	-.030**	-.069**	.072**	-.014**	.134**	-.046**	.277**	-.084**	-.098**	-.079**
14	-.009**	.015**	-.027**	.033**	-.033**	-.059**	-.120**	.075**	-.101**	.050**	-.007**
15	.030**	-.037**	.017**	-.020**	.013**	.083**	.186**	-.047**	.073**	-.028**	-.019**
16	-.056**	.020**	-.024**	.015**	.046**	-.064**	-.101**	-.051**	.045**	-.030**	.059**
17	-0.004	.009**	.015**	-.023**	.042**	.009**	-.014**	-.019**	-.012**	-.035**	.107**
18	-.060**	.020**	-.051**	.044**	.035**	-.069**	-.109**	-.055**	.049**	-.028**	.053**
19	-.025**	-.013**	-.112**	.118**	-.030**	-.014**	-.118**	.017**	-.040**	.024**	.024**
20	.018**	.022**	.138**	-.146**	.037**	.028**	.103**	-.026**	.034**	-.027**	-.014**
21	.019**	-.019**	-.043**	.047**	-.021**	.012**	0.003	.034**	-0.003	-.008**	-.019**
22	-.007**	-0.003	-.031**	.032**	-0.001	-.032**	-0.001	-.007**	.004*	.014**	0.003

*. Correlation is significant at the 0.05 level (2-tailed) **. Correlation is significant at the 0.01 level (2-tailed).

1 – GENDER
2 - AGE AT FIRST ARREST
3 - RACE – WHITE
4 - RACE – BLACK
5 - RACE – OTHER
6 - AGE AT RELEASE
7 - PRIOR ARRESTS
8 - VIOLENT OFFENSE
9 – PROPERTY OFFENSE
10 – DRUG OFFENSE
11 – PUBLIC ORDER OFFENSE
12 - OFFENSE - OTHER
13 - TIME SERVED
14 - NEW COURT COMMITMENT
15 - PAROLE VIOLATION
16 - PROBATION VIOLATION
17 - OTHER ADMISSION TYPE
18 – UNKNOWN ADMISSION TYPE
19 - DISCRETIONARY PAROLE
20 - MANDATORY SUPERVISED RELEASED
21 - EXPIRATION OF SENTENCE
22 – OTHER RELEASE TYPE

Table 2B: Correlation Matrix of Individual Level Characteristics (Part 2)											
	12	13	14	15	16	17	18	19	20	21	22
1	-.013**	.076**	-.009**	.030**	-.056**	-0.004	-.060**	-.025**	.018**	.019**	-.007**
2	.023**	-.030**	.015**	-.037**	.020**	.009**	.020**	-.013**	.022**	-.019**	-0.003
3	.050**	-.069**	-.027**	.017**	-.024**	.015**	-.051**	-.112**	.138**	-.043**	-.031**
4	-.049**	.072**	.033**	-.020**	.015**	-.023**	.044**	.118**	-.146**	.047**	.032**
5	-.005**	-.014**	-.033**	.013**	.046**	.042**	.035**	-.030**	.037**	-.021**	-0.001
6	.008**	.134**	-.059**	.083**	-.064**	.009**	-.069**	-.014**	.028**	.012**	-.032**
7	.022**	-.046**	-.120**	.186**	-.101**	-.014**	-.109**	-.118**	.103**	0.003	-0.001
8	-.073**	.277**	.075**	-.047**	-.051**	-.019**	-.055**	.017**	-.026**	.034**	-.007**
9	-.097**	-.084**	-.101**	.073**	.045**	-.012**	.049**	-.040**	.034**	-0.003	.004*
10	-.094**	-.098**	.050**	-.028**	-.030**	-.035**	-.028**	.024**	-.027**	-.008**	.014**
11	-.045**	-.079**	-.007**	-.019**	.059**	.107**	.053**	.024**	-.014**	-.019**	0.003
12	1	-.046**	-.036**	.026**	-.026**	-.012**	-.023**	-.047**	.083**	-.022**	-.046**
13	-.046**	1	.149**	-.109**	-.075**	.023**	-.082**	.214**	-.205**	.080**	-.028**
14	-.036**	.149**	1	-.695**	-.271**	-.101**	-.242**	.086**	-.177**	-.030**	.174**
15	.026**	-.109**	-.695**	1	-.145**	-.054**	-.130**	-.146**	.283**	-.059**	-.192**
16	-.026**	-.075**	-.271**	-.145**	1	-.021**	.895**	.147**	-.087**	-.047**	-.030**
17	-.012**	.023**	-.101**	-.054**	-.021**	1	-.019**	.013**	-.060**	-.007**	.077**
18	-.023**	-.082**	-.242**	-.130**	.895**	-.019**	1	.145**	-.053**	-.044**	-.079**
19	-.047**	.214**	.086**	-.146**	.147**	.013**	.145**	1	-.665**	-.139**	-.217**
20	.083**	-.205**	-.177**	.283**	-.087**	-.060**	-.053**	-.665**	1	-.279**	-.436**
21	-.022**	.080**	-.030**	-.059**	-.047**	-.007**	-.044**	-.139**	-.279**	1	-.091**
22	-.046**	-.028**	.174**	-.192**	-.030**	.077**	-.079**	-.217**	-.436**	-.091**	1

*. Correlation is significant at the 0.05 level (2-tailed)   **. Correlation is significant at the 0.01 level (2-tailed).

1 – GENDER
2 - AGE AT FIRST ARREST
3 - RACE – WHITE
4 - RACE – BLACK
5 - RACE – OTHER
6 - AGE AT RELEASE
7 - PRIOR ARRESTS
8 - VIOLENT OFFENSE
9 – PROPERTY OFFENSE
10 – DRUG OFFENSE
11 – PUBLIC ORDER OFFENSE
12 - OFFENSE - OTHER
13 - TIME SERVED
14 - NEW COURT COMMITMENT
15 - PAROLE VIOLATION
16 - PROBATION VIOLATION
17 - OTHER ADMISSION TYPE
18 – UNKNOWN ADMISSION TYPE
19 - DISCRETIONARY PAROLE
20 - MANDATORY SUPERVISED RELEASED
21 - EXPIRATION OF SENTENCE
22 – OTHER RELEASE TYPE

CHAPTER 4 - EXPLORING THE IMPACT OF INDIVIDUAL LEVEL CHARACTERISTICS ON TYPES OF REARREST

4.1: Introduction

While Langan and Levin's (2002) publication detailing the individual level characteristics of offenders released from prison in 15 states in 1994 provided invaluable information about a majority of prisoners released in the United States for that year, one thing it neglected to do was break down the released prisoners by state of release. Table 3 on the following page shows that a great deal of between state variation exists in the cumulative individual level characteristics of those who were released. One characteristic that differs widely among states that would also be expected to influence recidivism rates is the average number of prior arrests for released prisoners, with a low of 4.59 in Michigan and a high of 14.20 in Delaware. Given the strong relationship which has been shown to exist between prior arrests and recidivism, states that release prisoners with a higher average number of prior arrests would also be expected to have higher recidivism rates. Similarly, the percentage of prisoners released via discretionary parole runs the complete spectrum from 0 percent in California, Delaware, Florida and Illinois to 100 percent in Michigan. Although the previous chapter revealed that release type had a more modest impact than number of prior arrests, the variation in the number of prisoners released via discretionary parole would also be expected to have an influence on the recidivism rates of offenders released from different states.

Table 3: Individual Level Characteristics of 1994 Release Cohort by State of Release																	
Demographic Characteristic	**Mean**	**St. Dev.**	**AZ**	**CA**	**DE**	**FL**	**IL**	**MD**	**MI**	**MN**	**NJ**	**NY**	**NC**	**OH**	**OR**	**TX**	**VI**
Gender																	
Male	91.13%	28.40%	90.93%	91.15%	92.50%	89.96%	93.49%	93.54%	92.94%	93.42%	92.21%	91.64%	87.40%	89.79%	92.73%	91.97%	91.32%
Female	8.87%	28.40%	9.07%	8.85%	7.50%	10.04%	6.51%	6.46%	7.06%	6.58%	7.79%	8.36%	12.60%	10.21%	7.27%	8.03%	8.68%
Average Age at First Arrest	21.60	6.45	22.33	22.06	18.10	20.94	19.59	21.71	21.08	21.75	20.81	20.74	22.16	22.19	22.37	21.89	21.88
Race																	
White	50.34%	50.00%	77.29%	65.33%	31.88%	42.71%	28.17%	22.31%	45.19%	60.09%	31.01%	35.73%	35.40%	46.08%	81.67%	51.68%	35.24%
Black	48.64%	50.00%	17.02%	33.17%	68.13%	57.15%	71.75%	77.69%	54.17%	30.97%	68.86%	64.04%	62.86%	53.67%	15.57%	48.24%	64.52%
Other	1.02%	10.10%	5.69%	1.50%	0.00%	0.14%	0.08%	0.00%	0.64%	8.94%	0.13%	0.23%	1.74%	0.24%	2.76%	0.08%	0.05%
Average Age at Release	32.30	8.47	33.66	33.04	31.26	32.26	29.64	31.95	32.88	31.15	31.28	31.87	30.86	31.55	34.35	33.14	32.25
Average Prior Arrests	8.78	8.59	6.95	10.41	14.20	10.89	8.66	7.56	4.59	6.03	7.27	9.56	5.81	5.02	14.06	5.86	6.79
Current Offense																	
Violent	22.35%	41.70%	16.54%	20.68%	29.53%	24.32%	24.96%	27.44%	28.52%	43.58%	26.39%	26.73%	14.08%	25.55%	38.42%	19.38%	21.96%
Property	33.84%	47.30%	32.64%	33.81%	13.75%	36.54%	38.55%	17.58%	37.08%	39.17%	21.12%	21.39%	42.87%	39.56%	32.06%	41.52%	43.92%
Drugs	32.28%	46.80%	23.94%	32.65%	38.91%	32.35%	28.66%	23.73%	23.79%	14.59%	45.57%	45.23%	26.28%	27.86%	21.03%	30.00%	28.90%
Public Order	9.71%	29.60%	26.08%	8.91%	17.81%	6.79%	7.76%	31.18%	10.48%	2.67%	5.16%	6.30%	16.41%	5.45%	7.93%	9.10%	4.92%
Other	1.81%	13.30%	0.79%	3.95%	0.00%	0.00%	0.07%	0.07%	0.12%	0.00%	1.77%	0.36%	0.37%	1.58%	0.56%	0.00%	0/29%
Average Time Served - Months	18.72	24.13	20.88	11.67	30.47	22.71	18.22	33.09	45.00	20.55	21.78	32.87	7.62	29.97	18.49	19.95	24.08
Type of Prison Admission*																	
New Court Commitment	59.10%	48.30%	32.82%	48.25%	85.16%	99.42%	80.99%	80.63%	67.57%	92.80%	67.73%	90.21%	35.50%	**	35.82%	66.55%	81.40%
Parole Revocation	28.29%	45.90%	17.27%	51.75%	3.13%	0.00%	17.78%	17.19%	7.51%	7.20%	30.69%	9.32%	20.38%	**	33.48%	32.40%	18.60%
Probation Revocation	10.58%	23.60%	34.54%	0.00%	11.72%	0.00%	0.00%	0.00%	19.57%	0.00%	1.38%	0.00%	43.47%	**	27.82%	1.05%	0.00%
Other Admission Type	0.81%	9.30%	15.38%	0.00%	0.00%	0.58%	1.22%	2.18%	5.35%	0.00%	0.20%	0.47%	0.64%	**	2.87%	0.00%	0.00%
Type of Prison Release																	
Discretionary Parole	23.53%	43.20%	35.69%	0.00%	0.00%	0.00%	0.00%	42.20%	100.00%	0.12%	77.79%	71.02%	38.07%	35.01%	52.10%	43.82%	41.80%
Mandatory Supervised Release	57.75%	49.95%	0.85%	100.00%	0.00%	0.71%	98.08%	49.00%	0.00%	76.66%	0.00%	11.06%	59.41%	0.00%	34.99%	33.48%	51.45%
Expiration of Sentence	5.70%	22.80%	4.32%	0.00%	8.59%	20.84%	1.53%	2.44%	0.00%	0.74%	20.23%	4.45%	2.46%	39.56%	0.41%	1.97%	2.76%
Other	10.29%	33.00%	59.14%	0.00%	91.41%	78.45%	0.39%	6.36%	0.00%	22.47%	1.87%	13.47%	0.06%	25.43%	12.50%	20.72%	3.99%

* Percentages of Type of Admission are calculated excluding those with unknown admission types. These cases are included in calculating percentages for other individual level characteristics.
** Data on Admission Type was not provided for any offender released in 1994 from prison in Ohio.

This chapter looks at the differences in recidivism across states for several, separate forms of rearrest. These include rates of rearrest for any offense, rearrest for a violent offense, rearrest for a property offense, rearrest for a drug offense, and rearrest for a public order offense (other than parole violation). In exploring these different forms of rearrest, the chapter evaluates the extent to which variation between states in rates of each rearrest type can be explained by differences in the individual level characteristics of the release cohorts from each state.

Differences between states are examined in two separate ways. The first of these methods is often referred to as a "fixed effects" approach. It involves estimating three models. The first is a model for each form of rearrest with state of release entered into the model (one of the states will serve as the omitted contrast). The second is a model for each form of rearrest with the nine individual level characteristics added. This model is similar to that shown at the conclusion of Chapter 3. The third is a model for each form of rearrest with both the nine individual level characteristics and the state of release entered into the model. After these three models are estimated, changes in the odds ratio for each of the states is examined to evaluate the impact that the nine individual level characteristics have on recidivism measures.

A second way to examine state differences in the effect of individual level characteristics on recidivism is to do a state-by-state comparison. In this approach, two sets of models are estimated for each possible state-by-state combination. Rather than odds ratios, these models estimate regression coefficients. In the first model, the only variables entered into the regression equation are the outcome variable (i.e., type of rearrest) and the contrast state. In the second model, the nine individual level characteristics are added.

To help understand what this approach involves, an example follows, comparing the states of Illinois and Minnesota using the recidivism measure of rearrest for any offense. These two states were chosen because they have quite different rearrest rates. For offenders from Illinois released in 1994, 77.80 percent were rearrested for a new offense within three years of their release. This is markedly higher than Minnesota where only 59.84 percent of offenders released in 1994 were rearrested for a new offense within three years of their release.

When the nine individual level characteristics are entered into the model, however, the difference in recidivism rates is accounted for by differences in the characteristics of the prisoners released in the two states. Comparing rearrest rates between Illinois and Minnesota using the states only model, the regression results are as follows:

Table 4: Logistic Regression comparing Rearrests for Prisoners Released from Illinois and Minnesota		
REARRD	Coefficient	Std. Error
Illinois	0.8552387***	0.0815106
Model Statistics		
Observations	Pseudo R^2	Log Pseudolikelihood
3724	0.0128	-8968.4084
* p<.05 , ** p <.01, *** p<.001		

When the rearrest rates of prisoners released from Illinois are compared with the rearrest rates of those from Minnesota (the contrast in the model), the coefficient is 0.855 (p<.001). This is a statistically significant finding that indicates that an offender released from prison in Illinois is more likely to be rearrested within three years of release than an offender released from Minnesota. This finding reflects the difference in the Illinois and Minnesota rearrest percentages previously noted.

The next question is whether differences in individual level characteristics of offenders from these two states can explain the difference in recidivism rates. To address this question, a second logistic regression model is estimated with the nine individual recidivism predictors added to the model. The logistic regression for this model is shown below. The results show that when the nine individual level characteristics are added, the coefficient for Illinois drops to 0.105 and is not significant.

Table 5: Logistic Regression comparing Rearrests for Prisoners Released from Illinois and Minnesota with Individual Level Characteristics Added to the Model

REARRD	Coefficient	Std. Error
Illinois	0.1050407	0.1163472
Gender	0.1973337	0.2463144
Age of First Arrest	-0.0186078	0.0194669
Black	1.020112	0.1380382
Other Race	0.5150573	0.2262295
Age at Release	-0.0930937	0.0118599
Prior Arrests	0.1331583	0.0190814
Property Offense	-0.1390874	0.1578478
Drug Offense	-0.1708313	0.1797831
Public Order Offense	-0.2104811	0.3362968
Other Offense	-1.42732	1.032146
Time Served	-0.0056398	0.0028321
Parole Violation	0.7893901	0.2433061
Probation Violation	(omitted)	
Other Admission Type	2.637833	0.5731931
Unknown Admission Type	(omitted)	
Mandatory Supervised Release	4.118075	1.077437
Expiration of Sentence	5.928235	1.179949
Other Release Type	3.850888	1.098412
_cons	-1.498496	1.197659

Model Statistics		
Observations	Pseudo R^2	Log Pseudolikelihood
3724	0.2143	- 7137.6965
* p<.05 , ** p <.01, *** p<.001		

To help explain why this change occurred, it is useful to compare the differences in the characteristics of prisoners released from Illinois and Minnesota. Looking at the state comparisons in Table 3, we might expect offenders released from Illinois to have a higher rearrest rate than offenders released from Minnesota, given the differences in the individual recidivism indicators between the two states. Compared with the prisoners released from Minnesota, those released in Illinois are more likely to be black, are younger at the age of release, and have more prior arrests – all predictors of elevated recidivism rates. These three factors alone explain nearly half of the difference in rearrest rates between Illinois and Minnesota (b=0.233, p<.05).

Before proceeding, it is necessary to discuss modifications that were made to the logistic regressions to deal with the problem of multicollinearity, which resulted because some states do not vary in their type of admission or release. For example, in California 100 percent of the offenders were released by mandatory supervised release, while in Michigan, 100 percent of the offenders were released by discretionary parole. In such instances, the statistical program either dropped one of the variables from the model or the estimation produced an unrealistically large coefficient on one of these variables (which was defined as an odds ratio of 10 or above). In total, multicollinearity was a problem in 14 of the 210 cases. To deal with the problem, either admission type or release type was dropped from the regression equation for these estimations

4.2: Exploring the Differences in Rearrest Probabilities across States

While Figure 1 in Chapter 1 showed that a wide degree of variation exists in three-year rearrest rates for offenders released from prison in 1994, with a low of 43.74 percent in Michigan and a high of 86.25 percent in Delaware, it is not known to what extent variation across states in individual level characteristics of released prisoners can account for these differences. To begin exploring this possibility, the three regression models described in the previous section are estimated. The results provide strong, consistent evidence that the individual level predictors help explain some, but not all, of the variation in rearrest rates between states. In the model without the individual level recidivism predictors, every state has a significantly higher odds ratio of rearrest than Michigan, the contrast, with the values ranging from a low of O.R.=1.720 ($p<.001$) for Texas to a high of OR=8.068 ($p<.001$) for Delaware. When the nine individual level factors are added to the model, every state continues to have a significantly higher odds ratio of rearrest than Michigan. The magnitude of the state effect is reduced in every case, however, in some cases substantially. For example, the odds ratio is reduced by 50.15 percent for Illinois, 45.38 percent for Delaware, and 41.14 percent for California. The average reduction in the magnitude of the state effects on recidivism after the individual recidivism predictors are added to the model is 35%. In other words, state differences in the characteristics of released prisoners explains on average about 35% of the state differences in rates of rearrest for any offense.

Table 6: Logistic Regression Results for Three Models for Rearrest for Any Offense			
	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Any Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.601***	1.630***
Age of First Arrest		1.006	1.003
Black		1.657***	1.665***
Other Race		0.672*	0.676
Age at Release		0.938***	0.940***
Prior Arrests		1.086***	1.079***
Violent Offense		0.710***	0.683***
Drug Offense		0.751***	0.731***
Public Order Offense		0.762***	0.733***
Other Offense		0.690	0.670
Time Served		0.998**	0.997***
Parole Violation		1.457***	1.517***
Probation Violation		1,386**	1.182
Other Admission Type		0.810	0.860
Unknown Admission Type		0.509***	0.730*
Mandatory Supervised Release		1.364***	1.123
Expiration of Sentence		1.528***	1.223*
Other Release Type		1.497***	0.892
Arizona	2.141***		2.100***
California	3.121***		1.837***
Delaware	8.068***		4.407***
Florida	4.917***		3.068***
Illinois	4.507***		2.247***
Maryland	3.139***		2.108***
Minnesota	1.916***		1.560***
New Jersey	2.122***		1.310***
New York	2.730***		1.845***
North Carolina	2.007***		1.364***
Ohio	1.724***		1.399***
Oregon	3.415***		2.141***
Texas	1.720***		1.321***
Virginia	2.272***		1.518***
Model Statistics			
Observations (Unweighted)	32,732	32,732	32,732
Pseudo R^2	0.0203	0.1100	0.1161
Log Pseudolikelihood	-161791.42	-146985.23	-145970.99
* p<.05 , ** p <.01, *** p<.001			

These results are based on comparing each state with a single contrast, Michigan, which has a comparatively low rate of rearrest for any offense. The second approach relaxes this restriction by comparing each state with every other state. The results are consistent with those from the former analysis. Without the individual level characteristics added to the models, the regression results show that slightly less than 20 percent of the state-by-state comparisons yield statistically similar odds of rearrest (refer to Table A1 in Appendix B).

Specifically, of 105 state-by-state comparisons, 20 combinations (19.05 percent) produce a non-significant difference in the rearrest rates of the two states. When the individual level characteristics are added to the models (refer to Table A2 in Appendix B), the number of state-by-state comparisons with similar rearrest rates increases to 50 (47.62 percent).

Not only do these results provide additional evidence regarding the impact of differences in release cohorts on state differences in rearrest rates, this second approach can be used to explore these effects for any state (for which the data are available) with any other state. The effect on the coefficient size adding the individual level characteristics varies greatly. Comparing California and North Carolina, for example, the regression coefficient is 0.442 and significant in the model without the individual characteristics of released prisoners. When the individual level characteristics are added this changes only slightly to 0.447 and remains significant. This differs sharply from the comparison of Delaware and New York. With only the states entered into the model, the coefficient for these two states is 1.099. This is significant and indicates that offenders from Delaware are more likely to be rearrested than offenders from New York. When the individual level characteristics are added to the model, however, the coefficient drops to a non-significant -0.122. Not only does the size of the coefficient drop by 88 percent, but the result goes from highly significant to non-significant. This tool may prove useful to state policymakers who may want to compare recidivism in their own state with that in only selected other states.

4.3: Exploring the Differences in Rearrest Probabilities across States by Type of Rearrest

The previous section highlights that differences in individual level characteristics can help to explain differences that exist in rearrest rates between states. Such a finding is not particularly surprising given that it is largely in line with the literature previously discussed in the introduction on the impact of individual level covariates. An additional question that this dissertation seeks to answer is the extent to which differences in individual level characteristics of release cohorts can be used to explain differences in rearrest for specific types of offenses. More specifically, can differences in the individual level predictors help explain variations in rearrest rates between states for violent offenses, property offenses, drug offenses and public order offenses excluding parole violations?[1]

Langan and Levin's (2002) analysis of prisoners released in 1994 provides mixed evidence on whether the type of offense for which an offender was serving

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[1] An analysis of parole violations is presented in Chapter 5.

time is related to the type of offense for which the offender was rearrested after release from prison. They found that certain categories of criminals were likely to be rearrested for the same offense for which they had been incarcerated. Specifically, 41.2 percent of released drug dealers, 33.9 percent of released larcenists, and 23.4 percent of released burglars were rearrested for the same type of offense. Other offenders, however, were unlikely to be rearrested for the same offense – only 2.5 percent of rapists and 1.2 percent of homicide offenders were rearrested for those offenses. These findings are similar to those reported by Beck and Shipley (1989) in their analysis of prisoners released in 1983. In their study, while 33.5 percent of released larcenists were rearrested for another larceny, 31.9 percent of released burglars were rearrested for another burglary and 24.8 percent of drug dealers were rearrested for another drug offense, only 7.7 percent of rapists were rearrested for another rape and 6.6 percent of released homicide offenders were rearrested for another homicide offense.

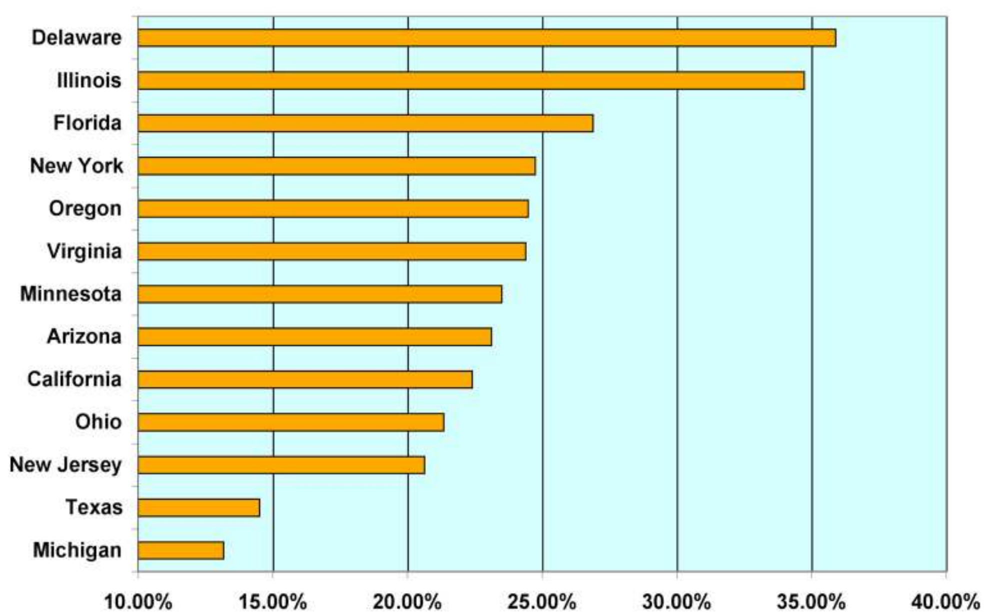
Table 7 - State by Whether Type of Rearrest is Known

State	# Type of Rearrest Known	# Type of Rearrest Not Known	Pct. Known
California	179,161	18	99.99%
New York	54,234	35	99.94%
Oregon	10,912	20	99.81%
Florida	51,495	199	99.61%
Arizona	9,872	55	99.44%
Illinois	43,199	334	99.23%
Delaware	2,396	28	98.84%
Virginia	8,556	110	98.73%
Ohio	15,415	280	98.21%
New Jersey	18,862	399	97.93%
Michigan	4,364	141	96.87%
Texas	20,733	1245	94.33%
Minnesota	2,475	177	93.33%
North Carolina	26,291	7365	78.12%
Maryland	2,374	15412	13.35%

Because of unclassified offense-of-rearrest data in the *Prisoners Released in 1994 dataset*, a state-by-state analysis of this information was conducted. Table 7 presents the numbers and percentages of the most serious rearrest offenses by state. Because less than 90 percent of rearrest offenses are known in North Carolina and Maryland, these two states were excluded from the analyses on rearrest by type of offense.

4.4: Exploring the Differences in Violent Rearrest Probabilities across States

FIGURE 2 - THREE YEAR VIOLENT REARREST RATES BY STATE



Unlike the figure on general rearrest rates, Figure 2 indicates less between-state variation in three-year violent rearrest rates for offenders released from prison in 1994. While Michigan and Texas are on the low end of violent rearrest rates with 13.18 percent and 14.51 percent, respectively, and while Delaware and

Illinois are on the high end of violent rearrest rates with 35.90 percent and 34.74 percent, respectively, the remaining nine states have relatively similar rearrest probabilities, all within about six percentage points of each other.

Table 8: Logistic Regression Results for Three Models for Rearrest for A New Violent Offense

	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Violent Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		2.208***	2.209***
Age of First Arrest		0.967***	0.967***
Black		1.800***	1.750***
Other Race		1.302	1.277
Age at Release		0.958***	0.960***
Prior Arrests		1.026***	1.023***
Property Offense		0.666***	0.670***
Drug Offense		0.543***	0.544***
Public Order Offense		0.726**	0.715***
Other Offense		0.538	0.562
Time Served		0.998*	0.997**
Parole Violation		1.271***	1.372***
Probation Violation		1.385**	0.905
Other Admission Type		0.799	0.647*
Unknown Admission Type		0.524**	1.048
Mandatory Supervised Release		1.350***	1.460***
Expiration of Sentence		1.864***	1.645***
Other Release Type		1.284***	1.045
Arizona	1.973***		2.350***
California	1.903***		1.095
Delaware	3.717***		2.216***
Florida	2.424***		1.777***
Illinois	3.492***		1.559**
Minnesota	2.025***		1.281
New Jersey	1.709***		1.123
New York	2.160***		1.585***
Ohio	1.787***		1.411*
Oregon	2.132***		1.720***
Texas	1.113		0.876
Virginia	2.116***		1.441**
Model Statistics			
Observations (Unweighted)	29,128	29,128	29,128
Pseudo R^2	0.0110	0.0683	0.0733
Log Pseudolikelihood	-123554.81	-116391.84	-115769.01
* p<.05 , ** p <.01, *** p<.001			

Using Michigan as the contrast state, the logistic regressions for the fixed effects model provide fairly strong support that the individual level characteristics help explain variation in violent rearrest rates between states. Without the individual level characteristics added to the model, the only state with a violent rearrest rate similar to Michigan is Texas (O.R.=1.113, n.s.). When the nine individual level characteristics are added to the model, however, not only does the difference between Michigan and Texas remain non-significant (O.R.=0.876, n.s.), but the findings also become non-significant for California (O.R.=1.095, n.s.), Minnesota (O.R.=1.281, n.s.) and New Jersey (O.R.=1.123, n.s.). Additionally, there is a noticeable reduction in the size of the odds ratio (all decreasing and becoming closer to one) in every state except for Arizona. Although the odds ratio increases for Arizona when all the variables are used (at which point O.R.=2.350, $p<.001$), this is a suppression effect which disappears when the variable race is removed from the model (at which point O.R.=1.881, $p<.001$). The average reduction in the magnitude of the state effects on violent recidivism after the individual recidivism predictors are added to the model is 31%. In other words, state differences in the characteristics of released prisoners explains on average about 31% of the state differences in rates of rearrest for a new violent offense. Thus, even though violent rearrest rates are not as variable across states as general rearrest rates, the individual recidivism predictors explain almost as much of the variation in rearrest for violent crimes as for rearrests for all crime types.

The results differ, however, using the second approach of comparing state-by-state regression models. Without the individual level characteristics added, the initial regression results show that of the 78 state-by-state comparisons, 30 combinations (38.46 percent) have statistically similar violent rearrest rates (refer to Table B1 in Appendix B). When individual level characteristics are added to the model (refer to Table B2 in Appendix B), only 33 combinations (42.31 percent) have statistically similar violent rearrest rates. This is only a small increase in the proportion of state-by-state comparisons for violent rearrest rates with the individual level characteristics added to the model. This approach indicates that very little variation of violent rearrest between states for the 1994 cohort can be explained by the inclusion of the individual level characteristics.

The findings, then, are mixed. The results of the regression model using a single state (Michigan) as the omitted contrast suggest that the individual recidivism predictors explain roughly a third of the variation between states in violent arrests. Using a state-by-state comparison approach, on the other hand, suggests that only a small portion of variation between states can be explained by the individual level characteristics. This leads to the question of why the two approaches yield contrasting results and, specifically, why the individual predictors account for so little of the variation in violent rearrests based on the state-by-state comparisons.

