Document Title: Extension of Current Estimates of Redemption Times: Robustness Testing, Out-of-State Arrests, and Racial Differences

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Document No.: 240100

Date Received: November 2012

Award Number: 2009-IJ-CX-0008

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Final Report Submitted to the National Institute of Justice

Grant No. 2009-IJ-CX-0008

October 2012

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This project was supported by Grant No. 2009-IJ-CX-0008 *awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. Points of view in this document are those of the authors and do not necessarily represent the official position or policies of the US Department of Justice.*

Abstract

As information technology has increased the accessibility of criminal-history records, and concern for negligent-hiring lawsuits has grown, criminal background checking has become an important part of the hiring process for most employers. As a result, there is a growing concern that a large number of individuals are handicapped in finding employment because of a stale criminal-history record.

The current study is an extension of a NIJ-funded project intended to provide the empirical estimates of what we call "redemption time," the time when an individual with a prior arrest record has stayed clean of further involvement with the criminal justice system sufficiently long to be considered "redeemed" and relieved of the stale burden of a prior criminal-history record. In the current study, we address new issues that that are important in moving the research on redemption forward and making the findings applicable to relevant policy.

In the first section, we introduce the background of this project by discussing the increasing use of criminal background checks by employers, the potential size of population with criminal records that such background checking can affect, and our initial research on redemption that empirically examines when a criminal record loses its relevance in predicting future crime ("redemption times").

In the second section, we explore the issue of robustness of redemption time estimates. In our previous project, we generated our estimates of redemption times using rap sheets from New York State of individuals first arrested in 1980. Using additional data from 1985 and 1990 sampling years in New York as well as data from two additional states, Florida and Illinois, we test the sensitivity of the 1980 New York results to these alternative data. The results show that

the redemption time estimates are reasonably robust across sampling years and states, and the range of estimates is presented to summarize the results.

In the third section, we examine the relationship between the crime type of the first crime event and the crime type of a possible second arrest. This recognizes that employers are concerned mostly about particular types of offense that their employees may commit, based on the nature of the job position. We estimate the recidivism risk and redemption time of particular second-offense types, focusing particularly on violent and property crimes, often an employer's primary concern, based on the prior offense type and age at the prior. We find that the prior crime type is associated with the recidivism crime type and thus redemption time, especially for violence, and the association is more prominent for older offenders. We also find that that association diminishes as time since the prior increases.

In the fourth section, we address the relationship between race and longer-term recidivism risk, which is relevant to the concern of the Equal Employment Opportunity Commission (EEOC) that criminal background checks have a disparate impact on minorities. The results show that 1) the racial rearrest-risk ratio is smaller than the arrest-prevalence ratio, and 2) the rearrest-risk ratio declines over time, so that the recidivism risk of blacks approaches the risk of whites over time.

In the last two sections, we conclude this report by summarizing our findings, discuss future work, and describe our outreach efforts to disseminate our findings on this important public policy issue to stakeholders.

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Extension of Current Estimates of Redemption Times: Robustness Testing, Out–of-State Arrests, and Racial Differences[1]

1. Introduction

Background checking, especially checking of criminal-history records, is becoming increasingly ubiquitous in the U.S. Recent advances in information technology and growing concern about employer liability have combined to increase the demand for such background checks. Also, a large number of individual criminal records have accumulated and been computerized in state repositories and commercial databases. As a result, many people who have made mistakes in their youthful past, but have since lived a law-abiding life, face hardships in finding employment.

The increasing availability and the widespread use of individual criminal history records for non-criminal justice purposes, combined with the sheer size of the cumulative population with a criminal record has started to create an immense public concern. The concern is evidenced by the report from the Attorney General sent to Congress in June, 2006 on criminal history background checks (U.S. Department of Justice, 2006). In the report, there is a recommendation for time limits on the relevancy of criminal records, which reflects the fact that the potentially lasting effect of criminal records is a common concern among many governmental and legal entities that have a say in this issue. Such entities include the U.S. Equal Employment Opportunity Commission (EEOC), which is concerned with discrimination based on criminal records because those with criminal records are disproportionally racial/ethnic minorities. The American Bar

[1] As the title here indicates, one of the objectives of this study was to examine the prevalence of out-of-state arrests for the 1980 NY cohort. The results of this examination are reported in the final report of our previous NIJ grant (2007-IJ-CX-0041) (Blumstein and Nakamura, 2010).