4.4.1: Reasons Why the Individual Covariates May Not Explain Variation in Violent Rearrest Rates across States

Based on the information presented up to this point, along with a review of the literature on violent reoffending, there appear to be two possible explanations for why the findings are mixed. The first is that because there is relatively little variation in violent rearrest rates between most of the states in the 1994 cohort, the addition of individual level characteristics does little to improve on the explanation when used in the state-by-state model; but does help explain variation in the fixed effects model due to the fact that the contrast state has a violent rearrest rate that is at least 35 percent less than all but one of the remaining 12 states. The second is that adding the nine individual level characteristics to the state-by-state model does not help explain much of the variation between states because other individual level factors not considered in this analysis have a stronger effect on violent recidivism than do the predictors under consideration.

There are several reasons to suspect that the lack of an effect using state-by-state models may have to do with the similarity of violent rearrest rates between states. This is a possibility because, as stated at the beginning of this section, for nine of the thirteen states, there is not much difference in the rates of rearrests for violent offenses. Without much variation, two things would be likely. First, one would expect that there would be more states with statistically similar violent rearrest rates without any individual level characteristics in the model. This is, in fact, the case when one compares rearrest for any offense and rearrest for a violent offense. With rearrest for any offense, there are only 20 statistically similar comparisons in the states only models, compared to 30 for violent rearrests. Second, since there is less variation in the percentages between states for violent offenses than general offenses, one would also expect that the inclusion of individual level characteristics would have less of an impact. And this is what occurs. When the nine individual level factors are added to the models, the number of statistically similar states increases by 30 for rearrest for any offense, but only by three for violent rearrest rates.

The second possible explanation is that there are different factors related to violent rearrests than related to general rearrests. In chapter three, it was shown that individual level factors might affect the risk of violent offending differently than general offending. Examining regressions for the entire 1994 cohort revealed that gender, age at first arrest, number of prior arrests and release type had odds ratios that were quite different for those who were rearrested for violent offenses compared to those who were rearrested for nonviolent offenses. Along the same lines, prior research has found that there are several individual level characteristics linked to violent crime other than the nine used in this dissertation.

While pointing out that three childhood behavior problems – enuresis, fire setting and cruelty to animals – had been known to be predictive of violence in adulthood since at least 1960, Justice, Justice and Kraft (1974) further found that childhood fighting, temper tantrums, school problems and truancy also served as warning signs related to future violent behavior. Lefkowitz, Eron, Walder and Huesmann (1977) similarly reported that aggressive behavior exhibited in third grade was the best predictor of aggression at age 19. Hare (1999) reported that offenders who suffered from psychopathy had much higher rates of violent offending than other offenders. Hanson and Bussière's (1998) meta-analysis of sex offenders also found that antisocial personality was a relatively reliable predictor of sexual offense recidivism. Additionally, while this dissertation has pointed out research findings indicating that the number of prior arrests was positively correlated with rearrest rates, Shah (1978) and Hall (1982) found that increased risk of violent recidivism was related to the number of prior acts of violent crime, as opposed to crime in general.

These findings highlight that predictors other than the nine used in this dissertation are related to violent recidivism. Additional evidence that these nine individual level characteristics are far from exhaustive in predicting violent recidivism comes from examining existing instruments used to predict violence. The VRAG (Harris, Rice, and Quinsey, 1993), for example, was judged to be an effective violence prediction instrument in a meta-analytic comparison of instruments used to predict violence conducted by Campbell, French and Gendreau (2009). That instrument includes very few of the individual level characteristics used in the present analysis.

The fact that instruments used to predict future violence make very little use of the nine individual level characteristics gathered from the *Prisoners Released in 1994 dataset*, along with the relationship that exists between violent behavior and childhood behavioral problems, prior aggression, psychopathy, antisocial personality and deviant sexual arousal, are important in helping to understand why the nine individual level characteristics previously described may not necessarily do a good job explaining violent rearrest rates across states.

4.5: Exploring the Differences in Property Rearrest Probabilities across States

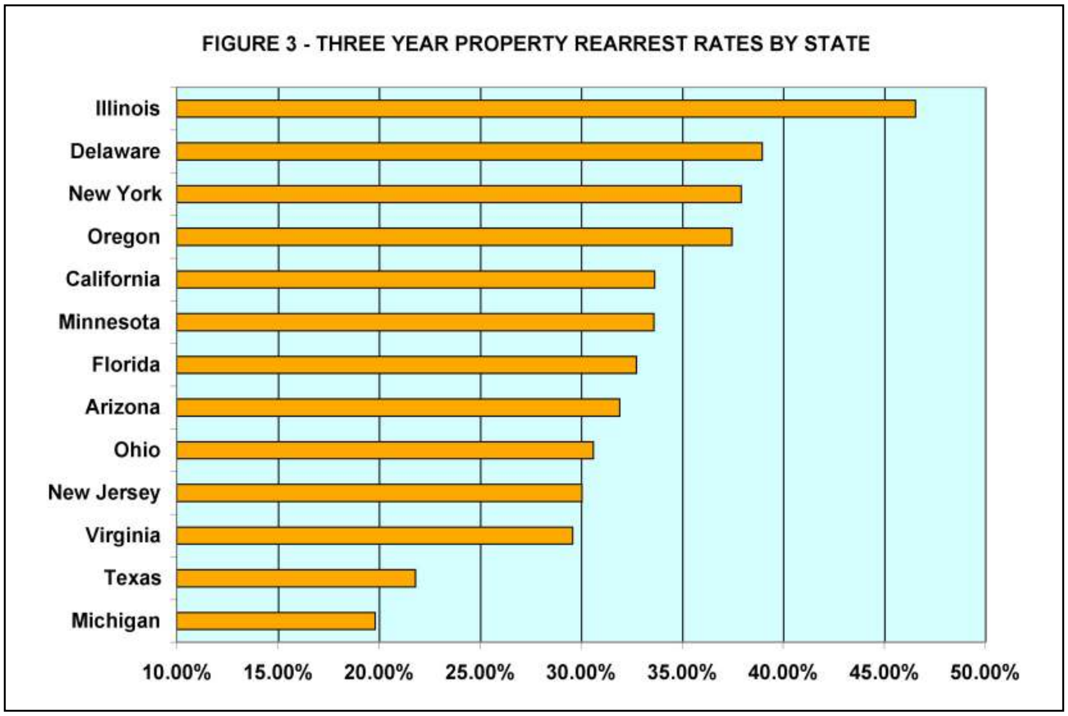


Figure 4.5 on property rearrest rates by state reveals a greater degree of variation than observed for violent rearrest rates, with a low property rearrest rate of 19.82 percent in Michigan and a high of 46.56 percent in Illinois.

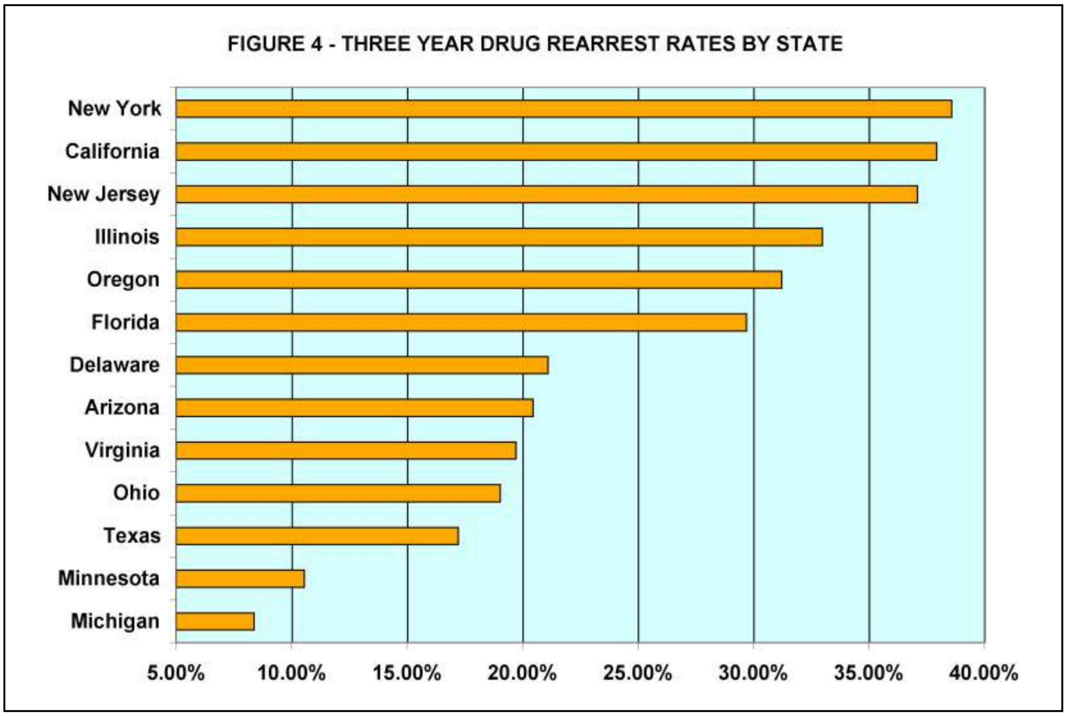
Table 9: Logistic Regression Results for Three Models for Rearrest for A New Property Offense			
	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.226*	1.221*
Age of First Arrest		1.006	1.006
Black		1.447***	1.377***

Other Race		0.772	0.758
Age at Release		0.959***	0.962***
Prior Arrests		1.057***	1.054***
Violent Offense		0.467***	0.450***
Drug Offense		0.366***	0.351***
Public Order Offense		0.464***	0.445***
Other Offense		0.541*	0.547*
Time Served		0.999	0.998*
Parole Violation		1.182**	1.288***
Probation Violation		1.624***	1.329*
Other Admission Type		0.958	0.876
Unknown Admission Type		0.565**	1.057
Mandatory Supervised Release		1.096	1.231*
Expiration of Sentence		1.325*	1.290**
Other Release Type		0.891	0.892
Arizona	1.895***		2.028***
California	2.048***		1.287
Delaware	2.573***		2.093***
Florida	1.980***		1.590***
Illinois	3.515***		2.124***
Minnesota	2.049***		1.720***
New Jersey	1.736***		1.537***
New York	2.466***		2.326***
Ohio	1.783***		1.661***
Oregon	2.422***		1.607***
Texas	1.121		0.949
Virginia	1.693***		1.235
Model Statistics			
Observations (Unweighted)	29,128	29,128	29,128
Pseudo R^2	0.0117	0.0844	0.0926
Log Pseudolikelihood	-145575.28	-134869.11	-133668.18
* p<.05 , ** p <.01, *** p<.001			

Using Michigan as the contrast state, the logistic regressions for the fixed effects model provide fairly strong support that the individual level characteristics help explain variation in property rearrest rates between states. Without the individual level characteristics added to the model, the only state with a property rearrest rate similar to Michigan is Texas (O.R.=1.121, n.s.). When the nine individual level characteristics are added to the model, however, not only does the difference between Michigan and Texas remain non-significant (O.R.=0.949, n.s.), but the findings also become non-significant for California (O.R.=1.287, n.s.) and Virginia (O.R.=1.235, n.s.). Additionally, there is a noticeable reduction in the size of the odds ratio (all decreasing and becoming closer to one) in every state except for Arizona. While the odds ratio increases for Arizona with the full model (from O.R.=1.895, $p<.001$ for the state effects model to O.R.=2.028, $p<.001$ for the full model), this is a suppression effect which disappears when the variable race is removed from the model (at which point O.R.=1.762, $p<.001$). The average reduction in the magnitude of the state effects on property offense recidivism after the individual recidivism predictors are added to the model is 20%. In other words, state differences in the characteristics of released prisoners explains on average about 20% of the state differences in rates of rearrest for a new property offense.

Using the second approach of comparing state-by-state regression models provides additional support for these results. Without the individual level characteristics added, the initial state-by-state results show that of 78 state-by-state comparisons, there are 21 combinations (26.92 percent) that have statistically similar property rearrest rates (refer to Table C1 in Appendix B). When individual level characteristics are added to the model (refer to Table C2 in Appendix B), this number more than doubles. With individual level characteristics added to the model, there are 43 combinations (55.13 percent) that have statistically similar property rearrest rates. This second approach, thus, provides more evidence that the variation in the prevalence of property rearrests between states for the 1994 cohort can be explained, in part, by differences in the characteristics of release cohorts across the states.

4.6: Exploring the Differences in Drug Rearrest Probabilities across States



Similar to the results on overall statewide rearrest rates, Figure 4 reveals a wide degree of variation in three-year drug rearrest rates for offenders released from prison in 1994, with a low of 8.38 percent in Michigan and a high of 38.60 percent in New York. Part of the reason for the wide variation in rearrest rates probably has to do with the amount of emphasis states and individual level police departments within states placed on seeking to arrest drug users and/or sellers. While arrests for violent and property crimes usually result after a victim reports the crime to the police, this is not the case for drug arrests. Instead, arrests for drug crimes often result when police take a proactive approach towards this crime. Such approaches are often the result of a policy decision made by state or local police. Therefore, even though drug arrests may vary considerably across states, the number of drug arrests which occur in a given state or municipality likely has more to do with drug enforcement policies than with the actual use and sale of drugs in a given area (Zimring and Hawkins, 1994).

Table 10: Logistic Regression Results for Three Models for Rearrest for A New Drug Offense

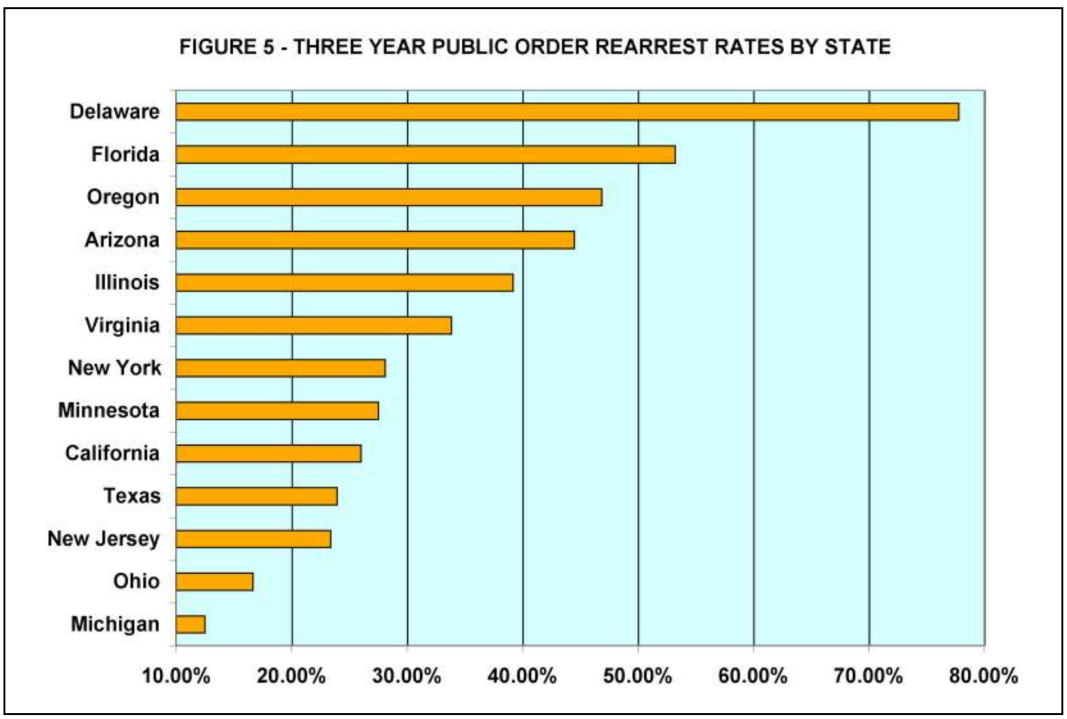
	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.225*	1.229*
Age of First Arrest		1.002	0.998
Black		1.445***	1.511***
Other Race		0.581*	0.573*
Age at Release		0.963***	0.966***
Prior Arrests		1.050***	1.043***
Violent Offense		0.458***	0.459***
Property Offense		0.488***	0.531***
Public Order Offense		0.503***	0.523***
Other Offense		0.631	0.601*
Time Served		0.996**	0.997*
Parole Violation		1.243*	1.197**
Probation Violation		1.051	1.073
Other Admission Type		0.697	0.811
Unknown Admission Type		0.330***	0.680
Mandatory Supervised Release		1.337***	1.132
Expiration of Sentence		1.243*	1.346**
Other Release Type		0.854*	0.919
Arizona	2.822***		2.840***
California	6.682***		4.080***
Delaware	2.866***		1.483*
Florida	4.645***		3.052***
Illinois	5.368***		2.886***
Minnesota	1.289*		1.142
New Jersey	6.460***		3.810***
New York	6.861***		4.336***
Ohio	2.572***		1.945***
Oregon	4.948***		3.583***
Texas	2.299***		1.795***

Virginia	2.671***		1.830***
Model Statistics			
Observations (Unweighted)	29,128	29,128	29,128
Pseudo R^2	0.0306	0.0745	0.0875
Log Pseudolikelihood	-141388.01	-134990.05	-133092.67
* p<.05 , ** p <.01, *** p<.001			

Using Michigan as the contrast state, the logistic regressions for the fixed effects model provide fairly strong support that the individual level characteristics help explain variation in drug rearrest rates between states. Without the individual level characteristics added to the model, every state has a significantly higher rearrest rate for drug offenses than Michigan. When the nine individual level characteristics are added to the model, however, the difference between Michigan and Minnesota becomes non-significant (O.R.=1.142, n.s.). Additionally, there is a noticeable reduction in the size of the odds ratio (all decreasing and becoming closer to one) in every state except for Arizona, where the increase is negligible. The average reduction in the magnitude of the state effects on drug offense recidivism after the individual recidivism predictors are added to the model is 34%. In other words, state differences in the characteristics of released prisoners explains on average about 34% of the state differences in rates of rearrest for a new drug offense.

Using the second approach of comparing state-by-state regression models provides additional support for the conclusions found using the fixed effect model. Without individual level characteristics added, the initial state-by-state results show that of 78 state-by-state comparisons, 16 combinations (20.51 percent) have statistically similar drug rearrest rates (refer to Table D1 in Appendix B). When individual level characteristics are added to the model (refer to Table D2 in Appendix B), this number increases by 81 percent. With individual level characteristics added to the model, 29 combinations (37.18 percent) have statistically similar drug rearrest rates. Both approaches provide evidence that a sizable fraction of the variation in the prevalence of drug rearrests between states for the 1994 cohort can be explained by the inclusion of individual level characteristics.

4.7: Exploring the Differences in Public Order Rearrest Probabilities across States[2]



Similar to the figures on overall statewide rearrest rates and on drug rearrest rates, Figure 5 shows a wide degree of variation in three-year public order rearrest rates for offenders released from prison in 1994, with a low of 12.50

[2] This section excludes rearrests for parole violations.

percent in Michigan and a high of 77.81 percent in Delaware. One reason for the wide degree of variation is differences in state laws, with some states mandating that certain offenses be recorded as an arrest while others issue citations, which do not count as arrests. Beyond that, arrest rates for public order offenses are also influenced by the amount of emphasis states and local jurisdictions place on seeking arrests for these offenses.

Table 11: Logistic Regression Results for Three Models for Rearrest for A New Public Order Offense

	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.304**	1.336**
Age of First Arrest		0.992	0.994
Black		1.088	1.047
Other Race		0.968	0.982
Age at Release		0.947***	0.947***
Prior Arrests		1.039***	1.035***
Violent Offense		0.669***	0.673***
Property Offense		0.648***	0.653***
Drug Offense		0.647***	0.667***
Other Offense		0.411**	0.470*
Time Served		0.999	0.997**
Parole Violation		1.081	1.214*
Probation Violation		2.232***	1.114
Other Admission Type		0.822	0.647*
Unknown Admission Type		0.303***	0.958
Mandatory Supervised Release		1.174**	1.483***
Expiration of Sentence		1.728***	1.236**
Other Release Type		2.110***	0.955
Arizona	5.539***		5.260***
California	2.454***		1.215
Delaware	24.083***		17.618***
Florida	8.004***		6.543***
Illinois	4.493***		2.128***
Minnesota	2.660***		1.703***
New Jersey	2.134***		1.606***
New York	2.731***		2.079***
Ohio	1.397**		1.208

Oregon	6.171***		4.090***
Texas	2.093***		1.653***
Virginia	3.571***		2.570***
Model Statistics			
Observations (Unweighted)	29,128	29,128	29,128
Pseudo R^2	0.0387	0.0745	0.0790
Log Pseudolikelihood	-135110.65	-149246.06	-129453.57
* p<.05 , ** p <.01, *** p<.001			

Using Michigan as the contrast state, the logistic regressions for the fixed effects model provide fairly strong support that the individual level characteristics help explain variation in public order rearrest rates between states. Without the individual level characteristics added to the model, every state has a significantly higher rearrest rate for public order offenses than Michigan. When the individual level characteristics are added to the model, however, the difference between Michigan and California (O.R.=1.215, n.s.) and Michigan and Ohio (O.R.=1.208, n.s.) become non-significant. Additionally, there is a reduction in the size of the odds ratio (all decreasing and becoming closer to one) in every state when the individual level factors are added to the model. The average reduction in the magnitude of the state effects on public order offense recidivism after the individual recidivism predictors are added to the model is 27%. In other words, state differences in the characteristics of released prisoners explains on average about 27% of the state differences in rates of rearrest for a new public order offense.

Similar results are obtained using the second approach of comparing state-by-state regression models. Without the individual level characteristics added, the initial state-by-state results show that of 78 state-by-state comparisons, there are only 6 combinations (7.69 percent) that have statistically similar public order rearrest rates (refer to Table E1 in Appendix B). As was the case with drug arrests, this largely reflects the great variation in public order arrest rates between states. When individual level characteristics are added to the model (refer to Table E2 in Appendix B), this number more than triples. With individual level characteristics added to the model, 22 combinations (28.21 percent) have statistically similar public order rearrest rates.

4.7.1: Explaining the Wide Degree of Variation in Public Order Rearrests Across States

While it has already been stated that differences in state laws are one reason that explains differences in public order rearrest rates, the large state variation in public order rearrests – especially the extremely high rearrest rate in Delaware -- makes a more detailed analysis of public order offenses helpful in understanding these differences. Table 12 partitions the public order rearrests by specific charge definitions and shows the percentage of released offenders from each of the thirteen states who were arrested on each of 25 separate public order offenses (including attempt to commit and conspiracy to commit offenses).

Examining these individual offense arrests, it becomes clear that one reason public order rearrests were so much greater in Delaware than in any other state is the large difference between Delaware and almost every other state for three specific offenses. In Delaware, 48.91 percent of released offenders were rearrested for a minor traffic violation, 34.22 percent were rearrested for a probation violation, and 33.91 percent were rearrested for contempt of court.

Looking at two of the charges – probation violations and minor traffic offenses – shows how state laws differ, with some requiring an arrest for an infraction while others do not. In Delaware, Florida and Oregon, over 14 percent of the offenders were rearrested for a probation violation, compared with less than 1 percent rearrested for such a charge in Arizona, California, Michigan, Minnesota, New York and Texas (in fact no offenders were rearrested for a probation violation in New York and only one offender--out of over 20,000 released--was rearrested for a probation violation in Texas). These wide variations in percentages do not indicate that probation violations are common in some states and rare in others. Instead, they indicate that in some states probation violations are initiated with a formal arrest while in other states this is a rare practice.

Another example involves minor traffic violation arrests in Delaware and in California. As shown in Table 12, 48.91 percent of released offenders from Delaware (313 out of 640 released offenders) were rearrested for a minor traffic violation, yet only 0.21 percent of released offenders from California (220 out of 103,325 released offenders) were rearrested for a minor traffic violation. The explanation for this huge difference comes from the different way traffic offenders are dealt with in each state. In Delaware, it appears that all traffic offenses are counted as arrests, while in California they are almost always dealt with as traffic violation citations and not as arrests.

While the explanation above helps explain the wide degree of variation in public order rearrests between states, it also points out a potential limitation of the *Prisoners Released in 1994 dataset*. Although the dataset is very clear about

Table 12 - Public Order Rearrests by Specific Charges													
	AZ	CA	DE	FL	IL	MI	MN	NJ	NY	OH	OR	TX	VI	TOTAL
OBSTRUCTION-JUSTICE	12.68%	9.86%	11.88%	18.27%	9.21%	1.90%	8.13%	8.86%	9.66%	4.79%	11.43%	6.02%	4.72%	**9.65%**
WEAPON-OFFENSE	5.63%	7.40%	7.19%	6.47%	10.59%	2.02%	4.10%	7.84%	10.88%	3.75%	9.05%	3.27%	7.08%	**7.18%**
PROBATION-VIOLATION	0.39%	0.11%	34.22%	26.55%	1.22%	0.09%	0.56%	0.24%	0.00%	3.92%	14.19%	0.00%	2.49%	**3.10%**
MINOR-TRAFFIC-OFFENSE	15.07%	0.21%	48.91%	6.71%	5.18%	6.47%	5.65%	0.76%	4.76%	0.26%	16.95%	4.37%	0.68%	**2.96%**
DRUNK-VAGRANT-DISORDERLY	8.92%	1.45%	8.75%	6.58%	11.64%	0.67%	0.93%	1.14%	2.89%	0.48%	2.41%	0.36%	1.67%	**2.75%**
COURT-OFFENSE	17.06%	0.81%	1.56%	9.68%	5.84%	0.07%	1.55%	0.69%	0.63%	1.64%	16.51%	0.55%	0.70%	**2.51%**
FLIGHT-TO-AVOID	1.59%	1.73%	3.28%	0.94%	1.46%	0.87%	5.40%	0.98%	0.00%	0.51%	5.26%	4.97%	1.23%	**1.68%**
CONTEMPT-OF-COURT	1.31%	0.83%	33.91%	2.56%	1.27%	0.00%	0.00%	2.35%	2.32%	0.16%	3.73%	0.00%	14.39%	**1.58%**
IMMIGRATION-OFFENSE	0.00%	3.49%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**1.55%**
INVASION-OF-PRIVACY	0.39%	0.50%	0.78%	5.84%	1.07%	0.19%	0.87%	1.78%	2.63%	0.97%	3.35%	0.22%	1.70%	**1.38%**
COMMERCIALIZED-VICE	1.59%	1.36%	0.94%	1.65%	2.26%	0.30%	0.31%	0.51%	1.77%	1.21%	0.63%	1.41%	0.26%	**1.37%**
OTHER-PUBLIC-ORDER	2.16%	1.57%	3.44%	1.16%	0.28%	0.39%	1.74%	1.01%	1.43%	0.17%	2.07%	0.18%	0.22%	**1.17%**
DUI	8.66%	1.05%	8.28%	1.01%	0.67%	0.36%	0.74%	0.47%	0.00%	0.26%	1.54%	0.31%	0.60%	**0.94%**
DWI	1.35%	0.00%	0.00%	0.00%	0.00%	0.00%	7.45%	0.00%	0.00%	0.19%	6.14%	7.79%	0.09%	**0.87%**
ESCAPE	1.16%	0.45%	7.34%	1.38%	0.68%	0.00%	1.24%	0.53%	0.31%	1.07%	3.82%	0.42%	1.23%	**0.66%**
MORALS-OFFENSE	0.33%	0.80%	0.63%	0.56%	0.23%	0.21%	0.25%	0.11%	0.59%	0.24%	0.72%	0.54%	0.40%	**0.59%**
FAMILY-RELATED-OFFENSE	0.81%	0.13%	1.41%	1.03%	0.00%	0.43%	0.25%	0.49%	1.72%	0.30%	0.41%	0.00%	0.33%	**0.43%**
RIOT	0.06%	0.06%	0.16%	0.09%	3.17%	0.00%	0.06%	0.11%	0.00%	0.00%	0.13%	0.02%	0.00%	**0.25%**
ATTEMPTED OFFENSE	0.06%	0.00%	0.31%	0.00%	0.00%	0.00%	0.00%	1.78%	0.03%	0.00%	0.00%	0.00%	3.28%	**0.16%**
LIQUOR-LAW-VIOLATION	1.38%	0.10%	2.66%	0.00%	0.18%	0.16%	0.25%	0.00%	0.07%	0.00%	0.34%	0.18%	0.09%	**0.13%**
CONTRIBUTING-TO-DELINQUENCY	0.37%	0.10%	0.16%	0.06%	0.56%	0.00%	0.19%	0.24%	0.00%	0.01%	0.25%	0.03%	0.42%	**0.13%**
HABITUAL-OFFENDER	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.53%	**0.08%**
BRIBERY	0.07%	0.02%	0.00%	0.01%	0.00%	0.00%	0.00%	0.11%	0.00%	0.07%	0.13%	0.03%	0.02%	**0.03%**
CONSPIRACY TO COMMIT	0.00%	0.07%	0.00%	0.00%	0.04%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**0.03%**
DUI-DRUGS	0.00%	0.00%	0.00%	0.16%	0.00%	0.00%	0.06%	0.09%	0.00%	0.00%	0.19%	0.00%	0.00%	**0.02%**
TOTAL	44.20%	25.96%	77.50%	53.02%	39.05%	12.51%	27.56%	23.27%	28.09%	16.30%	46.62%	23.13%	33.80%	29.28%

collecting data related to rearrests, it does not take into account how certain offenses (almost exclusively of a public order nature) are counted as arrests in one state but not another. This means some caution must be used when looking at the results between states for public order offenses. Due to differences in state laws, one offender who commits a public order violation may be caught and arrested in one state and end up counted as a recidivist, while another offender in another state may commit the exact same public order violation and be caught but issued a citation instead of an arrest and, as a result, may not be counted as a recidivist.

4.8: Discussion

Using two separate analytical approaches, the findings from the preceding sections provide fairly strong evidence that variation in the previously described characteristics of prison release cohorts explains roughly a fifth to a third of the variation between states in rearrests for any offense, rearrests for property offenses, rearrests for drug offenses and rearrests for public order offenses. The evidence related to rearrests for violent offenses was mixed, with the state-by-state comparisons showing much weaker effects of the individual recidivism predictors than shown by the standard regression approach using a single omitted contrast state. The reason for the mixed findings is likely due to one of two possibilities. The first is that there was little variation between most of the states in the cohort, but there was nevertheless a fair amount of variation in violent rearrest rates between the contrast state and all but one of the other states. This combination would produce a small amount of variation explained using a state-by-state comparison, yet would not produce a small variation using a single omitted contrast state. The second possibility is that other individual level factors not considered in this analysis have a stronger effect on violent recidivism than do the predictors under consideration. In the next chapter, three additional forms of recidivism are explored: reconviction, reimprisonment and parole violations.

CHAPTER 5 - EXPLORING THE IMPACT OF INDIVIDUAL LEVEL CHARACTERISTICS ON RECONVICTION, RECONFINEMENT AND PAROLE VIOLATIONS

5.1: Introduction

While the prior chapter showed that the nine individual level characteristics help to explain the variation between states for rearrest for any offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense, this fact does not mean that the characteristics will also be good predictors of variations between states for reconviction probabilities, reconfinement probabilities or parole violations. One reason for this is that not all of the individual level characteristics are likely to influence reconviction or reimprisonment probability. For example, the specific type of admission to prison for the last offense by itself probably matters little to a court in deciding whether to convict a defendant. Similarly, the amount of time served on the last sentence should not matter in determining whether to drop the charges or proceed for a prosecutor and whether to convict or acquit for a judge or jury. Beyond this, a second reason why individual level characteristics may have different influences depending on the measure of recidivism is because prior research has shown that the theoretical reasons that help explain why the variables have an impact are different for different measures of recidivism. One example of an individual level characteristic that would possibly increase the likelihood of reconviction and reimprisonment, but would do so for different reasons than for rearrests, is the number of prior arrests. In chapter three, the number of prior arrests was shown to be strongly associated with increased odds of rearrest based on differential association and social learning theory. These theories do not, however, explain why these offenders are more likely to be reconvicted or reimprisoned. Instead, the reason why the number of prior arrests would lead to an increased conviction rate is because prosecutors would be more willing to devote time and resources towards a defendant with a lengthy criminal record (Kingsnorth, MacIntosh, and Sutherland, 2002). Judges, similarly, would be more willing to imprison those with more prior arrests because they are viewed as more blameworthy and more of a threat to society. The rationale behind why judges are more likely to imprison offenders with lengthy arrest records is based on the focal concerns theory (Steffensmeier, Ulmer, and Kramer, 1998). According to this perspective, there are three concerns that judges take into consideration when sentencing defendants – blameworthiness and degree of harm caused, protection of the community, and practical constraints and consequences.

Although the study was published before Steffensmier et al.'s (1998) work, a good example of how judges' decision making is influenced by focal concerns and a further example of why one group of offenders is more likely to be sentenced leniently than another comes from a study published by Steffensmeier, Kramer and Streifal (1993). They analyzed over 60,000 cases from Pennsylvania that occurred between 1985 and 1987 and found that female defendants were about 12 percent less likely to be imprisoned than similarly situated male defendants. They further explored cases involving "judicial departures" – where judges sentenced defendants to a lesser term than was prescribed statutorily – and noted that female defendants were more likely than male defendants to receive a judicial departure (29% of female defendants vs. 15% of male defendants). In these cases, judges were required to provide a written explanation outlining the reasons for their departure. Reading through these reasons, the authors concluded that there were five primary reasons judges commonly gave and that these reasons were in line with the focal concerns that female defendants were less of a threat and had more ties to or responsibilities in the community. The five primary justifications given for sentencing both male and female defendants leniently (p. 433) were:

1. defendant has a nonviolent prior record (e.g., a high prior record score that consists solely of property offending),
2. defendant has mental or health problems (e.g., jailing would overburden the jail staff and would harm rather help the defendant),
3. defendant is caring for dependents or is pregnant (e.g., jailing would not protect the community in the long term and would be inhumane, risky, and possibly costly),
4. defendant played a minor role in the crime or was only an accomplice, and
5. defendant showed remorse (e.g., "felt bad about what he/she had done").

A second example of focal concerns influencing sentencing decisions comes from comparing the sentences received by young black defendants compared to similarly situated white defendants. Spohn and Holleran (2000) studied sentencing patterns of defendants from three jurisdictions – Chicago, Miami and Kansas City – and found evidence of a "penalty price" paid at sentencing for young male defendants who were either black or Hispanic. Viewed by judges as more culpable than their white counterparts, such defendants were sentenced more harshly. This sentencing disparity was even more amplified for young, male minority defendants who were unemployed. This finding is in line with Steffensmeier and Demuth's (2000) observation that, faced with incomplete information on criminal defendants, judges often revert to sentencing based on the stereotypical viewpoints they held that black offenders were more culpable than white offenders.

Thus, research has found that males and blacks are sentenced more harshly than females and whites because of focal concerns. An additional theoretical perspective that predicts females will be sentenced more leniently than male defendants is the chivalry/paternalism hypothesis, which suggests "women are awarded leniency in sentencing as a result of their inherent biological weaknesses and consequently, their need to be coddled both as offenders and as victims" (Franklin and Fearn, 2008, p. 279). Similarly, another theoretical rationale used to explain why blacks are more likely to be incarcerated than whites is the racial threat hypothesis (Blalock, 1967). This theory states that blacks are more likely to be imprisoned because they have been stereotyped in many segments of America as being a more dangerous or threatening form of criminal than white offenders. Crawford, Chiricos and Kleck (1998) wrote that trends in sentencing African Americans were becoming more punitive over time because African American criminal defendants were being seen more and more in terms of being a crime specific "racial threat" to the white status quo.

What is noteworthy about the focal concerns, chivalry/paternalism, and racial threat perspectives is that while they help explain research which has found that white and female defendants are less likely to be imprisoned than black and male defendants, (Rodriguez, Curry, and Lee, 2006; Daly, 1994; Crawford et al., 1998; Mitchell, 2005; Steffensmeier et al., 1993), these are not the same theoretical perspectives which predict that males and blacks will be more likely to be rearrested. Instead, differential association has been offered as an explanation for why men offend more than women and blacks are thought to be involved in crime more than whites because of social disorganization theory. Specifically, prior research has found that black offenders often live in or return to communities which contain factors such as residential instability, racial-ethnic heterogeneity, family disruption, resource deprivation and racial inequality (Harer, 1994; Anderson, 1999; Kubrin and Stewart, 2006; Reisig, Bales, Hay, and Wang, 2007; Mears, Wang, Hay, and Bales, 2008). These factors inhibit the development of protective, prosocial networks and, in turn, increase the risk of offending for persons who live in these neighborhoods.

Thus before proceeding on to the analyses, it is important to understand that the nine individual level factors may not have the same effect on different measures of recidivism. One reason for this is that some of the factors that have been found to have an influence on likelihood of rearrest may have no influence on the probability of reconviction or reimprisonment. A second reason is that while some of the factors may influence all forms of recidivism, the basis for their influence may be qualitatively different depending on the type of recidivism under consideration.

5.2: Exploring the Differences in Reconviction Probabilities across States

FIGURE 6 - THREE YEAR RECONVICTION PROPORTION OF REARRESTED OFFENDERS BY STATE

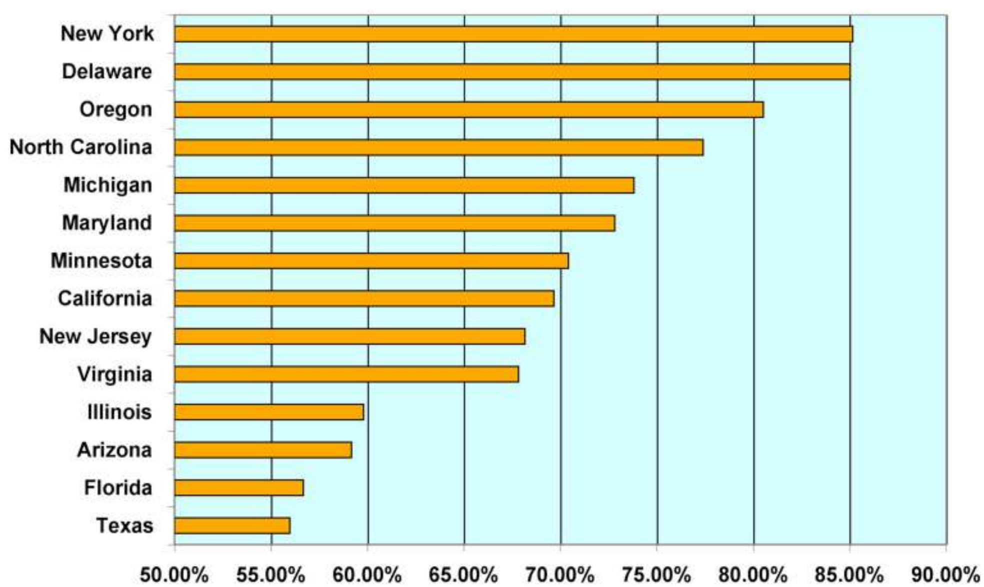


Figure 6 provides the reconviction proportions for those released offenders who are rearrested within three years of their release. This figure shows a moderate amount of variation, with a low of 55.99 percent of rearrested offenders being reconvicted in Texas and a high of 85.17 percent of rearrested offenders being reconvicted in New York. It should be noted that these percentages were based on a sample that was limited exclusively to those released offenders who had been rearrested for a new crime. As previously explained, this was done to prevent bias that would result because some individual level characteristics are associated with increased probability of arrest. Also, because data on reconviction were not provided for offenders released in Ohio, that state was dropped from the model.

Table 13: Logistic Regression Results for Three Models of Reconviction for a New Offense (for Rearrested Offenders)

	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.073	1.047
Age of First Arrest		1.001	0.999
Black		1.061	1.054
Other Race		0.778	0.714
Age at Release		0.988**	0.989*
Prior Arrests		1.020***	1.016***
Violent Offense		0.750***	0.700***
Drug Offense		0.937	0.870*
Public Order Offense		0.848	0.789*
Other Offense		0.724	0.681
Time Served		0.998	0.996***
Parole Violation		1.130*	1.129
Probation Violation		1.038	1.125
Other Admission Type		0.851	0.799
Unknown Admission Type		1.162	0.732
Mandatory Supervised Release		0.797***	1.105
Expiration of Sentence		0.929	1.859***
Other Release Type		0.637***	1.466**
Arizona	1.128		1.033
California	1.789***		1.678***
Delaware	4.346***		3.310***
Florida	1.024		0.737*
Illinois	1.155		1.089
Maryland	2.100***		2.423***
Michigan	2.197***		3.121***
Minnesota	1.858***		1.923***
New Jersey	1.673***		1.658***

New York	4.479***		4.884***
North Carolina	2.670***		2.855***
Oregon	3.220***		3.168***
Virginia	1.641***		1.703***
Model Statistics			
Observations (Unweighted)	18,521	18,521	18,521
Pseudo R^2	0.0273	0.0121	0.0390
Log Pseudolikelihood	-102998.38	-104612.78	-101761.05
* p<.05 , ** p <.01, *** p<.001			

Because Texas had the lowest probability of reconviction, it was used as the contrast state for the fixed effects model. The logistic regressions for these models indicate that the individual level characteristics explain little of the variation in reconviction probabilities between states. Without the individual level characteristics added to the model, the three states that have similar reconviction proportions to Texas are Arizona (O.R.=1.128, n.s), Florida (O.R.=1.024, n.s) and Illinois (O.R.=1.155, n.s). When the nine individual level characteristics are added to the model, although Arizona (O.R.=1.033, n.s.) and Illinois (O.R.=1.089, n.s.) continue to have statistically similar reconviction proportions as Texas, the difference between Florida and Texas becomes significant (O.R.=0.737, p<.05). Further, while there are no changes in the significance levels of the ten remaining states, a decrease in the size of the odds ratio occurs in only four of these states (California, Delaware, New Jersey and Oregon). The change from non-significant to significant in Florida and the increase in the size of the odds ratio for Maryland, Michigan, Minnesota, New York, North Carolina and Virginia are all suppression effects that disappear when particular variables are dropped from the models. The decrease in the size of the odds ratio for these states without all the variables in the model is not large in any case. In summary, the average reduction in the magnitude of the state effects on reconviction probabilities after the individual recidivism predictors are added to the model is negligible.

Using the second approach of comparing state-by-state regression models produces some support for the proposition that variations in individual level characteristics can help explain differences in reconviction proportion across states. Without individual level characteristics added, the initial state-by-state results show that of 91 state-by-state comparisons, 19 combinations (20.88 percent) have statistically similar reconviction probabilities for offenders who were rearrested within three years of their release from prison (refer to Table F1 in Appendix B). When individual level characteristics are added to the model (refer to Table F2 in Appendix B), 29 combinations (31.89 percent) have statistically similar reconviction probabilities. This increase of 53 percent thus provides some evidence that the variation in the proportion of rearrested offenders between states can be explained by individual level characteristics.

When each of the individual level characteristics is added separately to the state-by-state regressions, release type is found to be the variable with the greatest effect, as the number of states with statistically similar reconviction probabilities increases from 19 to 25 when this variable is added. Looking at the odds ratios for the release type variables in the individual level characteristics model and the combined model, it can be seen why release type has the greatest impact in a state-by-state comparison. In the individual level characteristics model, mandatory supervised released, expiration of sentence and other release type all have an odds ratio lower than one when compared to those released via discretionary parole, a difference which is statistically significant for mandatory supervised release and other release type. When state of release is added to the model, however, it becomes very clear that it was the specific release characteristics of individual states that drove these low odd ratios as all three release types increase to above one and as those released via expiration of sentence and other release type become significantly more likely to be reconvicted than those released via discretionary parole. Although type of release from prison is considered an "individual" characteristic in this analysis, it is quite different of course than characteristics such as sex, age, or race. Type of release is largely a matter of state policy, which explains why the inclusion of the state effects in the analysis has such an important effect on the results.

The findings, then, are mixed. The results of the regression model using a single state (Texas) as the omitted contrast suggest that the individual level characteristics are not useful in explaining variation between states in reconviction probabilities of rearrested offenders. Using a state-by-state comparison approach, on the other hand, provides some evidence that the variation in reconviction can be explained by individual level characteristics. This leads to the question of why the two approaches yield contrasting results and, specifically, why the individual predictors account for virtually none of the variation in reconviction proportions based on the fixed effects model.

5.2.1: Reasons Why the Individual Covariates May Not Explain Variation in Reconviction Probabilities across States

One very important reason why individual level factors may not affect the likelihood of a conviction stems from the nature of the American judicial system and the legal concept of reasonable doubt. In America, justice is supposed to be blind and the decision to seek a conviction along with having a judge or jury find a defendant guilty is supposed to result from the strength of the evidence and the State's ability to prove its case beyond a reasonable doubt. To the extent that this is actually true, it is not supposed to matter if a former prisoner is male or female, black or white, 20 or 40, or a former property offender or a former drug offender in determining whether an offender will be reconvicted. What is supposed to matter, instead, is whether the evidence can prove guilt beyond a reasonable doubt.

A second reason why the individual level factors may not have an impact is because they may not be the right factors to look at. One factor that might explain some of the variation between states is the desire prosecutors in some states have for high conviction rates. Since over 95 percent of chief prosecutors in office in 1994 were elected locally (DeFrances, Smith, and van der Does, 1996), some might have been influenced to select the most winnable cases, especially if their term of office was short or political competition was high (Rasmussen, Raghav, and Ramseyer, 2009). While such a strategy would undoubtedly increase conviction rates, it would also result in a lower arrest-conviction ratio, since weaker cases would not even be prosecuted. Under this scenario, one factor that would have more of an influence would be political motivation.

In addition to political motivation, research has also found that the amount of monetary resources a prosecutor's office has influences the number of cases it will prosecute. More resources would result in a higher arrest-conviction ratio, since an increase in the percentage of cases prosecuted should result in an increase in the number of convictions that result (even if the conviction rate declines). Support for this hypothesis comes from two papers. Rasmussen et al. (2009) examined data from over 2,000 county prosecutors' offices using the 2001 National Prosecutor's Survey administered by the Bureau of Justice Statistics. They found "that higher budgets are associated with both higher amounts of prosecution and higher conviction rates conditioning on the amount of prosecution" (p. 26). A second report by Blaine, Entwistle, Nystrom and Weaver (2010) looked at prosecution spending for individual counties within Oregon. They found "a strong positive correlation between the amount of money spent prosecuting a crime versus the number of overall convictions" (p. 8).

The fact that criminal justice convictions are supposed to be based on the strength of the evidence along with the likelihood that prosecutorial decisions may be influenced by both politics and financial considerations provide fairly good explanations as to why the nine individual level factors would not be useful in explaining between state variations in reconviction probabilities. These reasons, however, do not explain why there was an increase in the number of states with similar reconviction probabilities in the state-by-state model when individual level characteristics were included.

Part of the reason for this increase may be that prosecutors have discretion in determining which cases to prosecute and individual level factors may influence these decisions. The one individual level factor that will almost certainly have an impact on a prosecutor's decision is a defendant's prior record, as almost any prosecutor would choose to prosecute a defendant with 20 prior arrests as opposed to one with just two. Further, although justice is supposed to be blind, in some states or jurisdictions, prosecutors may be influenced to proceed with cases and juries may be swayed to convict based partly on an offender's age, gender and/or race. Thus, if individual level factors did, in fact, have an influence on the decision to prosecute and/or convict in some jurisdictions, this may explain why these factors influenced reconviction probabilities in certain state-by-state comparisons, even though this effect was not seen in the fixed effects model.

5.2.2: Individual Level Factors Related to Increased Probability of Reconviction

The results from the individual level characteristics model and combined model reveal that among offenders released from prison who are rearrested for a new crime, that those who are younger at the age of release are more likely to be reconvicted, those who have more prior arrests are more likely to be reconvicted, and those who are released for a violent offense are less likely to be reconvicted than property offenders. While not significant in the combined model, in the individual level characteristics model, those who entered prison via parole violation are more likely to be reconvicted than those who entered prison via a new court conviction. Additionally, while not significant in the individual level characteristics model, in the combined model those who served less time were more likely to be reconvicted and both those who had been released for a drug offense and those who had been released for a public order offense were less likely to be reconvicted than those released for a property offense.

The reason why those who have more arrests are more likely to be convicted goes back to the idea that prosecutors would be more willing to devote time and resources towards a defendant with a lengthy criminal record (Kingsnorth et al., 2002). Regarding the finding that older offenders are less likely to be reconvicted, one possible explanation is that, as offenders age, they become better at the crimes they do commit. Evidence for this comes partly from research that points out that older people who remain criminally active are more likely to start specializing in one specific crime (Farrington, 1986; Blumstein, Cohen, Das and Moitra, 1988). The reason they specialize is they begin to realize what crimes they are good at and, as a result, know how to commit these crimes without leaving enough evidence to lead to a conviction.

5.3: Exploring the Differences in Reimprisonment Probabilities across States

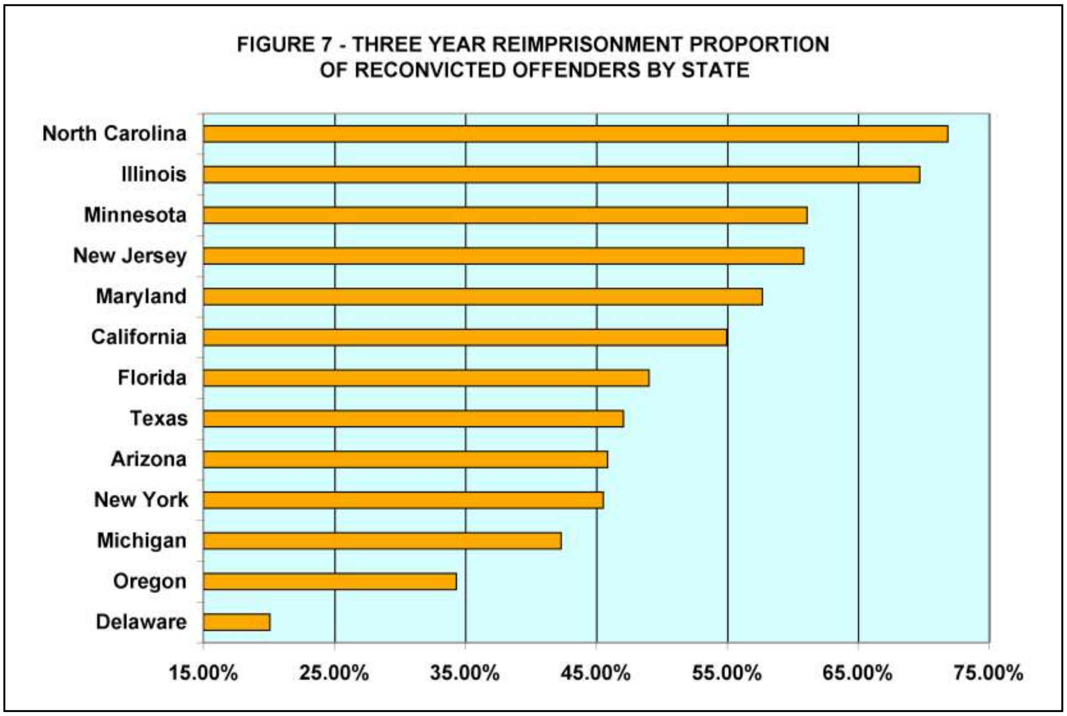


Figure 7 provides the reimprisonment probabilities for those released offenders who are reconvicted of an offense resulting from an arrest that occurred within three years of their release. This figure shows a wide degree of variation in reimprisonment rates, with a low of 20.09 percent of reconvicted offenders being reimprisoned in Delaware and a high of 71.87 percent of reconvicted offenders being reimprisoned in North Carolina. One notable observation that can be made looking at Figure 7 is that, although Delaware has the highest proportion of released offenders who are rearrested and the second highest reconviction rate of rearrested offenders, it has the lowest rate of giving reconvicted prisoners new prison sentences. While this fact is at least partly due to the high number of rearrests for minor public order offenses in Delaware, this observation also highlights that different state court systems deal with convicted offenders in different manners.

Before the regression models were estimated for this section, the sample was modified to only include a sample of released offenders who had been reconvicted of a new crime. As previously explained, this was done to prevent bias that would result because some individual level characteristics are associated with increased probability of arrest. Also, because data on reimprisonment were not provided for offenders released in Ohio or Virginia, these states were dropped from the model.

Table 14: Logistic Regression Results for Three Models for Reimprisonment for a New Offense (for Reconvicted Offenders)

	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.673***	1.672***
Age of First Arrest		1.018*	1.021**
Black		1.258***	1.132
Other Race		0.524*	0.488*
Age at Release		0.980***	0.980***
Prior Arrests		1.004	1.009
Violent Offense		0.757***	0.771**
Drug Offense		0.831*	0.880
Public Order Offense		0.800*	0.791*
Other Offense		0.643	0.675
Time Served		1.002	1.006***
Parole Violation		1.072	1.024
Probation Violation		0.612***	0.791
Other Admission Type		1.321	1.278
Unknown Admission Type		2.713***	1.055
Mandatory Supervised Release		1.405***	1.000
Expiration of Sentence		1.099	1.130
Other Release Type		1.126	1.631***
Arizona	1.622***		1.347
California	2.336***		2.404***
Delaware	0.481***		0.284***
Florida	1.842***		1.150
Illinois	4.407***		4.050***

Maryland	2.610***		2.317***
Michigan	1.406**		1.253
Minnesota	3.008***		2.907***
New Jersey	2.975***		2.744***
New York	1.600***		1.317*
North Carolina	4.890***		5.274***
Texas	1.704***		1.449*
Model Statistics			
Observations (Unweighted)	11,405	11,405	11,405
Pseudo R^2	0.0154	0.0335	0.0390
Log Pseudolikelihood	-102998.38	-104612.78	-101761.05
* p<.05 , ** p <.01, *** p<.001			

While this study has generally opted to use the state with the lowest rate or proportion of offenders who recidivate as the contrast state in the regression analyses, in this case a decision was made to use the state with the second lowest proportion of reimprisoned offenders as the contrast state. The reason for this had to do with the difficulty of explaining the findings that occurred when models were estimated using Delaware as the contrast state. When the individual level characteristics were added to the state of release model, the odds ratio increased for every state in the model. While the exact reasons for this are not totally clear, with this finding, along with the fact that Delaware had the highest rearrest rate and the second highest reconviction proportion yet a much lower reimprisonment proportion than any other state, it seemed likely that Delaware's sentencing laws relating to incarceration were not comparable to other states and that it would be inappropriate, for this reason, to use Delaware as the contrast state. As a result, Oregon was chosen as the contrast state as it had the second lowest proportion of reconvicted offenders who were resentenced to prison.

Using Oregon as the contrast state, the logistic regressions for the fixed effect models provide fairly strong support that the individual level characteristics help explain variation in reimprisonment probabilities between states for reconvicted offenders. Without the individual level characteristics added to the model, there are no states with reimprisonment proportions similar to Oregon. When the nine individual level characteristics are added to the model, however, the findings become non-significant comparing Oregon and Arizona (O.R.=1.347, n.s), Florida (O.R.=1.150, n.s.) and Michigan (O.R.=1.253, n.s.). Additionally, using all individual level characteristics in the model brings the odds ratio closer to one for Illinois, Maryland, Minnesota, New Jersey, New York and Texas. The odds ratio also becomes closer to one for California and North Carolina when the variable prior arrests is dropped from the model and the odds ratio for Delaware becomes closer to one when the model is run with the variable offense type as the only individual level characteristic in the model. The average reduction in the magnitude of the state effects on reimprisonment probabilities after the individual level characteristics are added to the model is 9%. In other words, state differences in the characteristics of released prisoners explain on average 9% of the state differences in the reimprisonment rates of reconvicted offenders.

Using the second approach of comparing state-by-state regression models provides additional support for the conclusions found using the fixed effect models. Without individual level characteristics added, the initial state-by-state results show that of 78 state-by-state comparisons, 14 combinations (17.95 percent) have statistically similar reimprisonment probabilities for offenders who were reconvicted within three years of their release from prison (refer to Table G1 in Appendix B). When individual level characteristics are added to the model (refer to Table G2 in Appendix B), 27 combinations (34.62 percent) have statistically similar reimprisonment probabilities for offenders who were reconvicted within three years of their release from prison. Using this second approach thus provides more evidence that the variation in the reimprisonment probabilities between states can be explained, at least in part, by the inclusion of individual level characteristics.

5.3.1: Individual Level Factors Related to Increased Probability of Reimprisonment

The results from the individual level characteristics model and combined model reveal that, among offenders released from prison who are reconvicted of a new crime, males are more likely to be resentenced to prison than females, that those who were first arrested or who were released at a younger age are more likely to be resentenced to prison than those first arrested or released at an older age, that ethnic minorities are less likely to be resentenced to prison than whites, and that those released from prison for a property offense are more likely to be resentenced to prison than those released for a violent offense or a public order offense. While the results were not significant in the full model, in the individual level characteristics models, blacks were more likely to be resentenced to prison than whites, those released for a property offense were more likely to resentenced to prison than those released for a drug offense, those released for a probation violation were less likely to be resentenced to prison than those sentenced to prison as a new court commitment and those released via mandatory supervised release were more likely to be resentenced to prison than those released via discretionary parole. Finally, although the results were not significant in the individual level characteristics model, using the full model, those who had served a longer prison term were more likely to be resentenced to prison as were those who had been released via other release type.

Many of the theoretical reasons for these sentencing patterns go back to the focal concerns theory discussed at the beginning of the chapter. While research has already been discussed about why females and whites are less likely to be resentenced to prison than males and blacks (Steffensmeier, et al., 1993; Spohn and Holleran, 2000; Steffensmeier and Demuth, 2000), research has also found that older offenders are treated more leniently than younger offenders because judges view them as less of a threat. Steffensmeier, Kramer and Ulmer (1995), for example, hypothesized that older offenders would be sentenced more leniently due to the fact that 1) doing time is harder for older offenders, 2) it costs more to incarcerate older offenders, 3) older offenders are seen as less blameworthy and 4) older offenders are seen as less dangerous. This theory could also apply to those with longer arrest records (Kingsnorth et al., 2002).

Table 15: Release Type and Most Serious Reconviction Type

Type of Offender	Proportion Whose Most Serious Reconviction is for a Violent Offense	Proportion Whose Most Serious Reconviction is for a Violent or Property Offense	Proportion Whose Most Serious Reconviction is for a Violent, Property or Drug Trafficking Offense
Violent Offender	17.97%	39.57%	45.20%
Property Offender	7.40%	45.22%	49.80%
Drug Offender	6.95%	19.61%	34.09%

Public Order Offender	8.78%	26.97%	33.22%

While prior research does not predict that those who were released from prison for a property offense would be more likely to be resentenced to prison if reconvicted than those released for a violent, drug or public order offense, a closer analysis of the reconviction charges of released offenders from the 1994 dataset may help provide clarification. Table 15 displays the most serious charge of reconviction for violent offenders, property offenders, drug offenders and public order offenders based solely on those who are reconvicted of a new offense. While the table does indeed show that violent offenders are more likely to be reconvicted for a violent offense than any other offense type, the table also shows that persons released from prison for a property offense had the highest proportion of reconvictions for a violent or property offense as well as the highest proportion of reconvictions for a violent, property or drug trafficking offense. The higher proportion of released property offenders reconvicted on new violent, property or drug trafficking offenses could explain why they are more likely to be resentenced to prison for their reconvictions. Judges, it would seem, would be most influenced by the current conviction when deciding to resentence an offender to prison. The fact that property offenders, as a group, have both the highest rate of being reconvicted for either a violent or property offense as well the highest rate of being reconvicted for a violent, property or drug trafficking offense could explain why they are more likely to be resentenced to prison. This finding would also help explain why property offenders are more likely to be reconvicted than other types of offenders. In line with this, Kingsnorth et al. (2002) noted that one of the factors that most influenced prosecutors' decisions whether to proceed or drop a case was the seriousness of the offense.

5.3.2: Discussing an Unexpected Non-Finding

While the preceding section provided fairly consistent evidence that variations in the individual level characteristics were useful in explaining some of the between state variation in reimprisonment probabilities for reconvicted offenders, one finding in particular merits further exploration: prior arrests. In the individual level characteristics model, the number of prior arrests an offender has is not related to imprisonment probability and this variable only becomes marginally significant ($p<.10$) when state of release is added. This finding appears quite unexpected given the literature that finds prior arrest record positively related to imprisonment (Clarke and Koch, 1976; Vigorita, 2001). Regarding this unexpected non-finding, estimating a new logistic regression model for reimprisonment probability including the entire population of rearrested defendants (as opposed to just those who have been reconvicted) helps provide a highly plausible explanation.

Table 16: Logistic Regression Model for Reimprisonment Probability of Rearrested Offenders using All Nine Individual Level Characteristics

Variable	Odds Ratio	Std. Err.
Gender	0.6489519***	0.1052541
Age of First Arrest	1.0133490*	0.0064385
Black	1.2098880***	0.0515438
Other Race	0.5732732*	0.2570719
Age at Release	0.9791914***	0.0047756
Prior Arrests	1.0129670**	0.0037080
Violent Offense	0.7096509***	0.0628794
Drug Offense	0.8301898**	0.0631884
Public Order Offense	0.7771931**	0.0900310

Other Offense	0.6110805	0.3238287
Time Served	0.9997242	0.0010622
Parole Violation	1.0824950	0.0598605
Probation Violation	0.6730711**	0.1257715
Other Admission Type	1.1030460	0.1884507
Unknown Admission Type	2.168336***	0.1610055
Mandatory Supervised Release	1.0400430	0.0562749
Expiration of Sentence	1.0288640	0.1004250
Other Release Type	0.6489519***	0.0760803
* p<.05 , ** p <.01, *** p<.001		

Table 16 shows that people who are rearrested and have more prior arrests are more likely to be reimprisoned. Previously, it was shown that people with more arrests were more likely to be reconvicted. This sets up a hypothesis that would explain the non-finding. Under this hypothesis, prosecutors are more willing to pursue legally weak cases against defendants with lengthy records, and settle for a plea that does not involve a new prison term. In similarly situated cases involving defendants without lengthy arrest records, prosecutors would be more likely to drop the charges. Because some of the cases against defendants with lengthy records are legally weak, prosecutors may be more willing to plea bargain some of the weaker non-violent cases, offering probation or a short jail term in exchange for a guilty plea, as opposed to dropping the charges or going to trial and risking acquittal. Under this scenario, offenders with lengthy criminal records who commit crimes which would have been dropped had the defendant not had a lengthy criminal record end up being offered plea bargains which don't involve a new prison sentence. While this hypothesis cannot be tested with the current dataset, it nevertheless is quite plausible and would explain why prior arrest record is not a significant predictor of reimprisonment for those reconvicted of a new crime.