Association (ABA) is also concerned about the negative lasting effect of criminal records in employment settings. Both these organizations are taking an initiative to broaden the discussion about the problem of the way in which criminal records are currently used and to address how to regulate the use of criminal records, including a time limit on their relevancy.

It is our goal in this project to provide guidance on possible redemption, which we define as the process of “going straight” and thereby being released from bearing the mark of crime. This research is of increasing relevance to state and local policy makers because of the growing concern over the large number of people handicapped from employment because of a stale criminal-history record. Addressing this issue should contribute to improved re-entry and reduction of correctional populations as former offenders have better employment prospects. The current project builds on and extends Blumstein and Nakamura (2009) (henceforth, BN 2009), the principal paper resulting from our prior grant from the National Institute of Justice. The study provides the measures of redemption as the time clean after which the risk of rearrest falls below the offending risk of others of the same age.

While the findings and the analytical approaches that BN 2009 employed represent the first empirical evidence on redemption times using a large official dataset from a state repository, those estimates of redemption times are based very specifically on the data of criminal-history records of individuals who had their first arrest in New York in 1980. Obviously, those data were extremely important because they provided us with the opportunity to develop and test the methodology for measuring redemption times and to communicate our results to relevant stakeholders in the issue and get feedback from them on issues they consider important. Obviously, the world is not particularly interested in first-time arrestees in New York in 1980, but our objective in this project is to test the robustness of those findings in New York against relevant conditions. To the extent that those results are found to be similar, then the results of that robustness testing becomes extremely valuable in providing guidance to those more generally involved in background checking.

In order to ensure that findings apply beyond people arrested in NY in the 1980s, we need robustness testing regarding many dimensions and examine to what extent the findings from the 1980 NY data are generalizable. In this report, we present the results of the robustness testing of the findings in the following ways:

- Sampling years: using additional data from NY on those who were first arrested in 1985 and 1990, and how their redemption patterns relate to the 1980 cohort
- Geographical locations: using additional data from two other states, Florida and Illinois

Furthermore, BN 2009 considers the risk of a new arrest for *any* crime. Thus, for example, a new arrest is noted when a person whose first arrest was for burglary, is rearrested for burglary or for any non-burglary offense. In reality, most employers are concerned not about *any* crime, which could include minor offenses such as disorderly conduct or drunkenness, but about particular crimes that are *most relevant* to the job positions under consideration, particularly property and violent crimes (Fahey et al., 2006; Holzer et al., 2007). Property crimes are mostly of concern for positions such as a cashier or a bank teller and violence crimes are mostly of concern for positions that require frequent one-on-one contact with clients, particularly for vulnerable populations like children and elderly. This is an important issue, not only for the employer's interest in assessing a potential employee's relevant risk, but also for the legal requirements that the employer needs to consider. In order to address this issue, we estimate redemption times as a function of the "next crime type", a crime type of the second arrest.

Another issue that we address is the relevance of race in the problem of redemption. The EEOC's primary concern over discrimination against those with criminal records stems from the fact that such discrimination does not affect all racial/ethnic groups uniformly, but affects minority groups disproportionally. Minority groups, in particular blacks and Hispanics, are over-represented in the U.S. criminal justice system, and so are more likely to have criminal records that can be revealed by background checking. Despite the importance of race/ethnicity in the problem of redemption, there is little empirical evidence as to whether and how much redemption times vary with race and ethnicity. Thus, in this report we generate information about the relationship between longer-term patterns of recidivism and race/ethnicity in the context of redemption.

A. Prevalence of Criminal Background Checking and Criminal Records

With the recent advances in information technology and the Internet, individuals' criminal records have become increasingly accessible. Many states make their criminal-history information publicly available on the Internet (Samuels and Mukamal, 2004; SEARCH, 2001),[2] and a growing number of record-tracing companies compile individual criminal-history information from the police and courts and provide access to their database of criminal records for a fee (SEARCH, 2005).[3] The growing accessibility of criminal records has made criminal

[2] States are clearly moving in the direction of making individual criminal records more publicly accessible (Jacobs, 2006).