5.4: Exploring the Differences in Parole Violation Rearrests and Reimprisonment on Parole Revocations across States

Analyzing the differences that exist across states for both parole violation arrests and for reimprisonment for parole violations is not quite as straightforward as the rearrest, reconviction and reimprisonment analyses. While data are available from 13 states regarding rearrests that take place for parole violations, looking at these data alone can be misleading because of wide variations in state law. Oregon Statute 144.350, for example, reads:

> (1)(a) The Department of Corrections or other supervisory authority may order the arrest and detention of any person then under the supervision, custody or control of the department or other supervisory authority upon being informed and having reasonable grounds to believe that such person has:
>
> (A) Violated the conditions of parole, post-prison supervision, probation, conditional pardon or other conditional release from custody;

This statute explains that the procedure for dealing with parole violators in the state of Oregon involves issuing a warrant for the offender’s arrest. Presumably as a result of the wording of this statute, 1,127 of the 3,192 offenders released from prison in Oregon in 1994 were rearrested on charges of violating parole. Most states, however, do not mandate that parole violators be arrested for technical violations of parole. This can clearly be seen in looking at Table 17, which shows that the percentage of offenders rearrested on charges of violating parole ranges from less than one tenth of one percent in Michigan and New York to over 35 percent in Oregon. The rarity of arrests for parole violations in all but a few states also makes a state-by-state analysis of rearrests for parole violations an unwise proposition. While such an analysis could be conducted, the results would not be meaningful given the rarity of the event in many states.

Table 17: Offenders Rearrested for Parole Violations by State

State	Offenders Released	Rearrest for Parole Violation	Percent Rearrested
Oregon	3192	1127	35.29%
Florida	21035	2086	9.92%
Ohio	11497	627	5.45%
Illinois	14890	262	1.76%
Delaware	640	8	1.25%
Minnesota	1611	13	0.81%
Virginia	5464	41	0.75%
Arizona	5416	21	0.38%
Texas	20507	45	0.22%
California	103325	145	0.14%
New Jersey	12275	14	0.11%
Michigan	6696	5	0.08%
New York	25709	6	0.02%

To adequately explore this issue, arrests for parole violations will have to be analyzed alongside data on technical violations for parole resulting in reimprisonment. Although data on technical violations are only available for nine of the 15 states in the sample, Table 18 provides the number of offenders who were sent back to prison on technical violations. The percentages from this table are very different from the percentages in Table 16. California, for example, revoked the parole of 38.65 percent of offenders even though only 0.14 percent of offenders were rearrested for a parole violation offense. Due to these differences, both technical violations of parole and parole violations that resulted in new arrests were analyzed.

Table 18: Offenders Returned to Prison for Parole Violations by State			
State	**Offenders Released**	**Returned to Prison for Technical Violation**	**Percent Returned to Prison for Technical Violation**
California	103325	39933	38.65%
New York	25709	7693	29.92%
Oregon	3192	860	26.94%
Florida	21035	5427	25.80%
Michigan	6696	1299	19.40%
North Carolina	22208	3199	14.40%
Minnesota	1611	177	10.99%
Texas	20507	2113	10.30%
Illinois	14890	929	6.24%

To explore the extent to which between-state variation in parole violation rearrests and reimprisonment on parole revocations across states can be explained by differences in individual level risk factors across states, two separate sets of analysis were run. Both of these were limited to the nine states where information on revocations for technical parole violations exists. The first of these analyses involved estimating models that combine parole violation rearrests and technical violations of parole resulting in revocation. The second of these analyses involved estimating models that combined parole violation rearrests resulting in reincarceration and technical violations of parole resulting in reimprisonment. Though similar in many respects, these two sets of analyses provide a more in depth understanding of how parole violation arrest and parole revocation rates vary across states and the influence that individual level risk factors have on each of them.

5.4.1: Offenders Rearrested for Parole Violations or Reimprisoned for Technical Violations

Table 19: Offenders Rearrested for Parole Violations or Reimprisoned for Technical Violations by State			
State	**Offenders Released**	**Rearrested for Parole Violation or Returned to Prison for Technical Violation**	**Percent Rearrested for Parole Violation or Returned to Prison for Technical Violation**
Oregon	3192	1357	42.51%
California	103325	40004	38.72%
New York	25709	7698	29.94%
Florida	21035	6180	29.38%
Michigan	6696	1303	19.46%
North Carolina	22208	3292	14.82%
Minnesota	1611	187	11.61%
Texas	20507	2147	10.47%
Illinois	14890	1143	7.68%

Table 19 displays the number of offenders from Oregon, California, New York, Florida, Michigan, North Carolina, Minnesota, Texas and Illinois who were either rearrested on a parole violation charge or who were returned to prison for a technical violation. Not included are offenders who were charged with a technical violation of parole but not returned to prison. Table 19 highlights a wide degree of variation in combined rates for parole violation rearrests and technical violations resulting in a return to prison with a low of 7.68 percent of offenders in Illinois and a high of 42.51 percent in Oregon.

To explore whether individual level characteristics have an influence on variation in rearrests for parole violations and reimprisonments for technical violations between states, estimates were obtained from the three models used in the fixed effects model approach described in previous sections. Because Illinois had the lowest rate of offenders with parole violations used in the analysis, it was chosen as the contrast state. The logistic regressions for the fixed effect models do not provide much evidence in support of the hypothesis that the individual level characteristics help explain variation in parole violations between states.

Table 20: Logistic Regression Results for Three Models for Rearrests for Parole Violations and Reimprisonment for Technical Violations			
	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.183	1.205
Age of First Arrest		1.002	0.992
Black		1.030	1.286***
Other Race		1.414	1.349
Age at Release		0.998	1.002
Prior Arrests		1.023***	1.013**
Violent Offense		1.192**	1.048
Drug Offense		0.993	0.857*
Public Order Offense		1.106	1.065
Other Offense		1.965*	1.435
Time Served		1.003*	1.003*
Parole Violation		1.242***	1.108
Probation Violation		1.219	0.504***
Other Admission Type		0.417***	0.533**
Unknown Admission Type		0.508***	2.234***
Mandatory Supervised Release		1.690***	1.555***
Expiration of Sentence		0.521***	0.973
Other Release Type		2.067***	5.361***
California	7.596***		8.204***
Florida	5.003***		1.971***
Michigan	2.906***		4.636***
Minnesota	1.579***		1.204
New York	5.139***		7.640***
North Carolina	2.092***		2.602***
Oregon	8.889***		12.064***
Texas	1.406*		1.767***
Model Statistics			
Observations (Unweighted)	23,269	23,269	23,269
Pseudo R^2	0.0613	0.0310	0.0788
Log Pseudolikelihood	-123677.75	-127662.42	-121367.45
* p<.05 , ** p <.01, *** p<.001			

With the fixed effects model, there are no states that are statistically non-significant compared to Illinois. When all nine individual level characteristics are added to the model, Minnesota (O.R.=1.204, n.s.) becomes statistically non-significant and there is a very large decrease in the size of the odds ratio for Florida (which goes from O.R.=5.003, p<.001 in the fixed effects model to O.R.=1.971, p<.001 in the full model). Aside from these two states, however, the odds ratio increases in size for all of the remaining states. Thus, the evidence that individual level characteristics can be used to explain variations between states in the number of offenders rearrested for parole violations or reimprisoned for technical violations is relatively weak using this approach.

Conversely, using the second approach of comparing state-by-state regression models produces some support for the proposition that variations in individual level characteristics can help explain how parole violation arrest and parole revocation rates vary across states. Without individual level characteristics added, the initial state-by-state results show that of 36 state-by-state comparisons[3], only two combinations (5.55 percent) have statistically similar parole revocation and parole rearrest rates (refer to Table H1 in Appendix B). When individual level characteristics are added to the model (refer to Table H2 in Appendix B), this number increases to 25 percent. With individual level characteristics added to the model, nine combinations have statistically similar parole revocation rates. This increase is more than fourfold and thus provides evidence that the variation in the revocations for technical violations of parole and

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[3] Three of the 36 state-by-state comparisons were run without the variables admission type or release type to deal with multicollinearity which resulted when technical violations and parole violation arrests were combined.

rearrests for parole violations can be explained, in part, by differences in individual level characteristics.

5.4.2: Offenders Reimprisoned for Technical Violations or Parole Violation Convictions

Table 21: Offenders Reimprisoned for Technical Violations or Parole Violation Convictions by State

State	Offenders Released	Returned to Prison for Criminal or Technical Violation of Parole	Percent Returned to Prison for Criminal or Technical Violation of Parole
California	103325	39976	38.69%
Oregon	3192	1172	36.71%
New York	25709	7693	29.92%
Florida	21035	6033	28.68%
Michigan	6696	1303	19.46%
North Carolina	22208	3210	14.45%
Minnesota	1611	180	11.17%
Texas	20507	2113	10.30%
Illinois	14890	1048	7.04%

While having offenders rearrested on charges of parole violations is a relatively rare event, an analysis of those reconvicted and reimprisoned on a parole violation criminal (as opposed to technical) charge finds that the event is exceedingly rare as it affected only 50 of the over 250,000 offenders in the prisoners released dataset. Further, as 27 of these 50 offenders also were sent back to prison for a technical violation, and two of the remaining parole violators came from Delaware (which was not one of the nine states which provided data on technical violations), Table 21 and Table 19 are quite similar. Like Table 19, Table 21 again shows that there exists a wide degree of variation in return to prison for criminal or technical parole violations for offenders released from prison in 1994, with a low of 7.04 percent in Illinois and a high of 38.69 percent in California.

To explore whether individual level characteristics have an influence on variation between states, estimates were obtained from the three models used in the fixed effects approach described in previous sections. Similar to the approach used with rearrests for parole violations and reimprisonment for technical violations, the logistic regressions for the fixed effect models do not provide evidence in support of the hypothesis that the individual level characteristics help explain variation in parole violations between states. With the fixed effects model, there are no states that are statistically non-significant compared to Illinois. When all nine individual level characteristics are added to the model, Minnesota (O.R.=1.258, n.s.) becomes statistically non-significant and there is a very large decrease in the size of the odds ratio for Florida (which goes from O.R.=5.310, $p<.001$ in the fixed effects model to O.R.=2.046, $p<.001$ in the full model). Aside from these two states, however, the odds ratio increases in size for all of the remaining states. Thus, the evidence provided that individual level characteristics can be used to explain variations between states in the proportion of offenders reimprisoned for criminal or technical violations of parole is relatively weak, just as it was in the previous analysis that looked at the combination of parole violation rearrests and technical violations of parole.

Table 22: Logistic Regression Results for Three Models for Rearrests for Parole Violations and Reimprisonment for Technical Violations			
	State of Release Model	Individual Level Characteristics Model	Combined Model
Rearrest (Property Offense)	Odds Ratio	Odds Ratio	Odds Ratio
Gender		1.176	1.200
Age of First Arrest		1.001	0.992
Black		1.031	1.287***
Other Race		1.389	1.328
Age at Release		0.999	1.003
Prior Arrests		1.023***	1.012**
Violent Offense		1.190**	1.048
Drug Offense		0.992	0.854
Public Order Offense		1.112	1.071**
Other Offense		1.984*	1.437
Time Served		1.003**	1.003***
Parole Violation		1.248***	1.110*
Probation Violation		0.946	0.493***
Other Admission Type		0.422****	0.558***
Unknown Admission Type		0.645**	2.282***
Mandatory Supervised Release		1.689***	1.503***
Expiration of Sentence		0.517***	0.966
Other Release Type		2.010***	5.291***
California	8.333***		9.024***
Florida	5.310***		2.046***
Michigan	3.191***		4.897***
Minnesota	1.661***		1.258
New York	5.638***		8.137***
North Carolina	2.231***		2.750***
Oregon	7.660***		10.046***
Texas	1.517**		1.870***
Model Statistics			
Observations (Unweighted)	23,269	23,269	23,269
Pseudo R^2	0.0628	0.0310	0.0802
Log Pseudolikelihood	-122976.59	-127662.42	-120698.8
* p<.05 , ** p <.01, *** p<.001			

Using the second approach of comparing state-by-state regression models produces some support for the proposition that variations in individual level characteristics can help explain differences in reconviction proportions across states. Without individual level characteristics added, the initial state-by-state results show that of 36 state-by-state comparisons[4], three combinations (8.33 percent) have statistically similar parole revocation and parole rearrests leading to reimprisonment rates (refer to Table I1 in Appendix B). When individual level characteristics are added to the model (refer to Table I2 in Appendix B), this number increases to eight (22.22 percent). This more than twofold increase provides evidence that the variation in the revocations for technical violations of parole and rearrests for parole violations that result in reimprisonment can be explained, in part, by differences in individual level characteristics.

5.4.3: Individual Level Factors Related to Increased Probability of Parole Violations

Looking at the models in Tables 20 and 22, we see that there are some common individual level characteristics associated with increased odds of violating parole. One characteristic that is significant for parole violations in both the individual level characteristics model and the full model is prior arrests. The reasons why those with more prior arrests would be more likely to violate parole goes back to the differential association and social learning theories related to the increased probability of rearrest for offenders with more prior arrests. Although a technical violation of parole is not the same as an arrest, it is nevertheless a violation of rules and those who have more prior arrests would be expected, based on these theories, to be more likely to violate parole, just as they would be more likely to be rearrested.

[4] Three of the 36 state-by-state comparisons were run without the variables admission type or release type in the model to deal with multicollinearity which resulted when reimprisonment for technical violations and parole violation convictions were combined.

Both tables also show that those released via mandatory supervised release are more likely to have their parole revoked than those released via discretionary parole. Part of the explanation for this has to do with the parole revocation policies in California and the fact that the state of California accounts for over 40 percent of parole violators sent back to prison (Travis and Lawrence, 2002). As California has the second highest parole failure rate in America (Travis and Lawrence, 2002) and as all the offenders released from California are released via mandatory supervised release, it should come as no surprise that those released via mandatory supervised release would be more likely to have their parole revoked in models where state of release was not controlled for. The fact that those released via mandatory supervised release had higher parole revocation rates even when state of release is added to the model likely has to do with the fact that those granted discretionary parole have been screened and represent a lower risk as a result. Solomon et al. (2005:2) wrote:

> Prisoners released to supervision via discretionary release have been screened by a parole board or other authority to determine "readiness" to return to the community. Parole boards, which often face substantial pressures to reduce prison overcrowding, determine who presents the lowest risk of reoffending and is most prepared for release. Among other factors, parole boards consider criminal histories, institutional conduct, and positive connections to the community such as employment, housing arrangements, and ties to family.

Similarly, Rosenfeld et al. (2005) found that those released via discretionary parole had far fewer rearrests than those released via mandatory supervised release. While it again needs to be pointed out that violations of parole are not necessarily the same as rearrests, they both result from failure to adhere to laws, rules and regulations and the evidence suggests that those released via discretionary parole are less likely to violate parole than those released via mandatory supervised release because they have been screened by a parole board and, thus, are better equipped to abide by the stipulations of parole.

Petersilia (2003:187-188) also argued that allowing states to maintain the option of discretionary parole could enhance the likelihood of success after release because it would motivate prisoners to become involved in and participate in prison programs, writing:

> We should reinstitute discretionary parole release in the 16 states that have abolished it. Eliminating discretionary release reduces the incentives for inmates to try to rehabilitate themselves while incarcerated. Some inmates may recognize the intrinsic value of improving themselves, but more inmates will participate if they believe it will reduce their prison stay. Research suggests that, regardless of a prisoner's initial motivation to participate in prison programs, positive benefits accrue. So what benefits are gained by reducing motivation and participation in prison programs? Eliminating discretionary release works against our attempts at rehabilitation.

Another factor related to increased probability of parole revocation that can be discussed in some detail is the finding that those who had entered prison because of a parole violation are either significantly more likely or marginally more likely to violate the conditions of their parole than those who had initially entered prison because of a new court commitment. Both Lynch and Sabol (2001) and Travis (2005) noted that offenders who cycle back into prison via multiple parole violations are at higher risk of offending than other offenders. These offenders have difficulty being successfully reintegrated back into society and following rules associated with parole. In their study of parolees returning back to Sacramento, Hipp and Yates (2009) speculated that the theoretical rationale behind previous parole failures being at increased risk of future parole failures had to do with the differential association and social learning theories, which were previously explained regarding why higher levels of prior arrests were associated with increased odds of recidivism.

In addition to prior arrests, release type and prior failure on parole, the other individual level characteristic found to be associated with increased odds of parole violations was time served, with those who had served more time in prison more likely to be charged with a parole violation. This finding is somewhat surprising as it is contrary to the earlier finding that those who had served longer time were less likely to be rearrested. Future research should address why this is the case.

5.4.4: Exploring the Different Findings using Different Approaches

While a detailed analysis exploring the issue is beyond the scope of this dissertation, there exists a very plausible reason why a fixed effects model would show that individual level characteristics have virtually no ability to explain differences in statewide parole violation rates, yet a state-by-state model would find some effect. This has to do with variations in state laws regarding technical parole violation policies resulting in reimprisonments. When the prisoners from the nine states which provided data on technical violations for parole were released, there were quite likely very different parole violation policies in place in different states which impacted who was sent back to prison and why. Many of these policies were statewide policies with some specifically recommending that offenders only be sent back to prison if their parole violation involved a new crime while others allowed technical violations for much less serious violations. Such statewide parole policy differences could help explain why Illinois returned only one fifth percent as many offenders back to prison for parole violation as California. In exploring the concept of parole in America, Travis and Lawrence (2002:19) commented on the policy differences that exist between states:

> Examining the phenomenon of successful parole discharges at the state level (as defined by BJS) shows enormous variation among the states. The percentage of parolees successfully discharged ranges from a low of 19 percent in Utah to a high of 83 percent in Massachusetts . . . However, following the above discussion on the definition of success, this variation is, to some extent, to be

> expected. It is unlikely that the parolees in Utah and California, the two states with the lowest rates of successful completion (under 20 percent) are so inherently different from the parolees in Massachusetts and Mississippi, the two states whose successful completion rates exceed 80 percent. More likely, the policies and practices of the parole agencies contribute significantly to these differences.

Thus policy differences between states could explain why there was no effect using a fixed effects approach. With that limitation pointed out, however, there were likely some states that had similar parole revocation policies in place during this period of time. For those states that had similar revocation policies in place, individual level characteristics would be useful in explaining differences in technical violations. This would help clarify why the inclusion of individual level characteristics helped explain differences in parole revocation rates in some states, but not for the entire sample.

5.5 Goodness of Fit of the Models

Although the models from the chapters 4 and 5 provide evidence that statewide differences in individual level characteristics do help explain some of the variation between states for five of the eight forms of recidivism, a closer look at the model statistics reveals that there remains a large amount of unexplained variation. The Pseudo R^2 values of each of these models reveals that, in the strongest case (that of rearrest for a new offense), there still remains over 88 percent of variation not explained by the state of release or in combination with the nine individual level factors. For the remaining seven measures of recidivism, over 90 percent of the variation remains unexplained. What these results indicate is that there are many additional individual, contextual, and policy variables that need to be added to the model to fully account for between state variations in recidivism rates. In addition to the findings related the Pseudo R^2 values, the log pseudolikelihood values decreases for all forms of recidivism when the individual covariates are added, indicating improved fit for all the models. Similar to the Pseudo R^2 values, the recidivism measure with the greatest decline exhibiting the greatest improvement in fit when the individual covariates are added to the model is rearrest for any offense.

5.6: Discussion

Using two separate analytical approaches, the findings from the preceding sections provide fairly strong evidence that variation in the previously described characteristics of prison release cohorts explains roughly nine percent of the variation between states in reimprisonment rates for reconvicted offenders. The evidence related to reconviction probabilities and parole violations (accompanied by either an arrest or a technical violation resulting in reimprisonment) was mixed, with the standard regression approach using a single omitted contrast state showing much weaker effects of the individual recidivism predictors than shown by state-by-state comparisons. The reason for the mixed finding related to reconviction probabilities has to do with the fact that while other factors, including political motivations and monetary considerations, generally have a stronger influence on reconviction probabilities, in some states individual level characteristics such as prior record, age, age-at-first-offense, gender and race have an influence on both prosecutorial and jury behavior. The reason for the mixed finding related to parole violations lies in policy differences in many states regarding when a technical violation of parole results in reimprisonment. The effects of the individual factors should be stronger for states with similar revocation policies.

In addition to these findings, looking at the effects of individual level characteristics reveals that offenders who were rearrested were more likely to be reconvicted if they were younger when released, had more prior arrests or were most recently released for a property offense. The factors related to these increased odds of reconviction were likely related to prosecutors taking prior record into account in deciding which cases to move forward with, the idea that older offenders may be less likely to be convicted because they tend to specialize in the offenses they commit and the fact that those released for a property charge were more likely to be rearrested for a more serious violent, property or drug trafficking offense than other offenders.

For those offenders who were reconvicted of a new offense, the factors associated with being more likely to be resentenced to prison were being male, being first arrested at a younger age, being released at a younger age and having been released from prison for a property offense. One of the factors related to these increased odds of reimprisonment was based on focal concerns theory:

judges tend to see females and older offenders as less of a threat than males and younger offenders. A second factor was based on the seriousness of the charge of which certain offenders were reconvicted. Examining the reconviction charges from the dataset revealed that, of offenders who were reconvicted of a new offense, property offenders had a higher proportion who were reconvicted of a more serious violent, property or drug trafficking charge compared to reconvicted offenders who had been released from prison for a violent, drug or public order offense. One noteworthy non-finding was that prior record was not significantly related to odds of reimprisonment. While it was not possible to fully test the theory, one hypothesis that might explain the non-finding is that prosecutors are willing to offer plea bargains to offenders with lengthy records in weak cases while dropping the charges in similar cases where the defendant did not have a lengthy record.

Finally, four factors were related to increased probability of parole revocation across all models. The first was prior arrests, with those who had more prior arrests more likely to have their parole revoked. A second factor was prior admission to prison via parole violation. In both of these cases, the theoretical basis for this was differential association and social learning theory. A third finding was that those released via mandatory supervised released were more likely to have a parole violation than those released via discretionary parole. The reason behind this is probably that those released via discretionary parole were lower risk offenders specifically chosen for release because of their low risk. An unexpected finding was that those who had served longer time in prison were more likely to be revoked than offenders who had served less time. This finding is difficult to explain as it contradicts the prior finding that those who had served longer in prison were less likely to be rearrested than those who had served less time.

Overall, the results from these two chapters reveal that the individual level characteristics associated with increased odds of recidivism differ based upon the type of recidivism under consideration. While being male, black, younger at the age of release, having more prior arrests, being released from prison for a property offense, having previously entered prison on a parole violation and having previously been released from prison via expiration of sentence are all associated with increased odds of rearrest, these factors do not all relate to other forms of recidivism. The following list outlines some of the differences in risk factors based on the type of recidivism being measured:

1) **Gender** - While males who are reconvicted are more likely to be reimprisoned than females, they are not more likely to be reconvicted if rearrested and are not more likely to have their parole revoked.
2) **Race** – Although being black was found to be related to an increased probability of reimprisonment in the individual level characteristics model, it was not found to be a predictor of reconviction in either model.
3) **Age at Release** – While offenders who were younger at the age of release were more likely to be reconvicted if rearrested and more

likely to be reimprisoned if reconvicted, they were not more likely to have their parole revoked.

4) **Prior Arrests** – While those with more prior arrests were more likely to be reconvicted if rearrested and were more likely to have their parole revoked, they were not more likely to be reimprisoned if reconvicted.

5) **Offense Type** – While property offenders were more likely than other types of offenders to be reconvicted if rearrested and to be reimprisoned if reconvicted, they were not more like to have their parole revoked.

6) **Admission Type** – While people who had previously entered prison on a parole violation were more likely to have their parole revoked compared with those who previously entered on a new prison sentence, they were not more likely to be reconvicted if rearrested or to be reimprisoned if reconvicted.

7) **Release Type** – Although people released via expiration of sentence were found to more likely to be reconvicted if rearrested in the full model which included state of release, there were no significant findings either way regarding the probability of them being reimprisoned if reconvicted of a new offense.

While the proceeding two chapters have looked at whether differences in individual level characteristics can help explain variations in eight forms of recidivism rates across space, the focus of chapter six will be if the explanation of between state variations in all but one of these forms of recidivism can be further enhanced by the addition of three state-level ("contextual") variables.

CHAPTER 6 – DO CONTEXTUAL VARIABLES EXPLAIN RECIDIVISM RATES ACROSS STATES?

6.1: Introduction

Chapters Four and Five provided evidence that, with a few exceptions, nine individual level characteristics explain some of the differences across states in rearrest rates for any offense, rearrest rates for property offenses, rearrest rates for drug offenses, rearrest rates for public order offenses and new prison sentences for reconvicted offenders. This chapter extends the analysis to investigate whether the addition of three state-level ("contextual") variables accounts for additional variance in recidivism across states. The state-level contextual variables are: 1) drug arrests per 100,000 residents, 2) police officers per 1,000 residents, and 3) arrest-offense ratios.

Before providing the rationale for the inclusion of these contextual variables, it is informative to review the state averages for each of them. Table 23 shows that there is a fair amount of divergence between states for all three of the contextual variables. The average number of drug arrests per 100,000 residents for the years 1994 to 1997 ranges from 278.31 per 100,000 residents in Delaware to 835.24 per 100,000 residents in New York (mean = 559.6, s.d.=182.4). The average number of police officers for this time period ranges from 1.72 officers per 1,000 residents in Minnesota to 3.78 per 1,000 residents in New York (mean = 2.31, s.d.= .536); and the average arrest-offense ratio for this time period[5] ranges

[5] The arrest-offense ratio used for Florida is the two year average for that state from 1994 and 1995. The reason is that the data were not available though *Crime in the United States* for those

from 17.86 percent in Florida to 41.94 percent in Delaware (mean = 27.3, s.d.=6.237127). What these summary statistics do not tell is if they can explain variation in recidivism rates beyond the variation explained by the individual level characteristics previously examined.

Table 23 - Contextual Level Variable Averages By State			
	Drug Arrests per 100,000	Police per 1,000	Arrest-Offense Ratio
Arizona	601.46	2.0249	23.50
California	843.29	2.0469	26.59
Delaware	278.31	2.0321	41.94
Florida	506.22	2.3425	17.86
Illinois	683.26	2.8910	21.49
Maryland	809.65	2.5543	31.00
Michigan	406.01	1.9937	18.28
Minnesota	316.39	1.7236	27.22
New Jersey	722.92	2.8851	26.76
New York	835.24	3.7810	25.78
North Carolina	485.33	2.2793	27.51
Ohio	505.50	2.0489	29.77
Oregon	511.81	1.7909	25.80
Texas	470.74	2.2184	30.27
Virginia	418.54	1.9777	36.11

In the multilevel analyses that follow, each of the state level variables is added to a hierarchical linear model alongside the nine individual level characteristics. Because of the limited degrees of freedom that exist with a sample size of 15 states, each of the three state level variables is analyzed separately. In each of these models, the individual level variables are entered into the model grand mean centered, as literature emphasizes that this is the appropriate approach for research questions which have a primary substantive focus on a level two predictor variable (Enders and Tofighi, 2007).

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years. Additionally, the Florida Department of Law Enforcement website's (www.fdle.com) record of arrests for 1996 and 1997 excluded juvenile arrests, making the data substantially different than for the other states or for 1994 and 1995 for Florida.

The multilevel analyses use the software package HLM 6.0 (Raudenbush, Bryk, and Congdon, 2004). While the decision to conduct the multilevel analyses using HLM was based on several advantages that this program offers over others, it is also important to point out that there exists some disagreement among researchers as to whether an accurate multilevel analysis can take place using HLM with only 15 level two units. While there are 32,732 level one units represented within these 15 states, and while Maas and Hox (2005) found that large individual level sample sizes can partially compensate for a small number of groups, some researchers have found that using HLM with a sample size of less than 50 may lead to biased estimates of the second-level standard errors (Maas and Hox, 2005; Moineddin, Matheson, and Glazier, 2007). Not all researchers have found that a level two sample of between ten and fifteen is inappropriate, however. Snijders and Bosker (1999, p. 44) found that multilevel modeling was an attractive option when there were ten or more level two groups. Maas and Hox (2004) further found that ten groups was an adequate sample size if one was only interested in the fixed effects of the model.

Given the disagreement over what exactly constitutes an appropriate level two sample size for multilevel modeling, the following findings should be viewed with caution due to the small level two sample size and the possibility of biased estimates of the second-level standard errors. It should also be noted that the multilevel analyses that follow do not include parole violations as an outcome measure. This is because only nine states were able to provide data on technical violations of parole and no study has recommended conducting multilevel analysis with a level two sample size smaller than ten. A second note is that, because there were only 15 level two units, a decision was made to mark findings if they were marginally significant ($p<.10$).

6.2: The Effect of Statewide Drug Arrest Rates on Recidivism Rates

One undeniable fact about America's War on Drugs during the 1980s and 1990s is that it was one of the primary reasons for the tremendous increase in persons incarcerated in the United States. There were also changes to federal and state laws during this time that encouraged police departments to focus more on combating drug crimes. One such change in law was the passage of the Comprehensive Crime Act of 1984, which, among other things, allowed police departments to keep a portion of the proceeds of assets forfeited as a result of certain drug enforcement activities (Benson, Rasmussen, and Sollars, 1995). For federal cases, states were only allowed to share in a portion of the forfeited property for relatively large seizures. States did not, however, follow a uniform pattern in determining whether police departments profited directly from drug seizures: some passed laws allowing the police to retain a large portion of the seized property, while others dictated that the proceeds from the seized property go to a non-law enforcement agency or to the general fund. Where the money went had an effect on how aggressively states pursued drug crimes. Benson (2009) pointed out that "drug arrests per 100,000 population in states with significant limits on police retention of seizure proceeds averaged 363 during

1989, while states where police kept proceeds averaged 606 drug arrests per 100,000" (p. 52).

The conventional wisdom among many in law enforcement is that drug use causes crime and that stringent enforcement of drug laws is an effective tool to combat property and violent crimes. This line of thought is quite reasonable as the relationship between drug and alcohol use and criminal conduct seems fairly straightforward. Several Bureau of Justice Statistics publications have found that over half of the inmates in the correctional system have a history of drug use (Beck, 2000; Hughes, Wilson, and Beck, 2001; Mumola 1999). A 1999 Bureau of Justice Statistics publication found that in 1997, nearly 1 in 6 admitted to having committed the current offense to obtain money for drugs (Mumola, 1999). This finding was echoed by a 2001 publication that found that among prisoners expected to be released to the community by yearend 1999, 21 percent stated they had committed the offense to obtain money for drugs (Hughes et al., 2001). Such findings have led many to believe that increasingly targeting drug offenders would reduce both property and violent offending rates. Although there has been some research indicating that increasing the number of drug offenders in prison may lower property and violent crimes through incapacitation (Blumstein and Rosenfeld 1998; Kuziemko and Levitt, 2004), a substantial number of research studies have concluded that America's War on Drugs may have actually led to a decrease in the likelihood of arrest for property offenses and an increase in the levels of violent offending.

Benson et al. (1992) examined data from 67 counties in Florida for 1986 and 1987 to see if there was a relationship between drug arrests and property crime. They found that as the number of drug arrests increased, there was a rise in the number of property crimes reported. Two years later, Sollars, Benson and Rasmussen (1994) looked at data from 296 jurisdictions in Florida in 1987. Their findings echoed those from the earlier study. A ten percent increase in the number of drug arrests decreased the probability of arrest for a property offense, which, in turn, raised the property crime rate by an estimated 1.09 percent. Outside of the United States, Mendes (2000) examined a possible drug-property crime connection in 274 Portuguese municipalities in 1996. The study found that for a ten percent increase in the number of drug arrests, the probability of arrest for property crimes declined by about one percent. These studies indicate that there is a tradeoff in heightened enforcement of drug laws. Because law enforcement resources are relatively scarce, as more money is spent to combat drug crimes, less money is available to respond to property crimes. The results from these three studies highlight that when less money is available to combat non-drug crimes, property crime rates may increase.

A likely explanation for the findings that increased drug enforcement leads to an increase in property crimes lies in the fact that the majority of drug offenders are not property offenders (Benson et al., 1992; Sollars et al., 1994). Although numerous reports have indicated that a large portion of people in prison have used drugs, what this line of logic fails to take into account is that the vast majority of people who use drugs do not end up in prison, even if they are arrested. Benson et al. (1992) stated, "the fact that most property criminals use drugs does not prove that most drug users commit property crimes" (p. 680). A report by Trager and Clark (1989, as cited by Benson et al., 1992) notes that most drug offenders are not also property offenders:

> The history of persons having at least one misdemeanor or felony drug arrest in Florida during 1987 indicates that many have few previous recorded arrests for property crimes (Trager and Clark, 1989). Of the 45,906 people arrested for drug possession, over 80% had never been arrested for burglary and over 90% had never been arrested for other property crimes. Of those arrested for sales, only slightly more than 25% had prior burglary arrests, and again over 90% had no previous arrest for other property crimes (p. 681).

A second explanation put forth by Benson et al. (1992) is that because an increased drug enforcement policy will result in a lower probability of arrest for property offenses, some offenders will switch from committing drug crimes to property crimes. Under this scenario, the motivation for crime is an economic one and when the likelihood of getting arrested for one type of offense increases, an offender, being a rational being (Cornish and Clarke, 1986), would switch to a less risky form of criminal behavior. Thus, as the chance of being arrested for selling heroin increases because of more active enforcement, an offender may choose to switch to the less risky crime of daytime burglary.

As was the case with increased drug enforcement leading to higher levels of property offenses, there have also been several studies which have found that increased drug enforcement is related to increased levels of violent crime. The evidence that increased drug enforcement leads to higher rates of violent offending is not consistent with the crime switching hypothesis seen in the relationship between property and drug crimes, though there is some support for the notion that diverting law enforcement resources away from non-drug activity may lead to higher levels of violent offending.

Brumm and Cloninger (1995) looked at the relationship between drug enforcement activities and homicide rates in 57 cities in 1985. One of the hypotheses that they tested was the resource saturation hypothesis, which is “consistent with the view that increased drug enforcement activities divert scarce policing resources from controlling other offenses, thereby reducing the risk of punishment for committing those offenses” (p. 512). They found that homicide rates increased, on average, by 0.17 percent for every one percent increase in drug enforcement activities. A few years later, Miron (1999) studied homicide trends in the United States from 1900 to 1990 in relation to historical prohibition efforts against both alcohol and drugs in the United States. He found that the highest levels of homicide in America in the 20th century occurred from 1920 to 1933, when America was prohibiting alcohol, and from 1970 to 1990, after America began its War on Drugs. He stated: “the results show the expenditure for enforcement of alcohol and drug prohibition have been positively associated with the homicide rate in the U.S., consistent with the view that increased prohibition enforcement encourages the substitution of violent for non-violent dispute-resolution mechanisms” (p. 80). More recently, Shepard and Blackley (2005) estimated a set of models using data for 62 counties in New York State for 1996-2000 to determine the relationship between drug arrest rates and both violent and non-violent crimes. They found that drug arrests did not have a significant negative relationship with crime. Instead, they found that increases in arrests for hard drugs were associated with higher rates of all crimes, except assault, and increases in arrests for marijuana were associated with more larcenies.

While these studies provide evidence about the effect of increased drug enforcement on property and violent offending, they do not provide evidence of the effect that increased drug enforcement has on rearrest rates of those recently released from prison. Some information on this subject can be gleaned from Langan and Levin’s (2002) report on the recidivism rates of drug offenders released from prison in 1994. They found that, for those released from prison for a drug related offense in 1994, 41.2 percent were rearrested for a similar offense within three years of their release. This offense specialization was higher than for any other category of offender released in 1994. It is also 60.2 percent higher than the number of drug offenders released from prison in 1983 who were rearrested for a similar offense within three years of their release (Beck and Shipley, 1989). This information confirms that drug offenders were more likely to be rearrested for a new drug offense in 1994 than in 1983, although it still does not indicate if differences in state-level drug arrest rates could help explain variations in rearrest rates between states when the nine individual level characteristics previously discussed are controlled. The following multilevel modeling results address this shortcoming.

Table 24 lists the beta, standard error and odds ratio for the level two effect of drug arrests added to hierarchical linear models controlling for the nine individual level factors of gender, age of first arrest, age at release, number of prior arrests, time served, race, offense type, admission type and release type. This table includes results for the outcome of rearrest for any offense for a 15 state sample; for rearrest for a violent offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense for a 13 state sample; for reconviction for rearrested offenders for a 14 state sample; and for reimprisonment for reconvicted offenders for a 13 state sample. Each of these seven multilevel models is included in its entirety in Appendix C. For ease of interpretation, the findings related to the addition of the contextual variable are listed in a single table.

Table 24 - Multilevel Regressions for Seven Outcomes on Individual Level Characteristics and State Level Drug Arrests per 100,000
Final estimation of fixed effects (Unit specified model):

Drug Arrests per 100,000	*b*	S.E.	Exp(b)
Any Rearrest	0.000311	0.000497	1.000311
Rearrest for a Violent Offense	0.000146	0.000417	1.000146
Rearrest for a Property Offense	0.000812	0.000458	1.000813
Rearrest for a Drug Offense	0.002088***	0.000365	1.002090
Rearrest for a Public Order Offense	-0.001033	0.000942	0.998968
Reconviction	0.000760	0.000841	1.000760
Reimprisonment	-0.000112	0.000845	0.999888
* $p < .10$, ** $p < .05$, *** $p < .01$			

The results in Table 24 indicate that the state level characteristic of drug arrests per 100,000 is not useful in helping explain variation in various forms of recidivism between states when the nine individual level characteristics are controlled. While state level drug arrests per 100,000 is found to be a significant predictor of rearrest for a drug offense, controlling for the nine individual level factors, this significant finding is neither unexpected nor does it add to the explanation of why drug rearrest rates vary across states. If the likelihood of arrest for a drug offense were increased for people in the general population of a state, the same increased likelihood would apply to formerly incarcerated offenders. Beyond this, however, Rosenfeld et al. (2005) found that prisoners released from 13 states in 1994 were 23 times more likely to be arrested for a drug related offense between 1994 and 1997 than those from the general population. Thus, those states that heavily targeted drug offenders would, by default, have a higher proportion of released offenders rearrested for a new drug offense and this finding would result in a statistically significant impact, even when individual level characteristics are controlled.

6.3: The Effect of Statewide Police Per 1,000 Residents on Recidivism Rates

Although to date there does not appear to be any research which explores the effect of police per 1,000 residents on recidivism rates, a great deal of prior research has looked at the effect of police levels on crime rates and can serve as a proxy for how different police levels across states may affect the levels of various forms of recidivism after controlling for individual level factors. The review of studies will be limited to those published in the last 15 years because, as Marvell and Moody (1996) found, many early studies may have suffered from the specification problems of simultaneity and omitted variable bias, which they believed was responsible for many studies finding that increasing police size did not have an impact on crime rates. To correct for these specification problems, Marvell and Moody (1996) used lags between police levels and crime rates and also tested for casual direction with the Granger test. They further sought to "mitigate omitted-variable bias by entering variables that are proxies for the unknown factors and unusable variables" (p. 612). Employing these techniques, they found "Higher police levels reduce most types of crime, particularly at the city level" (p. 640).

Kovandzic and Sloan (2002) used the same techniques to test the effect of increased police levels on crime rates at the county level for fifty-seven counties from the state of Florida for the years between 1980 and 1998. Their analysis revealed "strong evidence that increased police levels lead to lower crime rates" (p. 72). They found evidence that increased police levels had significant impacts on the rates of robbery and burglary and further estimated that "a 10 percent increase in police levels lowered crime rates by 1.4 percent over time" (p. 73).

Research on whether police levels impact crime rates has not been limited solely to the United States and has not only been analyzed using official police data. Vollard and Koning (2009) used data obtained from the Dutch Victimization Survey (PMB) for the years 1996 to 2004 to estimate the impact that police force size had on victimization rates and on levels of victim precaution measures such as avoiding unsafe places and leaving valuables at home to avoid theft. The study found that increasing police size had a significant, negative impact on several forms of crime, including bicycle theft, theft from cars, littering, harassment, youth nuisance, public intoxication and drug nuisance. Negative, but not significant, effects were found for both assault and robbery. Increasing police size also resulted in a significant decrease in victim precaution measures. The authors summarized the impact of increased police levels by stating, "Our estimates imply that the 30 percent increase in police per capita in the Netherlands over the period 1996-2004 resulted in a decrease in crime and disorder by some 10 percent" (p. 340).

More recent research by Worrall and Kovandzic (2010) utilized an alternative instrumental variables approach to explore the prospect of a simultaneous relationship between policing and crime. Looking at data from yearly observations of 5199 cities between 1990 and 2001, the authors calculated a series of fixed effect models using the Generalized Method of Moments estimator. They found that higher police levels were associated with lower levels of homicide, robbery, assault, and burglary, particularly in cities with populations in excess of 100,000.

These findings offer evidence for an inverse relationship between police levels and crime rates. Under the deterrence theory (Beccaria, 1963 [1764]; Bentham, 1967 [1789]) such findings suggest that increased police presence could also lead to lower recidivism rates. If released offenders act as rational beings (Cornish and Clarke, 1986) and realize that they are more likely to be caught because there are more police on the street, they might decrease their involvement in crime, resulting in lower levels of reoffending.

There is an additional effect of increasing police levels, however, that must be addressed before anticipating the effect that increased police levels would have on rearrest rates. While deterrence theory would anticipate that more police would reduce the offending levels of those recently released from prison, this does not mean that rearrest rates will go down, because some studies have found that increasing police levels also increases the probability of arrest (Wilson and Boland, 1978; Mosher, 2001). The end result is that, even if increased police presence leads to lower reoffense rates by those released from prison, their overall rearrest rates may nevertheless increase if a greater proportion of those who reoffend are arrested. On this basis, two competing hypotheses exist:

1) Increased police levels will reduce the level of offending of those released from prison through deterrence with the end result being lower rearrest rates.
2) Increased police levels will increase the arrest probability of those released from prison with the end result being higher rearrest rates.

Table 25 - Multilevel Regressions for Seven Outcomes on Individual Level Characteristics and State Level Police Per 1,000 Residents
Final estimation of fixed effects: (Unit specified model):

Police per 1,000 Residents	*b*	S.E.	Exp(b)
Any Rearrest	0.053538	0.145160	1.054998
Rearrest for a Violent Offense	0.139806	0.101452	1.150050
Rearrest for a Property Offense	0.341012***	0.091807	1.406370
Rearrest for a Drug Offense	0.309174*	0.168984	1.362300
Rearrest for a Public Order Offense	0.073105	0.264072	1.075843
Reconviction	0.450621*	0.216014	1.569287
Reimprisonment	-0.145565	0.236350	0.864534

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 25 lists the beta, standard error and odds ratio for the level two effect of police per 1,000 residents added to hierarchical linear models controlling for the nine individual level factors of gender, age of first arrest, age at release, number of prior arrests, time served, race, offense type, admission type and release type. As before, this table includes results for the outcome of rearrest for any offense for a 15 state sample; for rearrest for a violent offense, rearrest for a property offense, rearrest for a drug offense and rearrest for a public order offense for a 13 state sample; for reconviction for rearrested offenders for a 14 state sample; and for reimprisonment for reconvicted offenders for a 13 state sample. Each of these seven multilevel models is included in its entirety in Appendix C.

The results of Table 25 suggest that the state level of police per 1,000 residents is significantly and positively related to probability of rearrest for a property offense and positively related, though only at a marginally significant level, to probability of rearrest for a drug offense. Thus, even if increased police presence does have a deterrent effect on offenders recently released from the prison, this decrease in offending is more than offset by an increase in the probability of arrest for both drug and property crimes.

Beyond its effect on the probability of rearrest, the results of the multilevel regression model of the statewide level of police officers from 14 states show that this contextual variable is marginally significant (p=.056) for the outcome of reconviction of offenders who have been rearrested. Although the finding is only marginally significant, it nevertheless suggests that states that employ more police officers are also more likely to seek to convict the offenders who are rearrested. This finding suggests that jurisdictions willing to hire more police officers may also encourage prosecutors to seek convictions for those who are arrested. This finding provides some support to the hypothesis raised in Chapter Five that contextual, as opposed to individual level, factors help explain variations in reconviction probabilities across states.

6.4: The Effect of Statewide Arrest-Offense Ratios on Recidivism Rates

While researchers have not directly explored how statewide arrest-offense ratios affect offender recidivism, several research studies have explored the relationship between the certainty of arrest and crime rates. Tittle and Rowe (1974) examined 1970 crime and arrest data gathered from the first annual report of the Department of Law Enforcement of the State of Florida. They found that there appeared to be a relationship whereby increasing arrest levels led to lower crime rates, but that this relationship only existed for communities that had an arrest-offense ratio of at least 30 percent. They referred to this percentage as a tipping point and wrote, “Thus it appears that there is a critical level that certainty of punishment much reach before there is a noticeable change in volume of crime” (p. 458).

Brown (1978) explored whether Tittle and Rowe’s (1974) tipping effect was a finding peculiar to the dataset used in the earlier study or if it would occur in places outside of Florida. In his work, he reanalyzed the two data sets used in the previous study along with analyzing 1971 crime and arrest rates in California cities with populations over 25,000 and 1973 data related to crime rates and arrest clearance rates for California counties. He was unable to identify a general tipping effect as had been found in the previous study, but his closer reexamination of the

Florida dataset data revealed evidence that the tipping point that had occurred in Florida was found only in smaller Florida cities and counties.

A year later, Greenberg, Kessler and Logan (1979) used a longitudinal model approach to see if arrest rates for a 98-city sample for the years 1964 to 1970 had an effect on crime rates. They developed models that included lags of one, two and three years, because "theoretical considerations suggest that lagged casual effects may exist" (p. 846). They found that increasing arrest rates (i.e., the certainty of arrest) had no appreciable affect on crime rates. While the authors stated that the findings from Tittle and Rowe (1974) and Brown (1978) provided evidence in support of the deterrence doctrine, the authors were clear that their findings did not. They speculated that the reasons for this had to do with the analytic method used and that "the correlations interpreted in these studies [conducted by other researchers] as evidence of crime deterrence may in fact have been spurious" (pp. 649-650).

Three years after that, Greenburg and Kessler (1982) expanded on the earlier research by adding 12 socioeconomic control variables into the 98-city sample model. Estimating models with both instantaneous and lagged effects (using separate one, two and three year lagged models), they found little evidence supporting a crime-prevention effect. Although they were able to find one model for both murder and aggravated assault that was statistically significant, the other models on these crimes were not significant, leading them to conclude that evidence for the existence of a crime prevention effect for either crime was not persuasive. Similarly, while their models did find a slight effect for burglary, "the evidence for a crime prevention effect here is ambiguous, and the effect is small in any event" (p. 781). Aside from these three findings, the authors found no other models for other Index I crimes with statistically significant results. Based on these findings, the authors wrote, "Our analysis finds no consistent evidence for the proposition that higher arrest clearance rates result in substantially lower index crime rates" (p. 784).

Chamlin (1988) explored whether a lagged relationship between arrest rates and crime rates did exist, but could only be seen through something other than a yearly lag. He did this by utilizing an autoregressive integrated moving average (ARIMA) approach to see if he could find evidence of an arrest-crime relationship in Oklahoma City and Tulsa, Oklahoma for the crimes of robbery, burglary, grand larceny and auto theft using a monthly (as opposed to yearly) lag. Although he found evidence that robbery arrests had a negative effect with a one month lag on robbery offenses for both Oklahoma City and Tulsa, he found no lagged relationship between arrest rates and crime rates for overall crime or for burglary, larceny or auto theft.

Three years later, Chamlin (1991) used the ARIMA approach to explore whether there was evidence in support of a tipping effect (Tittle and Rowe, 1974) and if this effect depended on the size of the city under observation (Brown, 1978). He conducted his analysis using monthly data obtained from the FBI for the period between January 1967 and December 1980. He examined four offense categories (robbery, burglary, grand larceny and auto theft) for seven Pennsylvania cities that had a 1970 population that ranged between 5,990 and

2,002,512. His analysis revealed that only five of the 28 arrest-crime relationships were statistically significant (which revealed little support for an overall tipping effect) but that there was some evidence of a deterrent effect in the smallest city for the crimes of robbery and auto theft when the mean clearance rate equaled or exceeded 40 percent.

The six research studies reviewed provide mixed evidence of a relationship between arrest certainty and crime rates. None indicates whether a relationship exists between arrest certainty and recidivism. To explore this relationship, multilevel regressions were estimated for each of the seven recidivism measures, controlling for the nine individual level risk factors. Each of these seven multilevel models is included in its entirety in Appendix C. For clarification, the arrest-offense ratio is defined as the number of arrests for Index Crimes (which include the crimes of murder, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson) divided by the number of these crimes reported to the police.

Table 26 - Multilevel Regressions for Seven Outcomes on Individual Level Characteristics and Statewide Arrest-Offense Ratios Final estimation of fixed effects (Unit specified model).

Arrest-Offense Ratio	*b*	S.E.	Exp(b)
Any Rearrest	-0.024463	0.073690	0.975834
Rearrest for a Violent Offense	-0.014311	0.015594	0.985791
Rearrest for a Property Offense	-0.010984	0.018681	0.989076
Rearrest for a Drug Offense	-0.017078	0.025529	0.983067
Rearrest for a Public Order Offense	-0.029950	0.034942	0.970494
Reconviction	0.023951	0.032943	1.024240
Reimprisonment	-0.003458	0.034677	0.996548

* $p < .10$, ** $p < .05$, *** $p < .01$

The results offer no evidence that the arrest-offense ratio helps to explain variation in any form of recidivism between states, when individual level factors are controlled. There are several possible explanations for this non-finding. One explanation is that a relationship does, in fact, exist between recidivism and the arrest-offense ratio but that it only exists in states where arrest certainty is above a certain level (the tipping effect) and the analysis run was unable to pick this effect up. A second possibility is that the non-finding is based on the low level-two sample and that if a larger number of level two units had been used, a relationship would have been found. A third possibility is that the non-finding is correct and that between state variation in arrest certainty has no bearing on recidivism rates when individual level characteristics are controlled.

6.5: Discussion

This chapter has explored whether the inclusion of three separate contextual variables helps to explain the variation between states in various forms of recidivism with nine individual level characteristics controlled. The results of these multivariate analyses reveal that the state-level variables of statewide drug arrest rates and arrest-offense ratio do not help to explain variation in recidivism rates. Although the multivariate analysis revealed a statistically significant finding for the outcome measure of drug arrest rates when the state level contextual variable of statewide drug arrests was added to the model, this finding is substantively meaningless. What the finding basically says is that in states where people are more likely to be arrested for drug offenses, people released from prison are more likely to be arrested for drug offenses.

The state-level variable of police per 1,000 residents revealed one statistically significant finding and two marginally significant findings. In states with more police per 1,000 residents, released offenders were significantly more likely to be rearrested for a property offense, their likelihood of being rearrested for a drug offense was marginally greater and the likelihood of an offender who had been rearrested being reconvicted is also marginally greater. The finding of a contextual variable being related to probability of reconviction is noteworthy in light of the earlier finding that variations in individual level characteristics did not help explain variation between states in probability of reconviction. Future research should explore the effect of additional contextual variables on this measure of recidivism. While the proceeding three chapters have looked at whether individual level or contextual characteristics can help explain variations in recidivism rates across space, the focus of chapter seven is on how useful individual level characteristics are at explaining changes in rearrest rates over time.

CHAPTER 7 - EXPLORING THE IMPACT OF INDIVIDUAL LEVEL CHARACTERISTICS ON REARREST RATES OVER TIME

7.1: Introduction

While the results from chapter four have shown that variations in individual level characteristics help explain differences in rearrest rates across space, they do not tell if changes in the individual characteristics of released prisoners also help to explain changes in recidivism rates over time. To more fully explore this, two separate logistic regressions models were run, using a combined dataset that included offenders released from the same 11 states in 1983 and 1994. Although the *Prisoners Released in 1994 dataset* included inmates from four additional states (Arizona, Delaware, Maryland and Virginia) that were not included in the 1983 dataset, these inmates were not included in the combined dataset as offender information was not available for offenders from those states released in 1983. In total, the sample consisted of 42,301 weighted cases that represented 342,602 offenders.

In the dataset, year of release is coded as a dichotomous variable, with a value of zero meaning the offender was released in 1983 and a value of one meaning the offender was released in 1994. In line with the "fixed effects" models used in chapters four and five, these models again estimate the odds ratio (with 1994 as the contrast state). In the first logistic regression model, the only variables entered into the regression equation are the outcome variable (i.e., rearrest) and the year of release. This tells if and to what extent there is a difference in rearrest rates over time. In the second logistic regression model, the nine previously described individual level characteristics are added to the model.

Table 27 outlines the results of a logistic regression model based on year of release. These results show that those released in 1994 were significantly more likely to be rearrested than those released in 1983. This is not surprising, given that the proportion of offenders rearrested was over four percentage points higher for the 1994 cohort than for the 1983 cohort.

Table 27: Logistic Regression Results for Rearrest for Any Offense Comparing Offenders Released in 1983 and 1994		
REARRD	Odds Ratio	Std. Error
Released in 1994	1.271295***	.0357694
Model Statistics		
Observations	Pseudo R^2	Log Pseudolikelihood
42301	0.0021	-218762.08
* p<.05 , ** p <.01, *** p<.001		

When each of the nine individual level characteristics is added to the model, most of the individual level characteristics remain significant in the predicted direction. Females are less likely to be rearrested than males (O.R.=1.592, p<.001); blacks are more likely to be rearrested than whites (O.R.=1.601, p<.001); those released at a younger age are more likely to be rearrested than those released at an older age (O.R.=0.936, p<.001); those with more prior arrests are more likely to be rearrested than those with fewer prior arrests (O.R.=1.092, p<.001); property offenders are more likely to be rearrested than violent offenders (O.R.=0.759, p<.001), drug offenders (O.R.=0.752, p<.001) and public order offenders (O.R.=0.749, p<.001); inmates who served less time in prison during their last incarceration are more likely to be rearrested than those who served more time in prison (O.R.=0.998, p<.001); those admitted via parole violation are more likely to be rearrested than those admitted via new court sentence (O.R.=1.526, p<.001); and those released via discretionary parole are less likely to be rearrested than those released via mandatory supervised release (O.R.=1.353, p<.001) or expiration of sentence (O.R.=1.499, p<.001). In addition to these findings, the model reveals that those of other races are less likely to be rearrested than whites (O.R.=0.697, p<.05); that there is no significant difference in the prevalence of rearrest of property offenders and those offenders released for an offense classified as other (O.R.=0.737, n.s); that those who entered prison on a probation violation have a lower prevalence of rearrest than those released on a new court commitment (O.R.=0.780, p<.01); and that those released via other release types (beyond discretionary parole, mandatory supervised release and expiration of sentence) are more likely to be rearrested compared to those released via discretionary parole (O.R.=1.263, p<.05). Finally, with the individual level characteristics in the model, age of first arrest is not a significant predictor of rearrest (O.R.=1.005, n.s.). This model is displayed in Table 28.

Table 28: Logistic Regression Results for Rearrest for Any Offense Comparing Offenders Released in 1983 and 1994 with Individual Level Characteristics Added to the Model

REARRD	Odds Ratio	Std. Error
Released in 1994	1.439505***	0.0493237
Gender	1.592985***	0.1015887
Age of First Arrest	1.004918	0.0044235
Black	1.601155***	0.0540726
Other Race	0.6968868*	0.1201743
Age at Release	0.9356963***	0.0029949
Prior Arrests	1.091794***	0.0050182
Violent Offense	0.7591705***	0.0298471

Drug Offense	0.7516201***	0.0362762
Public Order Offense	0.749285***	0.0492074
Other Offense	0.7375587	0.1664747
Time Served	0.9981553**	0.0006829
Parole Violation	1.5257***	0.0793994
Probation Violation	0.7804044**	0.056075
Other Admission Type	1.263271*	0.1410873
Unknown Admission Type	1.057993	0.0447077
Mandatory Supervised Release	1.353116***	0.0509955
Expiration of Sentence	1.49922***	0.0748854
Other Release Type	1.424681***	0.0779771
Model Statistics		
Observations	Pseudo R^2	Log Pseudolikelihood
42301	0.1132	-194405.63
* p<.05 , ** p <.01, *** p<.001		

Most importantly, however, is that with individual level characteristics included in the model, the odds ratio for the release year variable increases by 13.23 percent. This indicates that changes in individual level characteristics cannot be used to explain the increase in rearrest rates that occurred between the 1983 and 1994 cohorts. If they did explain differences in prevalence of rearrest over time, then the odds ratio for the year variable would have decreased. What the increase indicates, instead, is that there are factors other than individual level characteristics responsible for the increase in prevalence of rearrest between 1983 and 1994.

Table 29: Logistic Regression Results for Rearrest for Any Offense Comparing Offenders Released in 1983 and 1994 with Individual Level Characteristics and State of Release Added to the Model

REARRD	Odds Ratio	Std. Error
Released in 1994	1.471607***	0.0512288
California	1.206444*	0.0992839
Florida	1.723475***	0.1330589
Illinois	1.389428***	0.1178957
Michigan	0.7613157***	0.0510884
Minnesota	1.10703	0.0891658

New York	1.136958	0.0866285
North Carolina	0.988149	0.0712122
Ohio	0.6418645***	0.0493907
Oregon	1.652417***	0.1251161
Texas	0.7161433***	0.0544163
Gender	1.580552***	0.1018312
Age of First Arrest	1.001957	0.0044159
Black	1.62208***	0.0569342
Other Race	0.6674645*	0.1162995
Age at Release	0.9380546***	0.0030096
Prior Arrests	1.082739***	0.0049907
Property Offense	0.7094233***	0.0286814
Drug Offense	0.7258174***	0.035602
Public Order Offense	0.7353339***	0.0489907
Other Offense	0.6872783	0.1561032
Time Served	0.998389*	0.0006979
Parole Violation	1.594247***	0.0851933
Probation Violation	0.8310647*	0.0648874
Other Admission Type	1.446371**	0.1731308
Unknown Admission Type	1.410627***	0.0774637
Mandatory Supervised Release	1.148271*	0.0638529
Expiration of Sentence	1.278675***	0.0715531
Other Release Type	1.152716*	0.0730878
Model Statistics		
Observations	Pseudo R^2	Log Pseudolikelihood
42301	0.1213	-192636.37
* p<.05 , ** p <.01, *** p<.001		

When states are added to the model which includes individual level characteristics (as displayed in Table 29), most of the findings remain unchanged. Age of first arrest and serving time for another offense remain non-significant. One notable finding, however, is that the odds ratios for mandatory supervised release, expiration of sentence and other release type each drop by at least 14 percent when the state variables are added. This change indicates that a nontrivial amount of the difference in rearrest rates based on release type is the result of distinctive release patterns used by different states.

Similar to the models on rearrest rates over time, the Pseudo R^2 value from the logistic regression model with year of release and the nine individual level characteristics in the model indicate that there still remains over 88 percent of variation not explained by the state of release or the nine individual level factors. When state of release is added to the model, the Pseudo R^2 value increases by less than one percent (from 0.1132 to 0.1213). This indicates, again, that many additional individual, contextual and policy variables need to be added to the model to fully account for differences between time periods in rearrest rates. The log pseudolikelihood value indicates improved fit when individual level characteristics are added to the model and further improvement when state of release is added.

7.2: Using Predicted Probability Models to Clarify the Findings

Before proceeding on to possible explanations of why the models produced the findings that they did, it will first be informative to graphically display the differences between the actual changes in rearrest rates over time and the expected rearrest rates over time based on the predicted probabilities from the regression models. For the following graphical displays of rearrest rates for 1983 and 1994, information is displayed for 42,301 cases representing 99,681 offenders released from 11 states in 1983 and for 242,921 offenders released from the same 11 states in 1994. On the following page, Figure 8 displays the actual rearrest rates of prisoners released from 11 states in 1983 and 1994 while Figure 9 displays the predicted 1983 prisoners based on the coefficients from 1983 and

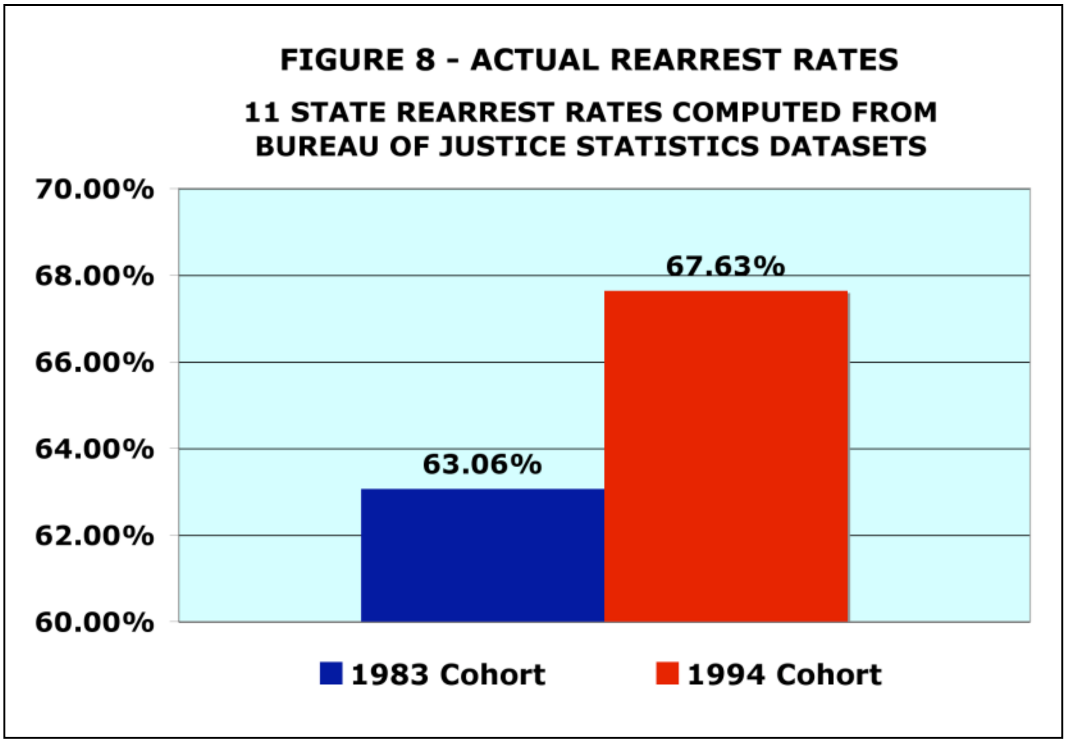
FIGURE 8 - ACTUAL REARREST RATES
11 STATE REARREST RATES COMPUTED FROM BUREAU OF JUSTICE STATISTICS DATASETS
70.00%
68.00%
66.00%
64.00%
62.00%
60.00%
63.06%
67.63%
1983 Cohort
1994 Cohort

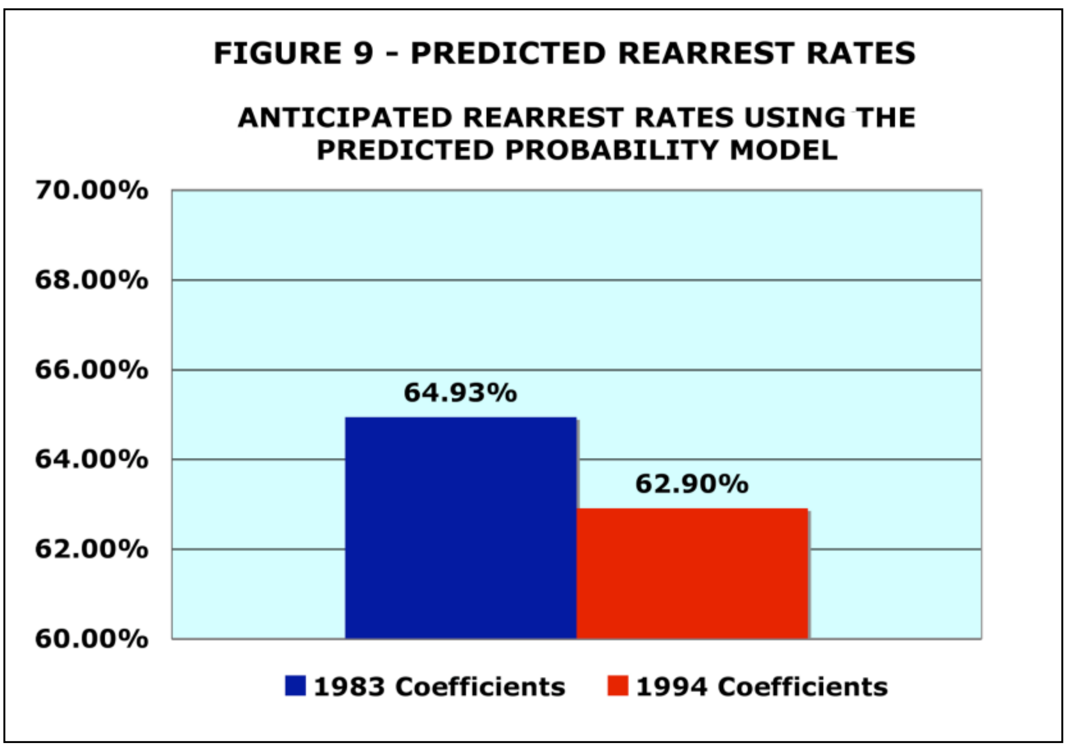
FIGURE 9 - PREDICTED REARREST RATES
ANTICIPATED REARREST RATES USING THE PREDICTED PROBABILITY MODEL
70.00%
68.00%
66.00%
64.00%
62.00%
60.00%
64.93%
62.90%
1983 Coefficients
1994 Coefficients

1994. The graphs clearly show that the rearrest rates would have been predicted to *decrease* had the individual level characteristics had the anticipated effect.