[3] In recent years, the size of the pre-employment screening industry has grown dramatically to a market size of $2-$3 billion due to factors such as security concerns after September 11, 2001, the increase in negligent-hiring lawsuits, and technology that makes background checks faster and cheaper (Roberts, 2010). The National Association of Professional Background Screeners (NAPBS), a professional organization for the background screening industry, reports a membership of over 700 companies (NAPBS, 2009).

background checking an increasingly common part of pre-employment screening.[4] According to surveys of human resource professionals, 80-90 percent of large employers in the U.S. now run criminal background checks on their prospective employees (Society for Human Resource Management, 2004, 2010).

As the use of criminal background checks by employers has become widespread, criminal records could have lingering effects on employment prospects of those with stale criminal records, making it difficult for them to find employment (Goode, 2011). The concern over employers' reluctance to hire those with criminal records has been well documented (e.g., Holzer et al., 2004; Pager, 2003).

The impact of widespread criminal background checks is magnified by the sheer number of people with criminal histories. In 2009, according to the Uniform Crime Report (UCR), law enforcement agencies across the U.S. made nearly 14 million arrests (Federal Bureau of Investigation, 2010). On December 31, 2008, over 92 million criminal-history records were in the state criminal-history repositories (Bureau of Justice Statistics, 2009). The increasing automation of criminal history records in the repositories has increased the number of records that are electronically accessible. At the end of 2006, about 93 percent of the records were automated (Bureau of Justice Statistics, 2009).

Prior research suggests that the general public's chance of being arrested in their life time is rather high. Over forty years ago, it was estimated that fifty percent of the U.S. male population would be arrested for a non-traffic offense in their lifetime (Christensen, 1967). Based on more recent data, a study shows an even higher estimate of life-time arrest prevalence, reflecting that

[4] Criminal background checks are used not only by employers, but also by other entities such as public housing authorities are concerned about the recidivism risk of prospective tenants (Carey, 2004). This report focuses primarily on the context of employers' use of criminal background checks, but the methods and the results are clearly generalizable to other contexts.

the criminal justice system has become more aggressive in dealing with crimes like drug offenses and domestic violence (Brame et al., 2012). Among those who have an arrest record, some have an isolated record that was acquired years ago and have maintained a clean record since then, but the evidence of contact with the criminal justice system, even if it was in the distant past, could remain in the repositories forever.

B. Relevance of Criminal-History Record

One of the motivations that drive employers' use of background checks is their desire to identify those who may commit criminal acts in the workplace. Employers are increasingly aware of the risk of liability for negligent hiring that could result from such acts (Bushway, 1998; Hahn, 1991; Harris and Keller, 2005; Jacobs and Crepet, 2008; Holzer et al., 2004). Negligent hiring occurs when an employee causes injury to co-workers or customers, and the employer failed to exercise "reasonable care" in preventing such injury (Scott, 1987). In the current environment where criminal records are increasingly accessible and background checks are inexpensive, it is likely that employers are expected to perform background checks to demonstrate reasonable care (Connerley et al., 2001; Levashina and Campion, 2009). This is reflected in the fact that many human resource experts and commercial vendors of criminal records strongly advertise the need for pre-employment criminal background checking and caution employers that failure to conduct such checks is likely to result in considerable financial as well as reputational cost (Babcock, 2003; Jacobs and Crepet 2008; Levashina and Campion, 2009).

Employers and criminal background checking providers recognize the positive relationship between past criminal conduct and future criminal involvement, a robust finding in the criminology literature (Brame et al., 2003; Gendreau et al., 1996; Nagin and Paternoster, 2000). While studies seem to support employers who would avoid hiring anyone with a criminal-history record, the employers' decision to exclude such a potential employee has legal bounds, and a blanket exclusion based solely on the presence of a criminal record is often prohibited.