Although the percentages in the figure do not include all inmates from both datasets, Figure 8 nevertheless displays findings very similar to those from Langan and Levin (2002) and from Beck and Shipley (1989). What the figure shows is that offenders released in 1994 were 7.25 percent more likely to be rearrested than offenders released in 1983. The logistic regression model shown in Table 27, however, reveals that this was not what was expected based on the changing demographics of the offenders released from prison in each respective year. According to this model, rearrest rates should have gone down, not up, if the only factors that influenced rearrest rates were the nine individual level factors.

This is shown in Figure 9, which displays the anticipated rates using two predicted probability models. The first model answers the question: Using predicted probabilities, what would have been the anticipated rearrest rates of prisoners released in 1983 using the 1983 sample and 1983 coefficients? This is an important question to answer as it tells what the expected rearrest rates for 1983 should have been based on the nine individual level characteristics of offenders released that year. It is also important because it gives a base percentage to compare the 1994 cohort to. The second model answers the question: What would the anticipated rearrest rates in 1994 have been if the 1994 coefficients were used but the sample of released prisoners were identical to that in 1983? This question is relevant because it helps us understand what the predicted rearrest rates for 1994 would have been if the only variables which influenced the rearrest rates were the nine individual level characteristics.

While Figure 8 shows that rearrest rates went up over time, the results displayed in Figure 9 show that, based on the predicted probabilities of changing demographics between the 1983 and 1994 cohort, rearrest rates should have gone down if the only factors that influenced variation in rearrest rates were changes in demographic characteristics of the release cohorts. These findings indicate that the nine individual level factors previously discussed do not explain the increase over time in the rearrest rates of released prisoners.

This leads to the question: Since variations in individual level factors do not do a good job at explaining changes in rearrest rates over time, what other factors might be used to explain the variation? While the discussion that follows is necessarily speculative, evidence will be presented suggesting that three factors which may help to explain variations in rearrest rates over time include: 1) America's War on Drugs, 2) Increased Numbers of Police Officers and 3) Changing Police Procedures.

7.3: America's War on Drug

The single factor which likely had the greatest impact on why prevalence of rearrest went up involves the changing political climate in America and the increased focus on combating drug crime. One clear example of why this factor had an impact on prevalence of rearrest comes from the reports written by Beck and Shipley (1989) and Langan and Levin (2002). These reports highlight that the percentage of offenders released from prison for drug offenses more than tripled from just 9.28 percent of releases in 1983 to over 33.12 percent of releases in 1994. A further analysis of these two datasets reveals that the proportion of inmates released from prison in 1983 rearrested *only* on drug related charges, increased by over 170 percent between 1983 and 1994. While only 3.51 percent of releases in 1983 were rearrested solely on drug related charges within three years of their release from prison, this percentage increased to 9.55 percent of releases in 1994. It should be noted that, alone, the increase in the number arrested solely on drug related charges explains the increase in prevalence of rearrest between 1983 and 1994.

The United States prison population's steady increase in size began in 1974, a few years after the punitive shifts began in America following the Republican Party adopting a tough on crime platform in the late 1960s (Tonry, 1999) and the publication of a widely influential piece by Martinson (1974) that "nothing works" in rehabilitating criminal offenders. But many of the enhanced sentencing strategies aimed at drug offenders weren't implemented until the rise of drug related crime began in the mid 1980s. In line with the increasing public concern that coincided with this crime increase, the federal government passed two laws – the Anti-Drug Abuse Act of 1986 and the Anti-Drug Abuse Act of 1988 – both containing new mandatory minimum sentences for specific drug offenses.

Although these federal laws did not directly affect state court cases, the "tough on drug crime" trend nevertheless followed in state criminal filings.

Roberts (1993) wrote, “In New York State, for example, drug felony filings increased by 288% between 1985 and 1989; the rate of felony drug convictions increased by 21.6% in the first quarter of 1989; and the number of prison inmates serving sentences for drug-related offenses increased by over 300% between 1986 and 1990” (footnote 53, page 1957). The massive increase in drug incarceration rates was not unique to New York, however. Zimring and Hawkins (1994) reported: “Between 1980 and 1990 the annual total of males in prison for drug offenses in California grew fifteenfold from approximately 1,500 to 22,600” (p. 88). They further suggested that the actual cause of the tremendous increase in drug arrests and drug incarceration rates had more to do with changes in drug enforcement policies than with an actual increase in drug use, as national surveys conducted throughout the 1980s showed a fairly persistent decline in illegal drug use during that decade.

7.4: Increased Numbers of Police Officers

A second factor which likely contributed to the increase in prevalence of rearrest for offenders released from prison in 1994 compared to those released in 1983 was the increase in the number of full time police officers patrolling American cities during this time period. This number was undoubtedly affected by the passage of the Violent Crime Control and Law Enforcement Act (VCCA), which was signed into law in September 1994. One of the components of VCCA established the Community Oriented Police Services (COPS) office and authorized the distribution of grants to local police. The bulk of these grants were designated for the Universal Hiring Program, which provided grants to local police agencies to pay 75% of the cost of new police hires. The grants provided for the hiring of additional police officers beginning in 1995 and as of the end of the 2008 Fiscal Year, the COPS Office had provided funding for approximately 117,000 additional officers.

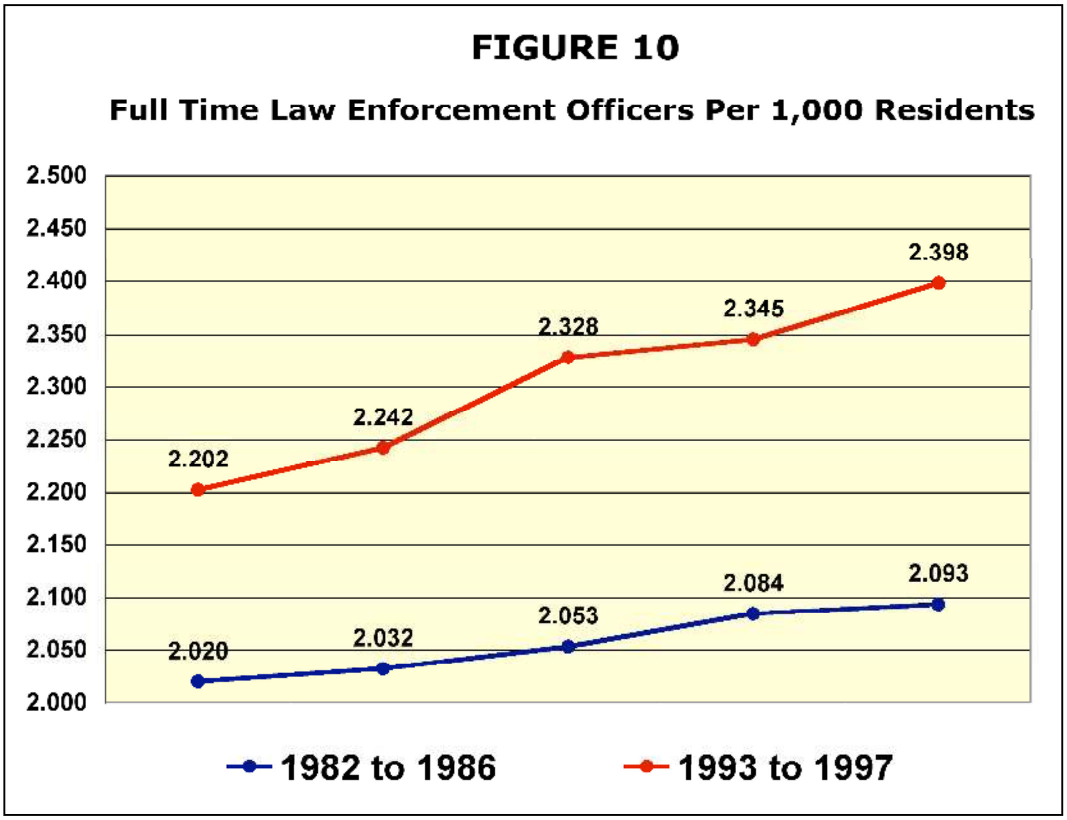

Figure 10 highlights that the number of law enforcement officers increased between October, 1982 and October, 1993 by 8.27 percent, as the average number of police officers per 1,000 residents increased from 2.020 per 1,000 to 2.202 per 1,000. This averages out to an annual increase of 0.75 percent per year between October 1982 and October 1993. The chart also shows that the rate of law enforcement officers per 1,000 residents increased at a substantially higher rate than in previous years in the year following the passage of VCCA. From 1994 to 1995, the ratio of police per 1,000 residents increased by 3.84 percent. This increase is over five times the average increase that occurred between 1982 and 1993.

As previously stated, findings by Zhao, Schneider and Thurman (2003) indicated that more police were related to more arrests for violent crimes, drug offenses and social disorder offenses. Additionally, although the multilevel analyses conducted in chapter six did not find a significant relationship between police per 1,000 residents and rearrest rates across states, there was a marginally significant relationship between police per 1,000 residents and rearrest for drug offenses. It is reasonable to assume that the growth in the number of police officers contributed to the very large increase in the percentage of released prisoners rearrested for a drug related offense between 1983 and 1994

7.5: Changing Police Procedures

In addition to the increase in the number of law enforcement officers on the street, another possible reason for the increase in prevalence of rearrest has to do with changes in police procedures which occurred between 1983 and 1994. These changes involved a shift away from a reactive response to a proactive one.

One such change involved increased use of what is commonly referred to as community policing. According to a United States Department of Justice (2009b) report, "Community policing is a philosophy that promotes organizational strategies, which support the systematic use of partnerships and problem-solving techniques, to proactively address the immediate conditions that give rise to public safety issues such as crime, social disorder, and fear of crime" (p. 3). Even though community policing techniques probably did not become widespread until the passage of VCCA in 1994, Eck and Maguire (2006) report that the implementation of this form of policing began in the early 1980s.

A second change in policing involved a combination of aggressive policing strategies known as "order maintenance" or "zero-tolerance" policing. This strategy was widely influenced by the work of Wilson and Kelling (1982) which described the "Broken Windows" thesis. Under this thesis, community level disorder and crime are closely related because disorder ("broken windows") is a signal to the community that nobody cares. Under this strategy, the police attempt to control crime through strict enforcement of minor, public order offenses (Eck and Maguire, 2006). The most well known example of "zero-tolerance" policing was that implemented by former Police Commissioner William Bratton in New York City in 1993.

Regardless of whether community policing or zero-tolerance policing has any effect on crime rates, both could be expected to result in an increase in arrests for drug offenses and public order offenses. With community policing, this is because the police are on the street and are more likely to observe first hand what some people refer to as "victimless crimes" (such as public drunkenness, prostitution and drug sales), which would be unlikely to be reported to police if they utilized a reactive approach. With zero-tolerance policing, this is because the police are instructed to not be tolerant of minor offenses, which would have been overlooked in the past.

Some evidence in support of this hypothesis comes from looking at the change in the percentage of prisoners, by offense type, released from the 11 states for 1983 compared to 1994. While there was an increase from 1983 to 1994 in the numbers for all types of offenders released from prison, the percent increase was not uniform. Instead the percent increase was much greater for drug offenders and public-order offenders than for violent offenders and property offenders. Specifically, although the release of violent offenders increased by 51 percent and property offenders by 67 percent, the increase for public order offenders was 256 percent and the increase for drug offenders was 752 percent. The dramatic increase in the percentage of offenders who were released after serving time for drug related offenses could be explained by the national campaign against drug offenses that ensued in the mid 1980s. Similarly the large increase of offenders released from prison for public order offenses compared to violent and property offenses can be explained by changes to more proactive policing strategies. This change in strategy could also explain why prevalence of rearrest went up for the 1994 cohort. Since police took a more proactive approach in the 1990s than they did in the 1980s, arrests for public order and drug offenses would increase even if actual rates of offending did not.

7.6: Discussion

Although this chapter is limited in scope, the findings presented indicate that changes in the composite individual level characteristics of offenders released from prison in 11 states in 1983 and 1994 do not explain changes in rearrest rates over time. This finding stands in contrast to this dissertation's analyses regarding variation in rearrest rates across space for the 1994 cohort. The findings from those analyses revealed that changes in individual level characteristics help to explain variation in rearrest rates across states.

While multivariate analyses were not conducted to test these hypotheses, three possible explanations were given of why rearrest rates may have gone up in 1994, despite a predicted probability model anticipating that they would go down. The first of these was that the increase in rearrest rates was due to the increased emphasis placed on arresting drug offenders which occurred in the late 1980s and early 1990s. The second of these was that the increase in rearrest rates was due to the increase in the average number of police officers per capita which were employed across the United States. The third of these was that changes in police procedures, more specifically a shift away from a reactive response to a proactive one, were responsible for the increases in rearrest rates. While a multivariate test of each of these explanations is beyond the scope of this dissertation, future research should investigate the extent to which each helps to account for the increase in rearrests of released prisoners between the mid-1980s and mid-1990s.

CHAPTER 8 – CONTRIBUTIONS AND LIMITATIONS: POLICY IMPLICATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

8.1: Introduction

The results of the analyses presented in this study help provide a more detailed understanding of the individual and contextual factors related to specific forms of recidivism across both space and time. The major findings are reviewed below.

The study examined eight separate forms of recidivism across space and ran two sets of analyses to test whether variations in nine separate individual level characteristics could help explain variation between states in recidivism rates, using offenders from the *Prisoners Released in 1994 dataset* as the source. These eight types of recidivism are: 1) rearrest for a new offense, 2) rearrest for a new violent offense, 3) rearrest for a new property offense, 3) rearrest for a new drug offense, 5) rearrest for a new public order offense, 6) reconviction, 7) reimprisonment, and 8) parole violations.

Estimating separate models for each form of recidivism, one which involved an omitted state model and the second which involved a state-by-state comparison model, revealed that the variations in the individual level characteristics explain some of the between state variation for five of the eight forms of recidivism. The omitted state model revealed that variations in individual level characteristics helped explain on average about 35% of the state differences in rates of rearrest for any offense, 20% of the state differences in rates of rearrest for a new property offense, 34% of the state differences in rates of rearrest for a new drug offense, 27% of the state differences in rates of rearrest for a new public order offense and 9% percent of the state differences in reimprisonment probabilities of reconvicted offenders.

The results for the models involving rearrest for a violent offense, reconviction for rearrested offenders and parole violations were mixed. In each of the cases, one of the models revealed that the individual level characteristics helped to explain variation between states in recidivism rates, while the other revealed no such effect. For rates of rearrest for a new violent offense, while the omitted state model revealed that differences in the characteristics of released prisoners explained on average about 31% of the state differences in rates of rearrest for a new violent offense, the state-by-state comparison revealed a very small increase in the number of states with similar violent rearrest rates when the individual level characteristics were added to the model. For reconvictions of rearrested offenders and for parole violation, while a state-by-state comparison revealed a sizeable increase in the number of states with similar reconviction probabilities and parole violations when individual level characteristics were added, the omitted state model revealed that differences in the characteristics of released prisoners explained on average almost none of the variation in state differences.

Several possible explanations were given that might explain the mixed findings for three of the forms of recidivism. For rearrest for a violent offense, one possible explanation is that the omitted state model did not pick up a difference because of the similarity in violent rearrest rates across states. A second explanation pointed out that prior research has shown that factors other than the nine individual level factors being tested are associated with violent offending – including childhood behavioral problems, prior aggression, psychopathy, antisocial personality and deviant sexual arousal – and that it was quite possible that these other factors had a stronger effect than the nine investigated in this dissertation. For reconviction probability, evidence was presented that the nine individual level characteristics might not be useful predictors of recidivism rates because prior research (Rasmussen et al., 2009; Blaine et al., 2010) had found that contextual, as opposed to individual level, factors determined the conviction rate of a given jurisdiction. Evidence was presented from former studies that political motivation and monetary resources were two contextual level factors that influenced conviction rates. Evidence was also presented from the multilevel analysis conducted in Chapter 6 that the contextual factor of police per 1,000 residents may have had some influence on conviction probabilities between states. For parole violation differences, evidence was presented that it was likely that different statewide parole policies had a greater impact on explaining variations in parole revocation rates than individual level characteristics.

In addition to using these nine individual level characteristics to see to what extent they were useful in helping explain various forms of recidivism across space, two additional sets of analysis were conducted. The first was a multilevel analysis which looked at whether, with the nine individual level characteristics controlled, the state level factors of drug arrests per 100,000 residents, police per 1,000 residents, and the arrest-offense ratio help to explain between state variation for seven of the eight forms of recidivism previously described (parole violations were not analyzed due to only having data available from nine states). While there was no relationship found between the contextual variables of drug arrests per 100,000[6] or arrest-offense ratio and any form of recidivism, the number of police officers per 1,000 residents was found to be significantly related ($p<.01$) to the probability of rearrest for a property offense and marginally related ($p<.10$) to the probability of rearrest for a drug offense and the probability of reconviction for rearrested offenders.

Besides looking at the effect of contextual variables, a separate analysis was conducted to see if changes in the composition of individual level characteristics could help explain the increase in rearrest rates which occurred in 11 states comparing offenders released in 1983 with offenders released in 1994. The analysis revealed that the changes in individual level characteristics do not explain increases in rearrest rates over time. Using predicted probability models, it was found that, while rearrest rates had increased by 7.25 percentage points between 1983 and 1994, had the nine individual level characteristics produced the anticipated effect based on the predicted probability models, rearrest rates should have *decreased* by 3.13 percentage points. Evidence was given for three possible explanations: 1) America's War on Drugs, 2) Increased Number of Police Officers and 3) Changing Police Procedures.

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[6] Although there was a finding that as drug arrests per 100,000 inmates increased in a state, more offenders were rearrested for a drug offense, as described in Chapter 6, this finding is substantively meaningless.

8.2. The Impact of Individual Level Factors on Different Forms of Recidivism

While the primary goal of this dissertation was to examine the extent to which nine individual level factors explain eight forms of recidivism across space and one form of recidivism over time, a second finding was that some of the individual level characteristics by themselves help to explain increased risk for specific forms of recidivism while others do not. This finding has tremendous importance from both social and correctional policy perspectives. Perhaps the most important point to take away from this finding is that one size does not fit all in looking at different types of offenders and different forms of recidivism. Instead, each individual form of recidivism needs to be evaluated and dealt with separately.

When we look at offense rearrest and compare significant predictors across the nature of the rearrest, we see general stability in the characteristics associated with increased odds of rearrest, regardless of the offense. For rearrest for a violent offense, property offense, drug offense, and public order offense, common risk factors include: 1) being male, 2) being younger at age of release, 3) having more prior arrests, 4) having served less time in prison, 5) having entered prison on a parole violation, 6) and having been released from prison via expiration of sentence. Another notable result is evidence of specialization for every type of offense, with violent offenders being most likely to be rearrested for a violent offense, property offenders being the most likely type to be rearrested for a property offense, drug offenders being the most likely type to be rearrested for a drug offense, and public order offenders being the most likely type to be rearrested for a public order offense. This finding provides evidence that offenders would benefit if correctional officials developed programming designed specifically for the offense for which an inmate was currently incarcerated. In this regard, one question policy makers and corrections officials should ask is this: While there are prison based programs specifically designed for violent offenders which have been shown to reduce recidivism rates (Dowden and Andrews, 2000) along with similarly effective programs specifically designed for drug offenders (Knight, Simpson, and Hiller, 2004; Burdon, Messina, and Prendergast, 2004), would it not also make sense to design programs specifically for property offenders, especially given the finding that they have higher overall rates than any other type of offender?

Although there are many similarities among the offenders who were rearrested, regardless of the offense they were rearrested for, there were also a few differences. One notable difference with both treatment and social policy implications is that those who are first arrested at an earlier age are more likely to be rearrested for a violent offense (O.R.=0.967, $p<.001$). Given that violent offenses are the most serious type of offense, this finding points towards the need to develop early intervention programming specifically targeting those who begin engaging in serious criminal behavior at a young age. Prior literature has shown that children with serious behavioral problems often do not receive appropriate mental health treatment (Burns, Phillips, Wagner, Barth, Kolko, Campbell, and Landsverk, 2004). Instead, treatment is not provided, if it is provided at all, until a child has reached adolescence (Oliver, 2007). This is unfortunate because by then the problem is likely much more difficult to treat.

There is also quite a bit of variation in the extent to which individual level characteristics are risk factors for specific types of recidivism. These variations should lead to questions about how police, prosecutors, judges and probation and parole officials handle offenders with specific characteristics. For example, why is that males are more likely than females to be rearrested for a new offense and to be reimprisoned if reconvicted, but not more likely to have their parole revoked? Alternatively, why does serving a longer amount of time in prison significantly decrease the odds of rearrest and the probability of reconviction for rearrested offenders, but significantly increase the odds of parole revocation and the probability of reimprisonment for reconvicted offenders? These questions, and others like them, cannot be answered with data available from the datasets used for this dissertation, but they are nevertheless questions which future research should address.

8.3: Policy Implications

The findings from this dissertation provide evidence for four specific policy recommendations. The first is that to effectively lower recidivism rates, treatment services need to be based on offender need and risk level. The second is that certain contextual factors affect recidivism rates above and beyond individual level characteristics and these contextual factors need to be taken into account in deciding how to respond to crime. The third is that discretionary parole should be brought back in states that have abandoned it. The fourth is that states should consider offering offense-specific treatment programs to those offenders who have a criminal record associated with offense specialization.

8.3.1: Treatment Services Need to Be Based on Offender Need and Risk Level

The findings from this dissertation that differences between states in individual level characteristics can explain between 20 and 30 percent of the variation in rearrest rates for both overall arrests and arrests for specific types of offenses make it very clear that lawmakers and policymakers must be attentive to the specific risk factors that inmates in their jurisdictions face in deciding what programs to develop and how to appropriately implement them. In many states, inmates who get treatment end up involved in a relatively ineffective form of treatment in the form of a short-term program, designed not because studies have shown it was most effective, but instead because it is all the Department of Corrections can afford to offer (Harrison, 2001; Petersilia, 2001). Other states use a poorly designed, one-size-fits-all approach, which may be appropriate for some inmates but not others (Matthews, Hubbard, and Latessa, 2001; Latessa, Cullen, and Gendreau, 2002). While well-intentioned, such approaches can actually be detrimental to some offenders as research has found that placing low risk offenders in an inappropriate treatment setting, designed for moderate and high risk offenders, can actually increase their risk of reoffending (Lowenkamp and Latessa, 2005). Still other inmates find themselves receiving no treatment at all (Mumola, 1999; Harrison, 2001; Matthews et al., 2001; Burdon et al., 2004).

Several studies (Andrews, Bonta, and Hoge, 1990; Andrews and Dowden, 1999; Lowenkamp, Latessa, and Holsinger, 2006) have found that offenders receive the most benefit if the level of services they receive is congruent with their level of risk. Lawmakers and corrections officials need to be attentive to the specific risk factors faced by those in prison if they are to design programs that effectively reduce recidivism rates. It would be a mistake, for example, to have Delaware adopt the reentry procedures used in Michigan, because the backgrounds of offenders from these two states are vastly different. The most noticeable difference between the two groups of offenders is that offenders released from Delaware have, on average, over three times as many prior arrests as those released from Michigan. Therefore, the majority of programming designed for inmates being released from prison in Delaware should be tailored to meet the needs of high risk offenders while the majority of programming for inmates being released from prison in Michigan should be tailored to meet the needs of low risk offenders (in both states, however, the programming should be tailored to address the treatment issues associated with specific offense types – such as sex offender treatment, drug counseling and anger management). Programming in each respective state should be tailored to reflect the different levels of risk. Parole and correctional officials in Delaware should design longer, more intensive reentry programs to meet the needs of their returning high risk offender population.

The weaker findings related to predicting violent recidivism highlight that the individual level factors analyzed in this study are most certainly not the only risk factors that need to be looked at in determining the programs that need to be developed to enhance the chance of success. They also highlight that different types of offenders have different treatment needs and that what is appropriate for one class of offender may not be appropriate for a separate class of offender.

8.3.2: Certain Contextual Variables Affect Recidivism Rates Above and Beyond Individual Level Characteristics

The results from Chapters 6 and 7 provide some evidence that certain changes in policy have an effect on the rates of various forms of recidivism. In Chapter 6, while the contextual factors of drug arrests per 100,000 and arrest-offense ratio were not found to be related to significant increases or decreases in the probability of any type of recidivism, evidence was produced that, with the nine individual level characteristics controlled, the rate of police per 1,000 residents was significantly and positively related to probability of rearrest for a property offense and positively related, though only at a marginally significant level, to probability of rearrest for a drug offense. This model further provided evidence that police per 1,000 residents was positively related, though only at a marginal level, to reconviction rates. The finding related to reconviction rates provides additional evidence to that from previous studies (Rasmussen et al., 2009; Blaine et al., 2010) that differences in conviction rates between jurisdictions are largely the result of policy-driven contextual factors.

The results from the analysis in chapter 7 are a bit of a surprise in that it showed that changes in criminal justice policies can lead to an increase in rearrest rates even when models based on individual level characteristics indicate that the rearrest rates should have gone down. While there is certainly the likelihood that other individual level characteristics besides the nine used in the model had some influence in recidivism rates, in the case of recidivism over time, changes in law, policy and practice that occurred between the mid 1980's and mid 1990's across the United States apparently had a stronger influence on rearrest rates than the individual level characteristics used in the model.

The evidence presented suggested that three contextual changes that caused rearrest rates to go up between the mid 1980's and mid 1990's were America's increased emphasis on drug crimes, a larger number of police on the street, and a change to a more proactive style of policing. This is an important finding from both a political and an economic perspective because increased arrest rates also increase the costs for jailing, feeding, and prosecuting more defendants. Potential extra costs thus need to be taken into account when implementing new criminal justice policies. While the motive behind such changes may be to help make cities safer for the residents who live in them, policy makers need to be sure they also take into consideration potential extra costs such policy changes may require.

8.3.3: States Should Implement Discretionary Parole

Earlier in the dissertation, Petersilia (2003) was quoted as arguing that allowing states to maintain the option of discretionary parole could enhance the likelihood of success after release. Rosenfeld et al.'s (2005) study provided support for this claim by showing that those released via discretionary parole had markedly lower rearrest rates than those released via mandatory supervised release or expiration of sentence. The results from this dissertation provide further support that those released via discretionary parole do better than those released via mandatory supervised released or expiration of sentence. This study finds that those released via discretionary parole have lower rearrest rates for violent offenses, property offenses, drug offenses and public order offenses than those released via either mandatory supervised release or expiration of sentence. Additional evidence was produced in Chapter 5 showing that those released via discretionary parole had significantly lower rates of being sent back to prison for a parole violation than those released via mandatory supervised release, even when state of release was controlled (O.R.=1.503, $p<.001$). This new finding, that release via discretionary parole is related to significantly lower probability of parole revocation, provides evidence as to why states that have abolished this option should seriously consider bringing it back.

One reason why discretionary parole should be brought back is it gives greater discretion back to corrections officials' over when to release inmates, particularly when they have completed programming and no longer represent a high risk to society. This would help to free up scarce prison space for the most dangerous offenders. In addition to this, bringing back discretionary parole will serve as an incentive to many inmates to become involved in prison based therapeutic programming, education, self-help groups and other activities which will benefit them when they are released from prison. Numerous published reports have found that inmates involved in prison based drug treatment (Knight et al., 2004; Prendergast, Hall, Wexler, Melnick and Cao, 2004; Burdon et al., 2004), cognitive-behavioral treatment programming (Lipsey, Chapman and Landenberger, 2001; Pearson, Lipton, Cleland and Yee, 2002) and educational programming (Wilson, Gallagher and MacKenzie, 2000; Brewster and Sharp, 2002) have lower recidivism rates than those who are not involved in such programming. Thus, bringing back discretionary parole will increase the chances that inmates will become involved in prison based programming and this will likely result in lower recidivism rates.

One specific area that policymakers need to factor in if they switch back to a system that allows discretionary parole, however, deals with sentence length. In a Bureau of Justice Statistics Report, Hughes et al. (2001) found that those released via discretionary parole served on average more time in prison than those released by mandatory supervised release. This may because the sentence length given to those in states with parole was longer than those in states without parole, with the understanding that low risk offenders and offenders who do well in prison would be released by parole earlier while high risk offenders would not. Because determinate and indeterminate sentencing schemes do not necessarily operate under the same principals, some adjustments may have to be made to sentencing policies in states which switch to an indeterminate sentencing scheme to ensure the switch doesn't result in large variations related to the amount of time most inmates serve as a result of when they were sentenced. While longer sentences are certainly more appropriate for some inmates, judges and parole boards will need to take the new policies into account in sentencing and releasing offenders.

Another area policymakers will need to take into account if they switch to discretionary parole deals with how its existence may cause certain groups of offenders to be unfairly discriminated against. This is particularly true for those serving time for particularly violent crimes or for crimes of a sexual nature. Bringing back discretionary parole may cause additional harm to these offenders if parole boards bow to political pressure and refuse to parole these offenders because they would look soft on crime if they did, even when, in actuality, the inmates represent low risks to public safety. Parole statistics from the State of Missouri (Missouri Department of Corrections, 2010) highlight that violent offenders convicted of a class A or class B felony and sexual offenders convicted of any felony served a much longer percentage of their prison sentences than other types of offenders. While the average amount of time served in 2010 was 48.3 percent of their sentence for the entire 5,287 release cohort, the 612 offenders released for a class A or B violent felony served 68.0 percent of their sentence, the 226 offenders released for a class C or D sex offense served 69.4 percent of their sentence and the 211 offenders released for a class A or B sex offense served 72.1 percent of their sentence. Requiring violent and sexual offenders to serve a noticeably greater portion of their sentence by repeatedly denying them parole, due to the nature of their crime, can have negative consequences. Going to parole hearings and being repeatedly denied can cause additional stress. Repeated denial can also make these offenders less likely to become involved in treatment if they come to believe that it doesn't matter if they try to better themselves. This is a potential drawback for certain violent and sexual offenders who might fare better emotionally under a determinate sentencing scheme. For this reason, if discretionary parole exists in a state, parole boards need to be very careful in how they deal with these classes of offenders and need to ensure that their decisions are based on what is in the best interest of society and the offender's readiness to be released and not on political considerations.

Section 8.3.4: States Should Provide Offense Specific Treatment for Certain Repeat Offenders

One finding from this study with policy implications is that offenders convicted of one specific type of offense (violent, property, drug or public order) are more likely than any other type of offender to be rearrested for the same type of offense in the future. This finding provides evidence of offense specialization and corrections officials should consider offering offense-specific programming for offenders with a history of committing the same type of offense on multiple occasions. Such program would be tailored specifically to the offense and would, for example, teach property offenders how to find a job and earn a decent living, violent offenders how to resolve disputes in non-violent manners, and drug offenders of alternative ways to deal with stress.

Because of budgetary constraints, some of the programming might have to be limited to chronic offenders who commit repeat property, drug or public order offenses (i.e., requiring treatment for those with three or more similar convictions). However, officials might consider requiring non-violent offenders who have been convicted of the same offense two or more times in the past to complete a specialized treatment program as part of their prison sentence. The same could hold true for violent offenders who have one prior conviction. Due to prison overcrowding and other prison issues, states probably shouldn't mandate that an offender must complete treatment to be paroled, but it would seem quite feasible for parole boards to give weight to completion of this programming in making a release decision. Similarly, in states with determinate sentencing schemes, one possible solution would be to allow offenders who complete such a treatment program to have their release date moved up by three or more months.

8.4: Study Limitations

There are several limitations to this study that need to be acknowledged. One limitation that may have influenced the findings is the small number of states available for use in the multilevel analysis. As stated in Chapter 6, one problem with having only 15 states to use as level 2 units in the multilevel analysis is that it may bias estimates of the second-level standard errors. This means that the results from the multilevel analysis need to be viewed with caution. An additional limitation is that having so few level two units prevented hierarchal linear models with multiple level two units from being estimated. This prevented running tests to see if the level of police per 1,000 continued to have an impact on property crime rates when additional contextual variables were added to the model. In line with this limitation, it would be beneficial for researchers if the Bureau of Justice Statistics included information on the specific county to which the prisoners were released in future multi-state data sets of prisoners released during a specific year as this would provide much greater statistical power and allow much more detailed multi-level models to be estimated.

A second limitation that may have influenced the findings deals with the different ways different states handled public order offenses. Although the Bureau of Justice Statistics was very clear that they were examining the arrest histories of inmates released from 15 states in 1994, the fact that some states arrested offenders who committed minor traffic violations, probation violations and possibly other relatively minor public order offenses while others issued traffic tickets, sought probation violations without arrest or issued citations in lieu of an arrest may have had an influence on the findings. The problem inherent in having one state issue an arrest while a second does not for the same action which is a violation of law in both states is that there is no way of knowing if or how the missing data influenced the degree to which states varied in terms of rearrest for any offense or rearrest for a public order offense.

A third limitation is the limited number of individual level characteristics available for inclusion in analysis. Part of this problem resulted from certain variables having to be excluded due to problems with missing data in the Bureau of Justice Statistics datasets. Although prior research has found that suffering from a chemical dependency increases an offender's odds of recidivism (Harer, 1994; Gendreau et al., 1996; Mills, Kroner, and Hemmati, 2003), this individual level risk factor could not be included in either the analysis across space or the analysis over time. Although data on this variable were collected for some of the offenders in the *Prisoners Released in 1994 dataset*, the total number of cases coded as missing was over 70 percent. As a result, the variable could not be used in the models that explored various forms of recidivism over space. While a definite benefit involved in this study was the large number of offenders who were able to be included in the analysis (along with the fact that there were offenders released from 15 states from the 1994 cohort and from 11 states from the 1983 cohort), problems with missing data left several possible individual level characteristics unusable and this potentially limits the usefulness of the findings.

A fourth limitation of this research was that it did not include an analysis of the effect of either state level parole policies or individual level types of supervision for offenders. Runda, Rhine, and Wetter (1994, as cited by Peterselia, 1999) report that 90 percent of states use a classification system to assign parolees to specific levels of supervision. Having information on the level of supervision an inmate was under once released may help further explain some of the differences between states for various measures of recidivism. Additionally, examining the specific parole policies, particularly as they relate to arresting and prosecuting parolees who commit a criminal offense, may further help explain some of the variation across states for multiple forms of recidivism. These differences in policies may well explain differences in recidivism beyond just parole revocations if some states use technical violations in lieu of arrest for all but serious criminal offenses while others have a policy to rearrest any offender who has committed a new crime.

A fifth limitation of this study was that it failed to take into account individual level state's prison capacity / prison overcrowding as a contextual variable. Marvell (1995) reported that several states specifically included prison capacity as a factor to take into consideration in setting up sentencing guidelines. It is likewise reasonable to speculate that parole officials', police officers', prosecutors' and judges' decisions all may be influenced by the capacity of prisons to take in new inmates. This would be an especially important issue if a state were under a court order to reduce its prison population. In such states, officials may be less likely to revoke, rearrest, prosecute or imprison due to the fact that sending an offender back to prison would require the department of corrections to release someone else. Thus, the inclusion of this variable may further help explain differences in recidivism rates across states.

8.5. Suggestions for Future Research

While the findings from this study provide valuable information that differences in individual level characteristics do help explain variation between states in overall rearrest rates, rearrest rates for property offense, rearrest rates for drug offenses, rearrest rates for public order offenses and reimprisonment proportions for reconvicted offenders, there remain several avenues for future research. One avenue would be to replicate the analyses regarding variation over space for rearrests, rearrests for specific offenses, reconvictions and reconfinements using the *Prisoners Released in 1983 dataset*. Such a study replication using a large, multi-state sample of prisoners released during a different period of time would be useful in determining the robustness of the findings from this study. Such a replication would also be useful in specifically evaluating the policy recommendations made in this study.

Another avenue for future research would involve exploring the specific parole policies in place in California, Florida, Illinois, Michigan, Minnesota, New York, North Carolina, Oregon and Texas that led to the revocation rates that occurred for offenders released from each of the respective states. Travis (2005) reported that parole violators accounted for over one third of those admitted to prison in 1999. This staggering rate ends up costing states billions of dollars each year. Therefore, using the *Prisoners Released in 1994 dataset* along with information on specific parole policies that were in place would offer possible solutions to develop statewide parole policies that are able to be cost effective without compromising public safety.

A final avenue for future research would involve looking at the effect additional contextual variables have on recidivism rates when individual level characteristics are controlled. Such an avenue would be especially worthwhile if future multi-state datasets provide information that result in a larger number of level 2 units to be used. As mentioned, one possible solution to this would be to include county of release as a variable in future data

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APPENDIX A

MATCHING PROCEDURES FOR THE MERGED DATA FILE

Appendix A describes how the arrest recidivism outcome measure and the nine measures of the individual-level recidivism risk factors investigated in the dissertation were generated from the *Prisoners Released in 1994 dataset* and the *Prisoners Released in 1983 dataset*.

How Rearrest Was Measured

The variable REARRD was used as the rearrest measure for the *Prisoners Released in 1994 dataset*. The REARREST variable was further created using the following variables from the *Prisoners Released in 1983 dataset*. Variables v1049 (month of actual prison release date), v1050 (day of actual prison release date), and v1051 (year of actual prison date) give information related to the exact date of release from prison. Variables v2010 (month of arrest), v2011 (day of arrest) and v2012 (year of arrest) provide the exact date of arrest for offenses that are "cycle based," and variables v5012 (month of event), v5013 (day of event) and v5014 (year of event) give the exact date of arrest for offenses that are "event based". For each offender, separate cases exist for each arrest. To determine if an inmate who has been released from prison in 1983 should be designated as REARRESTED, all the inmate's arrests were examined. If an arrest was recorded as having occurred within three years of the release date, the inmate was designated as having been rearrested.

How Individual-Level Recidivism Risk Factors Were Be Measured

1) **Gender** – Offender gender was generated from variable SEX in the *Prisoners Released in 1994 dataset* and from v1018 in the *Prisoners Released in 1983 dataset*.

2) **Age at Release** – Offender age at release was generated from variable RELAGE in the *Prisoners Released in 1994 dataset* and from a newly created variable from the *Prisoners Released in 1983 dataset*. The new variable determines age at release by subtracting an offender's date of birth (v1015 – month of birth; v1016 – day of birth; v1017 – year of birth) from the date of the offender's release (v1049 – month of actual release; v1050 – day of actual release; v1051 – year of actual release).

3) **Race** – Race was divided into four separate categories: White, Black, Other and Unknown. The categorical variables were generated from variable RACE4 in the *Prisoners Released in 1994 dataset* and v1019 in the *Prisoners Released in 1983 dataset*.

4) **Age at First Arrest** – The age at first arrest was calculated for the *Prisoners Released in 1994 dataset* by subtracting the offender's date of birth (MONTHOB1 – month of birth; DAYOB1 – day of birth; YEAROB1 – year of birth) from the date of first arrest (A001MO – month of first arrest; A001DA – day of first arrest; A001YR – year of first arrest). Age at first arrest was generated from the *Prisoners Released in 1983 dataset* by subtracting an offender's date of birth from the offender's date of first arrest (calculated from v2010 – month of arrest, v2011 – day of arrest and v2012 – year of arrest, if the first arrest was a

"cycle based" arrest, or from v5012 – month of arrest; v5013 – day of arrest and v5014 – year of arrest, if the first arrest was an "event based" arrest).

5) **Number of Prior Arrests** – The number of prior arrests was generated from variable PRIR in the *Prisoners Released in 1994 dataset* and was calculated for the *Prisoners Released in 1983 dataset* based on the number of arrest cycles the inmate had gone through prior to their current release from prison (not including the arrest which led to the current imprisonment).

6) **Current Offense Type** – The current offense type was generated from variable SMPOFF5 in the *Prisoners Released in 1994 dataset* (Violent; Property; Drugs; Public Order; Other or Unknown). It was calculated based on the NCRP (National Corrections Reporting Program) code for the most serious offense gathered from variables v1030, v1033 and v1036 of the *Prisoners Released in 1983 dataset*.

7) Time Served – For the purpose of this dissertation, time served refers to the amount of time served on the current incarceration based on the date the offender was admitted to prison and the date the offender was released from prison. For the *Prisoners Released in 1994 dataset*, the date of admission to prison came from MONTHAD (Month of Admission), DAYAD (Day of Admission) and YEARAD (Year of Admission) and the date of release from prison came from MONTHRLS (Month of Release), DAYRLS (Day of Release) and YEARRLS (Year of Release). For the *Prisoners Released in 1983 dataset*, the date of admission to prison came from v1022 (Month of Admission), v1023 (Day of Admission) and v1024 (Year of Admission) and the date of release from prison came from v1049, v1050 and v1051.

8) Type of Admission – The type of admission was calculated based on the variable ADTYP in the *Prisoners Released in 1994 dataset* and from v1025 in the *Prisoners Released in 1983 dataset*.

9) Type of Release – The type of release was calculated based on the variable RELTYP in the *Prisoners Released in 1994 dataset* and from v1053 in the *Prisoners Released in 1983 dataset*.

APPENDIX B

Regression Coefficients for

State-by-State Comparisons

Table A1: Regression Coefficients for State-by-State Comparison of Rearrest Rates

	CA	FL	IL	MI	MN	NJ	NY	NC	OH	OR	TX	AZ	DE	MD	VI
CA	-------														
FL	-0.441	-------													
IL	-0.363	0.078	-------												
MI	1.140	1.581	1.503	-------											
MN	0.490	0.930	0.853	-0.651	-------										
NJ	0.387	0.828	0.750	-0.753	-0.103	-------									
NY	0.134	0.574	0.497	-1.007	-0.356	-0.253	-------								
NC	0.442	0.882	0.805	-0.699	-0.048	0.055	0.308	-------							
OH	0.594	1.034	0.957	-0.547	0.104	0.207	0.460	0.152	-------						
OR	-0.091	0.350	0.272	-1.231	-0.581	-0.478	-0.225	-0.533	-0.685	-------					
TX	0.570	1.011	0.933	-0.570	0.081	0.183	0.437	0.129	-0.023	0.661	-------				
AZ	0.369	0.809	0.732	-0.772	-0.121	-0.018	0.235	-0.073	-0.225	0.460	-0.201	-------			
DE	-0.966	-0.525	-0.602	-2.106	-1.455	-1.353	-1.099	-1.407	-1.559	-0.875	-1.536	-1.334	-------		
MD	-0.007	0.433	0.356	-1.148	-0.497	-0.394	-0.141	-0.449	-0.601	0.084	-0.578	-0.376	0.958	-------	
VI	0.317	0.758	0.681	-0.823	-0.172	-0.070	0.184	-0.124	-0.276	0.409	-0.253	-0.051	1.283	0.325	-------

States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue

Table A2: Regression Coefficients for State-by-State Comparison of Rearrest Rates with Individual Level Characteristics added to Model

	CA	FL	IL	MI	MN	NJ	NY	NC	OH	OR	TX	AZ	DE	MD	VI
CA	-------														
FL	-0.610	-------													
IL	-0.216	-0.332	-------												
MI	0.736	1.305	0.992	-------											
MN	-0.056	1.031	0.105	-0.673	-------										
NJ	0.357	0.923	1.258	-0.492	0.494	-------									
NY	-0.288	-0.140	0.050	-0.679	-0.300	-0.260	-------								
NC	0.437	0.566	0.563	-0.656	0.264	-0.147	0.011	-------							
OH	0.036	0.903	0.762	-0.520	0.162	-0.258	0.173	0.059	-------						
OR	-0.345	0.782	-0.161	-0.803	-0.194	-0.496	-0.213	-0.364	-0.423	-------					
TX	0.179	1.036	0.273	-0.467	-0.018	0.049	0.216	0.073	0.012	0.510	-------				
AZ	0.109	0.403	0.291	-0.572	-0.494	-0.222	0.131	0.040	-0.361	-0.034	-0.404	-------			
DE	-1.105	-0.318	1.628	-1.582	-1.229	-1.779	0.122	-0.923	-1.206	-1.188	-1.413	-0.891	-------		
MD	-0.358	0.492	0.051	-0.836	-0.218	-0.449	-0.293	-0.191	-0.303	0.018	-0.370	0.021	0.820	-------	
VI	-0.141	0.374	0.058	-0.491	-0.044	0.019	0.189	-0.058	0.163	0.365	-0.048	0.240	0.589	0.202	-------

States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue

Table B1: Regression Coefficients for State-by-State Comparison of Violent Rearrest Rates													
	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	-0.242	-------											
IL	-0.607	-0.365	-------										
MI	0.643	0.885	1.251	-------									
MN	-0.062	0.180	0.545	-0.705	-------								
NJ	0.107	0.349	0.714	-0.536	0.169	-------							
NY	-0.127	0.115	0.480	-0.770	-0.065	-0.234	-------						
OH	0.063	0.305	0.670	-0.580	0.125	-0.044	0.190	-------					
OR	-0.114	0.128	0.494	-0.757	-0.051	-0.221	0.013	-0.176	-------				
TX	0.536	0.778	1.143	-0.107	0.598	0.429	0.663	0.473	0.650	-------			
AZ	-0.036	0.206	0.571	-0.680	0.026	-0.144	0.091	-0.099	0.077	-0.573	-------		
DE	-0.670	-0.428	-0.063	-1.313	-0.608	-0.777	-0.543	-0.733	-0.556	-1.206	-0.633	-------	
VI	-0.106	0.136	0.501	-0.749	-0.044	-0.213	0.021	-0.169	0.007	-0.642	-0.070	0.564	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table B2: Regression Coefficients for State-by-State Comparison of Violent Rearrest Rates with Individual Level Characteristics added to Model													
	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	-0.257	-------											
IL	-0.301	-1.363	-------										
MI	0.609	0.711	0.847	-------									
MN	-0.218	0.237	0.307	-0.723	-------								
NJ	0.329	0.784	1.505	-0.364	1.139	-------							
NY	-0.492	0.091	0.003	-0.581	-0.371	-0.229	-------						
OH	0.479	0.032	0.993	0.006	-0.473	-0.287	0.256	-------					
OR	-0.361	-0.011	0.473	-0.649	0.022	-0.251	-0.114	-0.352	-------				
TX	0.250	0.098	0.612	0.154	0.267	0.347	0.692	0.158	0.371	-------			
AZ	1.773	-0.391	0.923	-0.861	-0.825	-0.738	-0.279	-0.670	-0.354	-0.637	-------		
DE	-0.417	-0.136	2.107	-0.853	-0.530	-1.413	-0.252	-0.077	-0.264	-0.152	0.583	-------	
VI	-0.278	-0.269	0.049	-0.560	-0.124	-0.152	0.122	-0.306	-0.012	-0.486	0.426	0.268	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table C1: Regression Coefficients for State-by-State Comparison of Property Rearrest Rates													
	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	**0.034**	-------											
IL	-0.540	-0.574	-------										
MI	0.717	0.683	1.257	-------									
MN	**-0.001**	**-0.034**	0.540	-0.717	-------								
NJ	0.165	**0.131**	0.705	-0.552	0.166	-------							
NY	-0.186	-0.220	0.354	-0.903	-0.185	-0.351	-------						
OH	**0.138**	**0.105**	0.679	-0.578	**0.139**	**-0.027**	0.324	-------					
OR	-0.168	-0.201	0.373	-0.884	-0.167	-0.333	**0.018**	-0.306	-------				
TX	0.602	0.569	1.143	**-0.114**	0.603	0.437	0.788	0.464	0.770	-------			
AZ	**0.077**	**0.044**	0.618	-0.639	**0.078**	**-0.088**	0.263	**-0.061**	0.245	-0.525	-------		
DE	-0.228	-0.262	0.312	-0.945	-0.228	-0.393	**-0.042**	-0.367	**-0.061**	-0.831	-0.306	-------	
VI	0.190	**0.156**	0.730	-0.527	0.191	**0.025**	0.376	**0.052**	0.358	-0.412	**0.113**	0.418	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table C2: Regression Coefficients for State-by-State Comparison of Property Rearrest Rates with Individual Level Characteristics added to Model													
	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	**-0.062**	-------											
IL	-0.533	-1.274	-------										
MI	0.364	0.350	0.792	-------									
MN	-0.402	**-0.254**	**0.005**	-0.707	-------								
NJ	**-0.090**	**-0.223**	**0.692**	-0.525	**-0.045**	-------							
NY	-0.679	-0.864	**-0.144**	-0.866	**-0.301**	-0.337	-------						
OH	**-0.321**	-0.292	**0.451**	-0.444	**-0.263**	**-0.091**	0.392	-------					
OR	**-0.045**	**-0.084**	0.486	-0.496	0.326	**0.118**	**0.133**	**0.220**	-------				
TX	0.310	**0.042**	0.611	**-0.037**	0.514	0.479	0.847	0.368	0.464	-------			
AZ	**-0.488**	**-0.179**	**-0.036**	**-0.326**	**-0.267**	**0.060**	**0.284**	**0.116**	**-0.155**	-0.548	-------		
DE	-0.410	**0.057**	**0.930**	-0.389	**0.119**	**0.018**	**0.490**	**0.549**	**0.021**	**-0.011**	**0.222**	-------	
VI	**-0.190**	-0.697	0.286	**-0.065**	0.332	0.367	0.691	0.454	**0.198**	**-0.192**	0.335	**0.047**	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table D1: Regression Coefficients for State-by-State Comparison of Drug Rearrest Rates

	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	0.363	-------											
IL	0.219	-0.145	-------										
MI	1.899	1.536	1.680	-------									
MN	1.645	1.282	1.426	-0.254	-------								
NJ	0.034	-0.330	-0.185	-1.866	-1.612	-------							
NY	-0.026	-0.390	-0.245	-1.926	-1.672	-0.060	-------						
OH	0.955	0.591	0.736	-0.945	-0.691	0.921	0.981	-------					
OR	0.300	-0.063	0.081	-1.599	-1.345	0.267	0.327	-0.654	-------				
TX	1.067	0.704	0.848	-0.832	-0.578	1.033	1.094	0.112	0.767	-------			
AZ	0.862	0.499	0.643	-1.037	-0.783	0.828	0.889	-0.093	0.562	-0.205	-------		
DE	0.846	0.483	0.627	-1.053	-0.799	0.813	0.873	-0.109	0.546	-0.221	-0.016	-------	
VI	0.917	0.553	0.698	-0.983	-0.729	0.883	0.943	-0.038	0.616	-0.150	0.055	0.071	-------

States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue

Table D2: Regression Coefficients for State-by-State Comparison of Drug Rearrest Rates with Individual Level Characteristics added to Model

	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	0.281	-------											
IL	0.192	0.141	-------										
MI	1.251	1.297	1.183	-------									
MN	1.121	0.540	0.683	-0.385	-------								
NJ	-0.088	0.163	-0.894	-1.428	-0.977	-------							
NY	-0.278	-0.867	-0.420	-1.541	-1.225	-0.058	-------						
OH	0.201	0.520	-0.316	-0.917	-0.279	0.343	0.737	-------					
OR	0.164	-0.416	-0.538	-1.359	-1.034	0.150	-0.006	-0.593	-------				
TX	0.828	0.437	0.260	-0.918	-0.384	0.710	0.721	-0.029	1.052	-------			
AZ	0.811	0.054	-1.039	-0.772	-0.823	0.548	0.753	-0.310	0.192	-0.424	-------		
DE	0.728	0.943	-0.205	-0.169	-0.054	0.801	1.583	0.455	0.821	0.067	0.508	-------	
VI	0.461	-0.567	0.152	-0.655	-0.514	0.780	0.831	0.337	0.881	0.102	0.274	-1.131	-------

States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue

Table E1: Regression Coefficients for State-by-State Comparison of Public Order Rearrest Rates													
	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	-1.182	-------											
IL	-0.605	0.577	-------										
MI	0.898	2.080	1.503	-------									
MN	-0.081	1.102	0.524	-0.978	-------								
NJ	0.140	1.322	0.745	-0.758	0.220	-------							
NY	-0.107	1.075	0.498	-1.005	-0.026	-0.247	-------						
OH	0.564	1.746	1.168	-0.334	0.644	0.424	0.670	-------					
OR	-0.922	0.260	-0.317	-1.820	-0.841	-1.062	-0.815	-1.486	-------				
TX	0.159	1.341	0.764	-0.739	0.240	0.019	0.266	-0.405	1.081	-------			
AZ	-0.814	0.368	-0.209	-1.712	-0.733	-0.954	-0.707	-1.378	0.108	-0.973	-------		
DE	-2.284	-1.102	-1.679	-3.182	-2.203	-2.424	-2.177	-2.847	-1.362	-2.443	-1.470	-------	
VI	-0.375	0.807	0.230	-1.273	-0.295	-0.515	-0.268	-0.939	0.547	-0.534	0.439	1.909	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table E2: Regression Coefficients for State-by-State Comparison of Public Order Rearrest Rates with Individual Level Characteristics added to Model													
	CA	FL	IL	MI	MN	NJ	NY	OH	OR	TX	AZ	DE	VI
CA	-------												
FL	-1.295	-------											
IL	-0.558	0.428	-------										
MI	0.621	1.822	1.142	-------									
MN	-0.356	1.075	0.186	-0.832	-------								
NJ	0.095	1.423	0.684	-0.634	1.044	-------							
NY	-0.605	0.767	-0.027	-0.787	-0.310	-0.195	-------						
OH	0.303	1.530	0.938	-0.193	0.350	0.198	0.586	-------					
OR	-0.980	0.390	-0.485	-1.079	-0.468	-1.030	-0.800	-1.016	-------				
TX	-0.339	0.903	0.138	-0.425	-0.057	-0.006	0.223	-0.387	0.595	-------			
AZ	-0.032	0.096	-0.301	-1.336	-0.873	-1.046	-0.702	-1.273	-0.303	-0.849	-------		
DE	-2.353	-0.981	-0.915	-2.918	-2.284	-3.052	-1.504	-2.540	-1.655	-2.106	-1.196	-------	
VI	-0.884	0.534	-0.363	-0.884	-0.427	-0.413	-0.237	-0.508	0.303	-0.453	0.564	1.427	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table F1: Regression Coefficients for State-by-State Comparison of Reconviction Probabilities for Rearrested Offenders

	CA	FL	IL	MI	MN	NJ	NY	NC	OR	TX	AZ	DE	MD	VI
CA	-------													
FL	0.558	-------												
IL	0.438	-0.121	-------											
MI	-0.206	-0.764	-0.643	-------										
MN	-0.038	-0.596	-0.476	0.167	-------									
NJ	0.067	-0.492	-0.371	0.272	0.105	-------								
NY	-0.918	-1.476	-1.355	-0.712	-0.880	-0.985	-------							
NC	-0.400	-0.959	-0.838	-0.195	-0.362	-0.467	0.517	-------						
OR	-0.588	-1.146	-1.025	-0.382	-0.550	-0.654	0.330	-0.187	-------					
TX	0.582	0.023	0.144	0.787	0.620	0.515	1.499	0.982	1.169	-------				
AZ	0.461	-0.097	0.023	0.666	0.499	0.394	1.379	0.861	1.049	-0.121	-------			
DE	-0.888	-1.446	-1.325	-0.682	-0.850	-0.954	0.030	-0.487	-0.300	-1.469	-1.349	-------		
MD	-0.160	-0.719	-0.598	0.045	-0.122	-0.227	0.757	0.240	0.427	-0.742	-0.621	0.727	-------	
VI	0.086	-0.472	-0.351	0.292	0.124	0.019	1.004	0.487	0.674	-0.495	-0.375	0.974	0.247	-------

States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue

Table F2: Regression Coefficients for State-by-State Comparison of Reconviction Probabilities for Rearrested Offenders with Individual Level Characteristics added to Model

	CA	FL	IL	MI	MN	NJ	NY	NC	OR	TX	AZ	DE	MD	VI
CA	-------													
FL	0.369	-------												
IL	0.315	-0.308	-------											
MI	-0.769	-1.013	-0.972	-------										
MN	-0.529	-0.719	-0.807	0.324	-------									
NJ	-0.098	-0.376	-0.439	0.469	0.864	-------								
NY	-1.262	-2.028	-1.452	-0.406	-0.649	-1.032	-------							
NC	-0.476	-2.030	-0.943	-0.049	-0.229	-0.647	0.280	-------						
OR	-0.602	-1.416	-1.001	-0.068	-0.111	-0.987	0.300	0.092	-------					
TX	0.503	0.210	0.007	0.680	0.764	0.367	1.354	1.025	1.575	-------				
AZ	1.648	-0.429	-0.368	1.126	0.165	0.228	1.444	1.233	0.777	-0.312	-------			
DE	-1.333	-1.484	-2.163	-0.630	-1.418	-2.111	-0.191	-0.115	-0.514	-2.346	-0.888	-------		
MD	-0.732	-0.859	-0.834	0.459	0.085	-0.081	0.804	0.225	0.512	-0.566	-0.412	0.895	-------	
VI	-0.371	-1.389	-0.658	0.484	0.257	0.126	1.168	0.528	0.649	-0.422	-0.430	1.667	0.100	-------

States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue

Table G1: Regression Coefficients for State-by-State Comparison of Reimprisonment Probabilities for Reconvicted Offenders													
	CA	FL	IL	MI	MN	NJ	NY	NC	OR	TX	AZ	DE	MD
CA	-------												
FL	0.237	-------											
IL	-0.635	-0.872	-------										
MI	0.508	0.270	1.143	-------									
MN	-0.253	-0.490	0.382	-0.761	-------								
NJ	-0.242	-0.479	0.393	-0.750	0.011	-------							
NY	0.378	0.141	1.013	-0.130	0.631	0.620	-------						
NC	-0.739	-0.976	-0.104	-1.247	-0.486	-0.497	-1.117	-------					
OR	0.848	0.611	1.483	0.341	1.101	1.090	0.470	1.587	-------				
TX	0.315	0.078	0.950	-0.192	0.568	0.557	-0.063	1.054	-0.533	-------			
AZ	0.365	0.127	1.000	-0.143	0.618	0.607	-0.013	1.104	-0.484	0.049	-------		
DE	1.580	1.343	2.215	1.073	1.833	1.822	1.202	2.319	0.732	1.265	1.216	-------	
MD	-0.111	-0.348	0.524	-0.619	0.142	0.131	-0.489	0.628	-0.959	-0.426	-0.476	-1.691	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table G2: Regression Coefficients for State-by-State Comparison of Reimprisonment Probabilities for Reconvicted Offenders with Individual Level Characteristics added to Model													
	CA	FL	IL	MI	MN	NJ	NY	NC	OR	TX	AZ	DE	MD
CA	-------												
FL	0.293	-------											
IL	-0.556	-1.298	-------										
MI	0.610	0.497	1.235	-------									
MN	-0.456	-0.026	-0.172	-1.126	-------								
NJ	-0.257	-0.392	0.671	-0.925	-1.879	-------							
NY	0.453	0.043	1.002	-0.254	0.911	0.585	-------						
NC	-0.936	-0.815	-0.355	-1.453	-0.600	-0.459	-1.131	-------					
OR	0.957	0.570	1.202	-0.156	1.250	0.971	0.261	1.918	-------				
TX	0.695	0.460	1.118	-0.706	0.894	0.447	-0.271	1.315	-0.424	-------			
AZ	0.701	0.025	1.095	-0.640	-0.066	0.516	-0.067	1.110	-0.579	-0.379	-------		
DE	1.500	1.508	2.622	0.964	1.409	3.440	1.839	2.887	0.726	0.878	1.527	-------	
MD	-0.166	-0.481	0.357	-0.657	0.233	0.158	-0.579	0.832	-0.992	-0.310	-0.103	-2.141	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue													

Table H1: Regression Coefficients for State-by-State Comparison of Rates of Technical Violations of Parole Resulting in Reimprisonment and Arrests for Parole Violations									
	CA	**FL**	**IL**	**MI**	**MN**	**NY**	**NC**	**OH**	**TX**
CA	-------								
FL	0.418	-------							
IL	2.028	1.610	-------						
MI	.0961	-0.543	1.067	-------					
MN	1.571	1.153	-0.457	0.610	-------				
NY	0.391	**<u>-0.027</u>**	-1.637	-0.570	-1.180	-------			
NC	1.289	0.872	-0.738	0.328	-0.282	0.899	-------		
OH	-0.157	-0.575	-2.185	-1.118	-1.728	-0.548	-1.446	-------	
TX	1.687	1.269	-0.341	0.726	**<u>0.116</u>**	1.296	0.397	1.844	-------
<u>States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue</u>									