Title VII of the Civil Rights Act of 1964 prohibits employers from denying employment to job applicants based on their race, sex, religion, or national origin. The Equal Employment Opportunity Commission (EEOC) has determined that refusing to hire applicants based on their criminal record may violate Title VII because the employers' use of criminal records will have a "disparate impact" on the protected groups under Title VII (EEOC, 1990). The EEOC stated that employers may base their hiring decision on the presence of criminal records only if they can demonstrate an associated "business necessity" (EEOC, 1987). In order for employers to establish a business-necessity defense, they need to take into account the following three factors: 1) the nature and gravity of the offense, 2) the time that has passed since the conviction or completion of the sentence, and 3) the nature of the job held or sought (EEOC, 1987). In recent years, the EEOC has stepped up its efforts to challenge employers' criminal background checking practices by filing lawsuits on the grounds that the employers failed to demonstrate business necessity.[5] The EEOC's growing scrutiny of employers' use of criminal background checks has resulted in employers' increased awareness of the business-necessity requirement (Smiricky, 2010; Smith, 2011). The second business-necessity requirement, the time limit on the relevance of criminal records, has been directly addressed by the recent studies on "redemption time".

[5] For example, in 2008, the EEOC filed a lawsuit against Peoplemark, Inc. (*EEOC v Peoplemark, Inc.*), alleging that they unlawfully denied employment to those with criminal records, thereby having a disparate impact on African-American applicants. The EEOC also sued a corporate events company, Freeman (*EEOC v Freeman*) in 2009 for similar allegations about the unlawful use of criminal records in violation of Title VII.

C. Redemption

There have been numerous studies showing that recidivism occurs relatively quickly (Beck and Shipley, 1997; Gottfredson, 1999; Langan and Levin, 2002; Maltz, 1984; Schmidt and Witte, 1988; Visher et al., 1991). However, little attention has been paid to the smaller population of ex-offenders who stay crime-free for a longer period of time. In recent papers, BN 2009, Kurlychek et al. (2006, 2007) and Bushway et al. (2011) have shed some light on the population characterized by long-time avoidance of crime. Examining the hazard of a new offense, they all show that the risk of re-offending for those with a criminal record converges toward the risk for those without a record as substantial time passes. For instance, BN 2009 used the concept of redemption to provide empirical estimates of how the recidivism risk declines to appropriate benchmarks. Using a large data set of rap sheets provided by New York State of individuals arrested for the first time in 1980, redemption times were estimated as time points when the rearrest risk, which was quantified by the hazard function, falls below the arrest risk of the general population and when it becomes “close enough” to the risk of those without a prior record.

2. Robustness of Redemption Patterns

The issue of criminal background checks using stale records has become an increasingly important public concern, and consequently research on redemption has attracted the attention of the media (e.g., Goode, 2011), policy-makers and various governmental agencies (NIJ, 2009; U.S. Department of Justice, 2006; EEOC, 2008), legal professionals (ABA, 2008), and organizations that facilitate successful reentry of people with criminal records (Legal Action Center, 2004; National Employment Law Project, 2011).

Although these stakeholders may find the redemption times estimated by BN 2009 to be of considerable relevance, they are interested in the robustness of the estimates in order to generalize beyond the particular population used, namely first-time arrestees in NY in 1980. The issue of robustness is of concern to employers as well – employers must routinely consider applicants with a record of arrest or conviction that occurred, not necessarily in 1980, but in other years, and not necessarily in New York, but in other states. The concern about the robustness deepens, given that 1980 might have been a unique year because it was the start of the aging of the baby boomers out of the high-crime ages, which resulted in a crime peak (Blumstein et al., 1980). Also, for a variety of factors such as demographic composition and economic conditions, arrest experiences in New York State could be rather different from those in other states.[6]

A. Robustness across Sampling Years

Considering the dramatic swings in the levels of crime over the 20 years following 1980 (Blumstein and Rosenfeld, 2008), one must anticipate the possibility that the rearrest risk patterns of offenders first arrested in 1980 would be different from those arrested more recently, so it is important that we test the robustness of the findings about redemption based on the 1980 NY arrest cohort. To the extent that there is stability in rearrest patterns across sampling years, it would then be possible to provide robust, generalized guidance on redemption times to employers and policy-makers. It is also important that, if the rearrest patterns are dissimilar