Table H2: Regression Coefficients for State-by-State Comparison of Rates of Technical Violations of Parole Resulting in Reimprisonment and Arrests for Parole Violations with Individual Level Characteristics added to Model									
	CA	**FL**	**IL**	**MI**	**MN**	**NY**	**NC**	**OH**	**TX**
CA	-------								
FL	**<u>-0.440</u>**	-------							
IL	2.012	2.659	-------						
MI	0.870	0.275	1.215	-------					
MN	1.669	1.252	**<u>-0.285</u>**	**<u>-1.179</u>**	-------				
NY	0.470	-3.648	-1.626	-0.524	-1.032	-------			
NC	1.134	**<u>-0.149</u>**	-0.801	0.793	**<u>-0.018</u>**	0.791	-------		
OH	**<u>-0.186</u>**	**<u>-0.074</u>**	-2.137	-0.837	-1.649	-0.820	-2.069	-------	
TX	1.359	0.792	-0.628	0.640	**<u>-0.339</u>**	1.179	**<u>0.249</u>**	1.375	-------
<u>States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue</u>									

Table I1: Regression Coefficients for State-by-State Comparison of Rates of Technical Violations of Parole and Criminal Convictions of Parole Violation Resulting in Reimprisonment									
	CA	FL	IL	MI	MN	NY	NC	OH	TX
CA	-------								
FL	0.594	-------							
IL	2.247	1.653	-------						
MI	0.962	0.370	0.962	-------					
MN	1.630	1.036	-0.617	0.668	-------				
NY	0.389	-0.205	-1.858	-0.573	-1.241	-------			
NC	1.320	0.726	-0.927	0.358	-0.310	0.931	-------		
OH	0.502	**<u>-0.092</u>**	-1.745	-0.460	-1.128	**<u>0.113</u>**	-0.818	-------	
TX	1.702	1.108	-0.545	0.740	**<u>0.072</u>**	1.313	0.382	1.200	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue									

Table I2: Regression Coefficients for State-by-State Comparison of Rates of Technical Violations of Parole and Criminal Convictions of Parole Violation Resulting in Reimprisonment with Individual Level Characteristics added to Model									
	CA	FL	IL	MI	MN	NY	NC	OH	TX
CA	-------								
FL	**<u>-0.456</u>**	-------							
IL	2.233	2.874	-------						
MI	-1.447	**<u>0.118</u>**	-.0870	-------					
MN	1.754	1.092	-0.404	**<u>-1.183</u>**	-------				
NY	0.466	-3.866	-1.840	-0.530	-1.117	-------			
NC	1.177	**<u>-0.252</u>**	-0.956	0.789	**<u>-0.002</u>**	0.814	-------		
OH	0.518	0.653	-1.594	**<u>-0.187</u>**	-0.970	**<u>-0.117</u>**	-1.481	-------	
TX	1.390	0.637	-0.802	0.652	-0.382	1.197	**<u>0.251</u>**	0.686	-------
States with Similar (p>.05) Probabilities are Bolded, Underlined and in Blue									

APPENDIX C

MULTI-LEVEL REGRESSION

TABLES

Table 6A - Multilevel Regressions of Rearrests on Individual Level Characteristics and State Level Drug Arrests per 100,000
Final estimation of fixed effects: (Unit specified model):

	b	S.E.	Exp(b)
Intercept, γ00	0.343223	0.325956	1.409483
Individual-Level			
Gender	-0.487658***	0.043548	0.614063
Age of First Arrest	0.003511	0.002771	1.003517
Age at Release	-0.061786***	0.00217	0.940084
Prior Arrests	0.075855***	0.002548	1.078806
Time Served	-0.002878***	0.000591	0.997126
Black	0.509141***	0.027707	1.663861
Other Race	-0.391184***	0.121698	0.676256
Property Offense	0.379605***	0.036661	1.461706
Drug Offense	0.066626*	0.035808	1.068896
Public Order Offense	0.069666	0.050021	1.07215
Other Offense	-0.020887	0.096547	0.97933
Parole Revocation	0.413448***	0.032869	1.512022
Probation Revocation	0.185581	0.152056	1.203918
Other Admission Type	-0.152339	0.147317	0.858698
Unknown Admission Type	-0.344545**	0.167951	0.708543
Mandatory Supervised Released	-0.344545**	0.047613	1.125342
Expiration of Sentence	0.223232***	0.069899	1.250111
Other Release Type	-0.06385	0.07392	1.250111
State-Level			
Drug Arrests per 100,000	0.000311	0.000497	1.000311

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6B - Multilevel Regressions of Violent Rearrests on Individual Level Characteristics and State Level Drug Arrests per 100,000
Final estimation of fixed effects: (Unit specified model):

	b	S.E.	Exp(b)
Intercept, γ00	-1.457979***	0.278645	0.232706
Individual-Level			
Gender	-0.792380***	0.066837	0.452766
Age of First Arrest	-0.033645***	0.003945	0.966915
Age at Release	-0.040651***	0.002614	0.960164
Prior Arrests	0.022899***	0.001974	1.023163
Time Served	-0.002914***	0.000755	0.997091
Black	0.561588***	0.031476	1.753455
Other Race	0.244696*	0.140161	1.277234
Property Offense	-0.400762***	0.039353	0.669810
Drug Offense	-0.608528***	0.040264	0.544151
Public Order Offense	-0.334533***	0.059785	0.715672
Other Offense	-0.576501***	0.116014	0.561861
Parole Revocation	0.307753***	0.035440	1.360365
Probation Revocation	-0.036893	0.160378	0.963779
Other Admission Type	-0.434499**	0.204893	0.647589
Unknown Admission Type	-0.036575	0.267429	0.964086
Mandatory Supervised Released	0.372755***	0.068844	1.451728
Expiration of Sentence	0.605104***	0.075445	1.831442
Other Release Type	0.264119***	0.083750	1.302284
State-Level			
Drug Arrests per 100,000	0.000146	0.000417	1.000146

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6C - Multilevel Regressions of Property Rearrests on Individual Level Characteristics and State Level Drug Arrests per 100,000
Final estimation of fixed effects: (Unit specified model):

	b	S.E.	Exp(b)
Intercept, γ00	-1.518187***	0.305483	0.219109
Individual-Level			
Gender	-0.197114***	0.049690	0.821097
Age of First Arrest	0.005540*	0.003170	1.005555
Age at Release	-0.038506***	0.002354	0.962226
Prior Arrests	0.052234***	0.001979	1.053622
Time Served	-0.001858***	0.000693	0.998143
Black	0.322055***	0.028541	1.379961
Other Race	-0.280005**	0.140781	0.755780
Property Offense	0.800331***	0.037109	2.226279
Drug Offense	-0.244618***	0.038966	0.783003
Public Order Offense	-0.009107	0.057061	0.990935
Other Offense	0.197726**	0.098328	1.218629
Parole Revocation	0.247695***	0.032328	1.281070
Probation Revocation	0.314289**	0.145601	1.369285
Other Admission Type	-0.145988	0.175626	0.864168
Unknown Admission Type	0.018913	0.225739	1.019092
Mandatory Supervised Released	0.226202***	0.063975	1.253829
Expiration of Sentence	0.370939***	0.071258	1.449094
Other Release Type	0.120510	0.078240	1.128072
State-Level			
Drug Arrests per 100,000	0.000812	0.000458	1.000813

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6D - Multilevel Regressions of Drug Rearrests on Individual Level Characteristics and State Level Drug Arrests per 100,000 Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	-2.626172***	0.244850	0.072355
Individual-Level			
Gender	-0.204735***	0.048726	0.814863
Age of First Arrest	-0.001566	0.003134	0.998435
Age at Release	-0.034835***	0.002337	0.965765
Prior Arrests	0.042163***	0.001906	1.043065
Time Served	-0.002931***	0.000752	0.997073
Black	0.411015***	0.028616	1.508349
Other Race	-0.556840***	0.158693	0.573017
Property Offense	0.145062***	0.039408	1.156111
Drug Offense	0.777919***	0.038038	2.176936
Public Order Offense	0.130370**	0.057915	1.139250
Other Offense	0.268918***	0.096652	1.308548
Parole Revocation	0.179209***	0.031886	1.196271
Probation Revocation	0.101977	0.156722	1.107358
Other Admission Type	-0.205593	0.200600	0.814164
Unknown Admission Type	-0.479645*	0.291257	0.619003
Mandatory Supervised Released	0.108287*	0.065638	1.114367
Expiration of Sentence	0.299452***	0.073111	1.349120
Other Release Type	-0.095989	0.082103	0.908474
State-Level			
Drug Arrests per 100,000	0.002088***	0.000365	1.002090

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6E - Multilevel Regressions of Public Order Rearrests on Individual Level Characteristics and State Level Drug Arrests per 100,000 Final estimation of fixed effects: (Unit specified model):			
	B	S.E.	Exp(b)
Intercept, γ00	-0.339791	0.626145	0.711919
Individual-Level			
Gender	-0.286883***	0.052268	0.750600
Age of First Arrest	-0.006055*	0.003425	0.993964
Age at Release	-0.054320***	0.002459	0.947129
Prior Arrests	0.034740***	0.001901	1.035351
Time Served	-0.002406***	0.000737	0.997597
Black	0.046413	0.029361	1.047507
Other Race	-0.024376	0.135019	0.975919
Property Offense	-0.028356	0.038483	0.972042
Drug Offense	-0.007035	0.038559	0.992990
Public Order Offense	0.394774***	0.054880	1.484049
Other Offense	-0.356521***	0.112737	0.700108
Parole Revocation	0.190726***	0.033433	1.210128
Probation Revocation	0.133172	0.140377	1.142446
Other Admission Type	-0.467820***	0.172307	0.626366
Unknown Admission Type	-0.076702	0.244847	0.926165
Mandatory Supervised Released	0.425357***	0.064839	1.530136
Expiration of Sentence	0.345620***	0.075473	1.412866
Other Release Type	0.213642***	0.080279	1.238179
State-Level			
Drug Arrests per 100,000	-0.001033	0.000942	0.998968
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6F - Multilevel Regressions of Reconviction Probabilities for Rearrested Offenders on Individual Level Characteristics and State Level Drug Arrests per 100,000
Final estimation of fixed effects: (Unit specified model):

	B	S.E.	Exp(b)
Intercept, γ00	0.306590	0.564046	1.358784
Individual-Level			
Gender	-0.055833	0.062622	0.945697
Age of First Arrest	-0.000800	0.003872	0.999200
Age at Release	-0.011394***	0.002878	0.988671
Prior Arrests	0.016276***	0.002429	1.016409
Time Served	-0.004148***	0.000863	0.995861
Black	0.052596	0.035386	1.054004
Other Race	-0.319940*	0.170189	0.726192
Property Offense	0.348763***	0.046478	1.417313
Drug Offense	0.212847***	0.047072	1.237195
Public Order Offense	0.114151*	0.066167	1.120922
Other Offense	-0.037316	0.124824	0.963372
Parole Revocation	0.119978***	0.039237	1.127472
Probation Revocation	0.083021	0.192618	1.086564
Other Admission Type	-0.165178	0.202570	0.847742
Unknown Admission Type	-0.277428	0.221756	0.757730
Mandatory Supervised Released	-0.003429	0.067138	0.996577
Expiration of Sentence	0.309010***	0.107038	1.362076
Other Release Type	-0.144670	0.109621	0.865307
State-Level			
Drug Arrests per 100,000	0.000760	0.000841	1.000760

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6G - Multilevel Regressions of Reimprisonment Probabilities for Reconvicted Offenders on Individual Level Characteristics and State Level Drug Arrests per 100,000
Final estimation of fixed effects: (Unit specified model):

	B	S.E.	Exp(b)
Intercept, γ00	0.230218	0.576054	1.258874
Individual-Level			
Gender	-0.523832***	0.074418	0.592247
Age of First Arrest	0.020876***	0.004766	1.021096
Age at Release	-0.019826***	0.003470	0.980370
Prior Arrests	0.008637***	0.002631	1.008674
Time Served	0.004851***	0.001111	1.004863
Black	0.127696***	0.041953	1.136207
Other Race	-0.702011***	0.224580	0.495588
Property Offense	0.250003***	0.056466	1.284029
Drug Offense	0.126288**	0.057328	1.134609
Public Order Offense	0.017624	0.080922	1.017780
Other Offense	-0.141371	0.154806	0.868167
Parole Revocation	0.028530	0.045979	1.028941
Probation Revocation	-0.288199	0.236519	0.749612
Other Admission Type	0.270440	0.258911	1.310541
Unknown Admission Type	0.117904	0.267334	1.125136
Mandatory Supervised Released	-0.078161	0.079387	0.924815
Expiration of Sentence	-0.188148	0.118226	0.828492
Other Release Type	-0.179221	0.136857	0.835921
State-Level			
Drug Arrests per 100,000	-0.000112	0.000845	0.999888

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6H - Multilevel Regressions of Rearrests on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	0.408421	0.367580	1.504441
Individual-Level			
Gender	-0.487645***	0.043548	0.614071
Age of First Arrest	0.003535	0.002771	1.003541
Age at Release	-0.061797***	0.002170	0.940074
Prior Arrests	0.075869***	0.002547	1.078822
Time Served	-0.002889***	0.000591	0.997115
Black	0.508769***	0.027713	1.663243
Other Race	-0.391022***	0.121697	0.676366
Property Offense	0.379352***	0.036657	1.461337
Drug Offense	0.066560*	0.035810	1.068825
Public Order Offense	0.069749	0.050022	1.072239
Other Offense	-0.020299	0.096544	0.979906
Parole Revocation	0.413983***	0.032871	1.512831
Probation Revocation	0.185534	0.152176	1.203862
Other Admission Type	-0.152167	0.147341	0.858845
Unknown Admission Type	-0.345728**	0.168037	0.707705
Mandatory Supervised Released	0.120829**	0.047661	1.128432
Expiration of Sentence	0.221354***	0.069857	1.247765
Other Release Type	-0.067349	0.073823	0.934869
State-Level			
Police per 1,000 Residents	0.053538	0.145160	1.054998
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6I - Multilevel Regressions of Violent Rearrests on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents
Final estimation of fixed effects: (Unit specified model):

	b	S.E.	Exp(b)
Intercept, γ00	-1.711056***	0.259809	0.180675
Individual-Level			
Gender	-0.792006***	0.066835	0.452935
Age of First Arrest	-0.033594***	0.003944	0.966964
Age at Release	-0.040626***	0.002614	0.960188
Prior Arrests	0.022916***	0.001973	1.023181
Time Served	-0.002941***	0.000754	0.997063
Black	0.559868***	0.031483	1.750441
Other Race	0.246504*	0.140159	1.279545
Property Offense	-0.400764***	0.039340	0.669808
Drug Offense	-0.609024***	0.040265	0.543881
Public Order Offense	-0.334968***	0.059778	0.715361
Other Offense	-0.575534***	0.116013	0.562405
Parole Revocation	0.308714***	0.035407	1.361673
Probation Revocation	-0.018011	0.160112	0.982151
Other Admission Type	-0.426868**	0.204758	0.652550
Unknown Admission Type	-0.054909**	0.266895	0.946571
Mandatory Supervised Released	0.385261***	0.067875	1.469997
Expiration of Sentence	0.613087***	0.074956	1.846121
Other Release Type	0.278507***	0.082645	1.321156
State-Level			
Police per 1,000 Residents	0.139806	0.101452	1.150050

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6J - Multilevel Regressions of Property Rearrests on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	-1.841191***	0.235243	0.158628
Individual-Level			
Gender	-0.196561***	0.049689	0.821552
Age of First Arrest	0.005679*	0.003170	1.005695
Age at Release	-0.038559***	0.002353	0.962175
Prior Arrests	0.052348***	0.001977	1.053742
Time Served	-0.001947***	0.000691	0.998055
Black	0.318929***	0.028522	1.375653
Other Race	-0.275791*	0.140800	0.758971
Property Offense	0.799288***	0.037089	2.223957
Drug Offense	-0.245558***	0.038966	0.782268
Public Order Offense	-0.010614	0.057045	0.989442
Other Offense	0.200574**	0.098340	1.222104
Parole Revocation	0.250465***	0.032269	1.284622
Probation Revocation	0.347531**	0.144294	1.415569
Other Admission Type	-0.132454	0.175274	0.875943
Unknown Admission Type	-0.024673	0.224098	0.975629
Mandatory Supervised Released	0.262409***	0.061578	1.300059
Expiration of Sentence	0.378509***	0.070308	1.460106
Other Release Type	0.131446***	0.076009	1.140477
State-Level			
Police per 1,000 Residents	0.341012***	0.091807	1.406370
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6K - Multilevel Regressions of Drug Rearrests on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	-2.049450***	0.433793	0.128806
Individual-Level			
Gender	-0.204921***	0.048726	0.814712
Age of First Arrest	-0.001548	0.003135	0.998453
Age at Release	-0.034843***	0.002338	0.965757
Prior Arrests	0.042036***	0.001908	1.042932
Time Served	-0.003054***	0.000755	0.996951
Black	0.409816***	0.028673	1.506540
Other Race	-0.555793***	0.158717	0.573617
Property Offense	0.145115***	0.039411	1.156172
Drug Offense	0.778627***	0.038043	2.178478
Public Order Offense	0.129681**	0.057925	1.138465
Other Offense	0.271949***	0.096649	1.312520
Parole Revocation	0.183994***	0.031957	1.202009
Probation Revocation	0.077469	0.159767	1.080548
Other Admission Type	-0.200755	0.201469	0.818112
Unknown Admission Type	-0.429589	0.294572	0.650777
Mandatory Supervised Released	0.151749**	0.069052	1.163868
Expiration of Sentence	0.265058***	0.074601	1.303506
Other Release Type	-0.157843*	0.085438	0.853984
State-Level			
Police per 1,000 Residents	0.309174*	0.168984	1.362300
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6L - Multilevel Regressions of Public Order Rearrests on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents
Final estimation of fixed effects: (Unit specified model):

	B	S.E.	Exp(b)
Intercept, γ00	-1.185286	0.677762	0.305659
Individual-Level			
Gender	-0.286794***	0.052266	0.750666
Age of First Arrest	-0.006066*	0.003425	0.993953
Age at Release	-0.054292***	0.002459	0.947155
Prior Arrests	0.034703***	0.001901	1.035312
Time Served	-0.002396***	0.000737	0.997607
Black	0.046398	0.029365	1.047491
Other Race	-0.024345	0.135020	0.975949
Property Offense	0.027924	0.038482	1.028318
Drug Offense	0.020769	0.034066	1.020986
Public Order Offense	0.422849***	0.051339	1.526303
Other Offense	-0.328789***	0.110836	0.719795
Parole Revocation	0.190399***	0.033431	1.209732
Probation Revocation	0.134174	0.140431	1.143591
Other Admission Type	-0.467820***	0.172363	0.626366
Unknown Admission Type	-0.072029	0.244939	0.930504
Mandatory Supervised Released	0.422962***	0.064879	1.526476
Expiration of Sentence	0.348797***	0.075462	1.417362
Other Release Type	0.217973***	0.080251	1.243553
State-Level			
Police per 1,000 Residents	0.073105	0.264072	1.075843

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6M - Multilevel Regressions of Reconviction Probabilities for Rearrested Offenders on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents Final estimation of fixed effects: (Unit specified model):			
	B	S.E.	Exp(b)
Intercept, γ00	-0.324498	0.552864	0.722890
Individual-Level			
Gender	-0.055823	0.062618	0.945707
Age of First Arrest	-0.000731	0.003872	0.999269
Age at Release	-0.011387***	0.002877	0.988678
Prior Arrests	0.016289***	0.002428	1.016423
Time Served	-0.004192***	0.000863	0.995817
Black	0.050899	0.035385	1.052217
Other Race	-0.318548*	0.170199	0.727204
Property Offense	0.348211***	0.046469	1.416531
Drug Offense	0.212111***	0.047073	1.236285
Public Order Offense	0.114413*	0.066158	1.121215
Other Offense	-0.036094	0.124821	0.964550
Parole Revocation	0.122149***	0.039230	1.129923
Probation Revocation	0.090786	0.192240	1.095035
Other Admission Type	-0.161607	0.202521	0.850776
Unknown Admission Type	-0.279493	0.221224	0.756167
Mandatory Supervised Released	0.006680	0.067057	1.006702
Expiration of Sentence	0.305307***	0.106714	1.357042
Other Release Type	-0.148446	0.108819	0.862047
State-Level			
Police per 1,000 Residents	0.450621*	0.216014	1.569287
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6N - Multilevel Regressions of Reimprisonment Probabilities for Reconvicted Offenders on Individual Level Characteristics and Statewide Level of Police Officers per 1,000 Residents
Final estimation of fixed effects: (Unit specified model):

	B	S.E.	Exp(b)
Intercept, γ00	0.521297	0.608975	1.684210
Individual-Level			
Gender	-0.523812***	0.074419	0.592259
Age of First Arrest	0.020855***	0.004766	1.021074
Age at Release	-0.019838***	0.003470	0.980358
Prior Arrests	0.008641***	0.002630	1.008679
Time Served	0.004874***	0.001111	1.004886
Black	0.128560***	0.041968	1.137190
Other Race	-0.702348***	0.224576	0.495421
Property Offense	0.250140***	0.056459	1.284205
Drug Offense	0.126655**	0.057333	1.135025
Public Order Offense	0.017668	0.080922	1.017825
Other Offense	-0.141753	0.154804	0.867835
Parole Revocation	0.027695	0.045990	1.028082
Probation Revocation	-0.292684	0.236530	0.746258
Other Admission Type	0.269249	0.258852	1.308982
Unknown Admission Type	0.121601	0.267279	1.129303
Mandatory Supervised Released	-0.082303	0.079529	0.920993
Expiration of Sentence	-0.189522	0.118075	0.827355
Other Release Type	-0.183027	0.136309	0.832746
State-Level			
Police per 1,000 Residents	-0.145565	0.236350	0.864534

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6O - Multilevel Regressions of Rearrests on Individual Level Characteristics and Statewide Arrest-Offense Ratios Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	1.182165**	0.472425	3.261427
Individual-Level			
Gender	-0.487598***	0.043549	0.614100
Age of First Arrest	0.003559	0.002771	1.003566
Age at Release	-0.061816***	0.002170	0.940056
Prior Arrests	0.075881***	0.002547	1.078834
Time Served	-0.002891***	0.000591	0.997113
Black	0.509112***	0.027701	1.663814
Other Race	-0.391308***	0.121690	0.676172
Property Offense	0.379173***	0.036654	1.461076
Drug Offense	0.066670*	0.035806	1.068942
Public Order Offense	0.070258	0.050018	1.072784
Other Offense	-0.020320	0.096541	0.979885
Parole Revocation	0.414070***	0.032864	1.512963
Probation Revocation	0.182533	0.151848	1.200254
Other Admission Type	-0.155509	0.147248	0.855979
Unknown Admission Type	-0.345114**	0.167736	0.708140
Mandatory Supervised Released	0.120994**	0.047416	1.128618
Expiration of Sentence	0.219513***	0.069759	1.245471
Other Release Type	-0.071638	0.073690	0.930868
State-Level			
Arrest-Offense Ratio	-0.024463	0.073690	0.975834
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6P - Multilevel Regressions of Violent Rearrests on Individual Level Characteristics and Statewide Arrest-Offense Ratios Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	-0.982991**	0.408147	0.374190
Individual-Level			
Gender	-0.792280***	0.066836	0.452811
Age of First Arrest	-0.033613***	0.003944	0.966945
Age at Release	-0.040640***	0.002614	0.960175
Prior Arrests	0.022860***	0.001974	1.023123
Time Served	-0.002917***	0.000755	0.997087
Black	0.561817***	0.031486	1.753857
Other Race	0.243604*	0.140161	1.275839
Property Offense	-0.400567***	0.039347	0.669940
Drug Offense	-0.608377***	0.040265	0.544234
Public Order Offense	-0.334515***	0.059787	0.715685
Other Offense	-0.575684***	0.116014	0.562320
Parole Revocation	0.307758***	0.035450	1.360372
Probation Revocation	-0.048505	0.160510	0.952653
Other Admission Type	-0.444475**	0.204955	0.641161
Unknown Admission Type	-0.037618	0.267615	0.963081
Mandatory Supervised Released	0.361330***	0.068359	1.435237
Expiration of Sentence	0.599165***	0.076683	1.820598
Other Release Type	0.258346***	0.084594	1.294787
State-Level			
Arrest-Offense Ratio	-0.014311	0.015594	0.985791
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6Q - Multilevel Regressions of Property Rearrests on Individual Level Characteristics and Statewide Arrest-Offense Ratios
Final estimation of fixed effects: (Unit specified model):

	b	S.E.	Exp(b)
Intercept, γ00	-0.703265	0.489060	0.494966
Individual-Level			
Gender	-0.197088***	0.049690	0.821119
Age of First Arrest	0.005604	0.003170	1.005620
Age at Release	-0.038536***	0.002354	0.962197
Prior Arrests	0.052265***	0.001980	1.053655
Time Served	-0.001916***	0.000694	0.998086
Black	0.321380***	0.028551	1.379030
Other Race	-0.280775**	0.140790	0.755198
Property Offense	0.799674***	0.037105	2.224815
Drug Offense	-0.244312***	0.038967	0.783244
Public Order Offense	-0.009827	0.057065	0.990222
Other Offense	0.199405**	0.098333	1.220676
Parole Revocation	0.249873***	0.032349	1.283862
Probation Revocation	0.301927**	0.146036	1.352462
Other Admission Type	-0.152757	0.175728	0.858338
Unknown Admission Type	0.020237	0.226194	1.020443
Mandatory Supervised Released	0.236166***	0.064079	1.266385
Expiration of Sentence	0.359807***	0.072088	1.433053
Other Release Type	0.103940	0.079116	1.109534
State-Level			
Arrest-Offense Ratio	-0.010984	0.018681	0.989076

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6R - Multilevel Regressions of Drug Rearrests on Individual Level Characteristics and Statewide Arrest-Offense Ratios
Final estimation of fixed effects: (Unit specified model):

	b	S.E.	Exp(b)
Intercept, γ00	-0.836000	0.668383	0.433441
Individual-Level			
Gender	-0.204984***	0.048727	0.814661
Age of First Arrest	-0.001582	0.003135	0.998419
Age at Release	-0.034857***	0.002337	0.965744
Prior Arrests	0.042007***	0.001908	1.042902
Time Served	-0.003015***	0.000755	0.996990
Black	0.411185***	0.028676	1.508605
Other Race	-0.556519***	0.158698	0.573201
Property Offense	0.145353***	0.039413	1.156448
Drug Offense	0.779069***	0.038044	2.179442
Public Order Offense	0.130341**	0.057928	1.139217
Other Offense	0.271286***	0.096646	1.311650
Parole Revocation	0.182903***	0.031968	1.200698
Probation Revocation	0.066267	0.159902	1.068512
Other Admission Type	-0.205083	0.201460	0.814580
Unknown Admission Type	-0.420531	0.294794	0.656698
Mandatory Supervised Released	0.137609**	0.069285	1.147526
Expiration of Sentence	0.260358***	0.075222	1.297394
Other Release Type	-0.168064*	0.086220	0.845300
State-Level			
Arrest-Offense Ratio	-0.017078	0.025529	0.983067

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6S - Multilevel Regressions of Public Order Rearrests on Individual Level Characteristics and Statewide Arrest-Offense Ratios Final estimation of fixed effects: (Unit specified model):			
	b	S.E.	Exp(b)
Intercept, γ00	-0.224166	0.914972	0.799182
Individual-Level			
Gender	-0.286842***	0.052267	0.750630
Age of First Arrest	-0.006066*	0.003425	0.993953
Age at Release	-0.054292***	0.002459	0.947155
Prior Arrests	0.034697***	0.001901	1.035306
Time Served	-0.002394***	0.000737	0.997609
Black	0.046518	0.029362	1.047617
Other Race	-0.024492	0.135017	0.975805
Property Offense	-0.027930	0.038482	0.972456
Drug Offense	-0.007121	0.038559	0.992905
Public Order Offense	0.394996***	0.054880	1.484379
Other Offense	-0.356759***	0.112733	0.699941
Parole Revocation	0.190374***	0.033432	1.209701
Probation Revocation	0.132899	0.140371	1.142135
Other Admission Type	-0.469136***	0.172335	0.625543
Unknown Admission Type	-0.074979	0.244841	0.927763
Mandatory Supervised Released	0.420395***	0.064753	1.522563
Expiration of Sentence	0.346325***	0.075706	1.413861
Other Release Type	0.215484***	0.080425	1.240463
State-Level			
Arrest-Offense Ratio	-0.029950	0.034942	0.970494
* $p < .10$, ** $p < .05$, *** $p < .01$			

Table 6T - Multilevel Regressions of Reconviction Probabilities for Rearrested Offenders on Individual Level Characteristics and Statewide Arrest-Offense Ratios Final estimation of fixed effects: (Unit specified model):

	B	S.E.	Exp(b)
Intercept, γ00	0.177213	0.868182	1.193886
Individual-Level			
Gender	-0.055843	0.062622	0.945687
Age of First Arrest	-0.000771	0.003872	0.999229
Age at Release	-0.011421***	0.002878	0.988644
Prior Arrests	0.016324***	0.002429	1.016458
Time Served	-0.004145***	0.000863	0.995864
Black	0.052305	0.035386	1.053697
Other Race	-0.320263*	0.170197	0.725958
Property Offense	0.348281***	0.046473	1.416630
Drug Offense	0.212909***	0.047072	1.237272
Public Order Offense	0.113756*	0.066169	1.120479
Other Offense	-0.036770	0.124824	0.963898
Parole Revocation	0.119885***	0.039242	1.127367
Probation Revocation	0.081794	0.192716	1.085232
Other Admission Type	-0.165598	0.202598	0.847387
Unknown Admission Type	-0.281813	0.221901	0.754415
Mandatory Supervised Released	-0.001452	0.067139	0.998549
Expiration of Sentence	0.310223***	0.107162	1.363729
Other Release Type	-0.143832	0.109838	0.866033
State-Level			
Arrest-Offense Ratio	0.023951	0.032943	1.024240

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6U - Multilevel Regressions of Reimprisonment Probabilities for Reconvicted Offenders on Individual Level Characteristics and Statewide Arrest-Offense Ratios Final estimation of fixed effects: (Unit specified model):			
	B	S.E.	Exp(b)
Intercept, γ00	0.244801	0.899047	1.277367
Individual-Level			
Gender	-0.523838***	0.074418	0.592243
Age of First Arrest	0.020870***	0.004766	1.021089
Age at Release	-0.019820***	0.003470	0.980375
Prior Arrests	0.008628***	0.002630	1.008665
Time Served	0.004851***	0.001111	1.004863
Black	0.127746***	0.041952	1.136264
Other Race	-0.701858***	0.224574	0.495664
Property Offense	0.250081***	0.056461	1.284129
Drug Offense	0.126267**	0.057329	1.134585
Public Order Offense	0.017713	0.080925	1.017871
Other Offense	-0.141461	0.154804	0.868089
Parole Revocation	0.028538	0.045986	1.028949
Probation Revocation	-0.287762	0.236495	0.749940
Other Admission Type	0.270581	0.258906	1.310726
Unknown Admission Type	0.118500	0.267369	1.125807
Mandatory Supervised Released	-0.078608	0.079271	0.924403
Expiration of Sentence	-0.188203	0.118387	0.828447
Other Release Type	-0.179033	0.137146	0.836079
State-Level			
Arrest-Offense Ratio	-0.003458	0.034677	0.996548
* $p < .10$, ** $p < .05$, *** $p < .01$			