[6] A recent report shows widely varying recidivism rates across states, indicating a possibility of different factors affecting different states' recidivism patterns (Pew Center on the States, 2011).

across years and especially the later years close to the redemption times, the guidance on redemption times should account for those differences.

i. Changes in Crime Patterns over the Last Three Decades

The period from the second half of the 1970s to the late 1990s is marked by dramatic changes in the levels of crime. The rate of violent crime started rising in the 1970s, experienced its first peak around 1980, declined until the mid 1980s, then sharply increased to another peak in the early 1990s, and then dropped dramatically until 2000 (Bureau of Justice Statistics, 2010a). During the same period, the rate of property crime followed a similar pattern as that of violent crime, but its ups and downs were much less dramatic (Bureau of Justice Statistics, 2010a).[7] The rate of arrests for drug crime has been in general on a steady increase with a sharp spike in 1989 (Bureau of Justice Statistics, 2010b).[8]

The rise and fall of the rate of violent crime during the period between the 1970s through the mid 1980s is largely attributed to the fact that the baby boomers entered and left the high crime ages (late teens to early 20s) during the period (Blumstein et al., 1980). The rise that started in the mid 1980s is most likely due to crack cocaine and the violence associated with its marketing (Blumstein, 1995; Blumstein et al., 2000).

The growth of the crack markets might also be responsible for the simultaneous increase in robbery and the decrease in burglary as drug users switched from burglary to robbery in need of quick money (Baumer et al., 1998). The striking drop in the second half of the 1990s until 2000 can be a result of many factors including the decline in the demand for crack (Blumstein and

[7] The property crime rate experienced a mild peak around 1990, which is driven largely by non-burglary crimes (e.g., larceny). The burglary rate, after its peak around 1980, has been mostly steadily declining.

[8] The peak in the drug arrest rate is due to the large increase in the arrests for heroin and cocaine in the 1980s and sharp decline around 1990.

Rosenfeld, 1998; Blumstein et al., 2000), increased incarceration (Useem and Piehl, 2008; Western, 2006), and changes in policing strategies targeted at young people's guns (Blumstein and Wallman, 2006).

The escalation of the "war on drugs" in the early 1980s dramatically shifted the focus and funding of law enforcement to drug-related crimes and introduced stringent laws and policies against drug offenses, exemplified by the Rockefeller drug laws in New York. The number of arrests for drug offenses almost tripled from 1980 to 1997 (Federal Bureau of Investigation, 1981-98), and exhibited strong racial disproportionality – the drug arrest rates for blacks rose to 4-5 times that of whites in the late 1980s (National Consortium on Violence Research, n.d.).

The shifts in crime rates over the last three decades indicate that the environment to which those arrested in 1980 were exposed was quite different from the environments to which more recent arrestees were exposed (i.e., period effect or the effect on arrest rates unique to particular periods); thus, the rearrest patterns across time could well be influenced by these different environments (Fabio et al., 2006). Since the effect of different environments is not likely to be uniform across ages and it is possible that the shifts in crime rates over time appear mostly among certain age groups (i.e. age effect), it is instructive to examine the age-crime curves (age-specific arrest rates or the ratio of the number of arrests to the population of a particular age) for the three different years. Figure 1a depicts the age-crime curves for all offenses in 1980, 1985, 1990 in NY. Figures 1b-1d show the age-crime curves by crime types (violent, drug, and property offenses).

The overall arrest rate in 1980 is clearly lower than the arrest rates in 1985 and 1990 for all ages, suggesting the presence of a period effect. The arrest rate for violence in 1990 is 1.4-2.0 times higher than the arrest rates in 1980 and 1985 at all ages, while the 1980 and 1985 rates are close to each other. The arrest rate for drugs in 1990 is clearly much higher than the arrest rate in 1980, with the ratio of the 1990 rate to 1980 rate increasing with age, from 1.7 at age 16 to 5.7 at age 39. During the teenage years, the arrest rate for drugs in 1985 and 1990 are close to each other; whereas, during the 20's the rate of decrease for the arrest rate is slower in 1990 than in 1985. It is also important to note that the arrest rates for drugs peaks at different ages across the three sampling years, which may indicate the presence of cohort effects, the effect on arrest rates unique to particular birth cohorts. While the arrest rate for violence peaks at around 17-18 for the three years, the peak age for drug arrests is 18 in 1980, 21 in 1985, and 23 in 1990. As seen in Figure 1d, the arrest rate for property crimes in 1990 is on average 1.5 times higher than the arrest rates in 1980 and 1985, which are close to one another.

The disaggregated age-crime curves suggest that the overall age-crime curve in 1980 is lower than that in 1985 and 1990, largely as a result of increased arrest rates for violent and drug offenses in 1985-90. The fact that different crimes seem to be driving the arrest prevalence in different years' curves makes it important for the robustness testing of recidivism and redemption patterns to take into account the crime types as well as age.

Figure 1a. NY Age-Crime Curves for 1980, 1985, and 1990 for all offenses

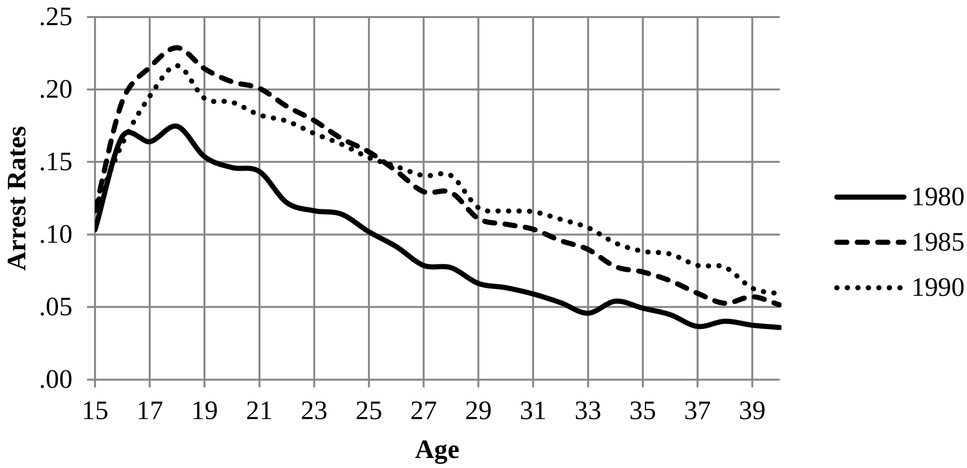


Figure 1b. NY Age-Crime Curves for violent offenses, 1980, 1985, and 1990

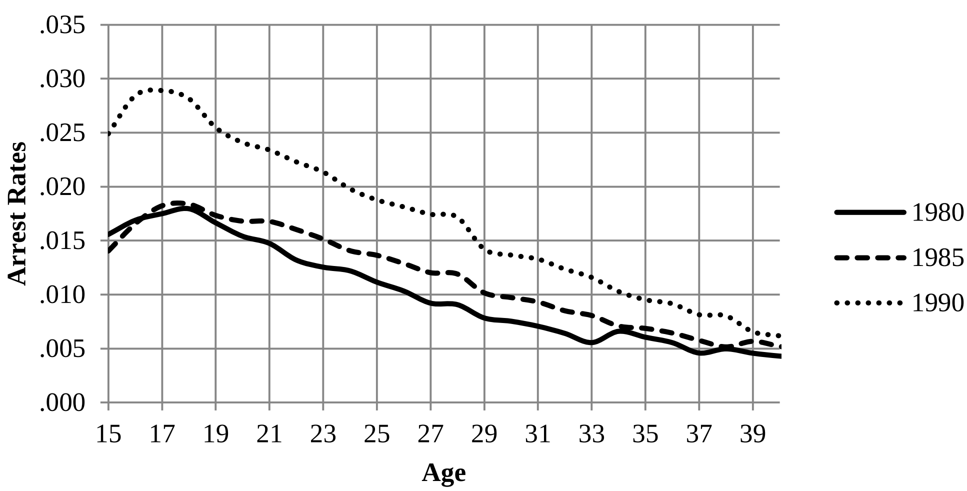


Figure 1c. NY Age-Crime Curves for drug offenses, 1980, 1985, and 1990

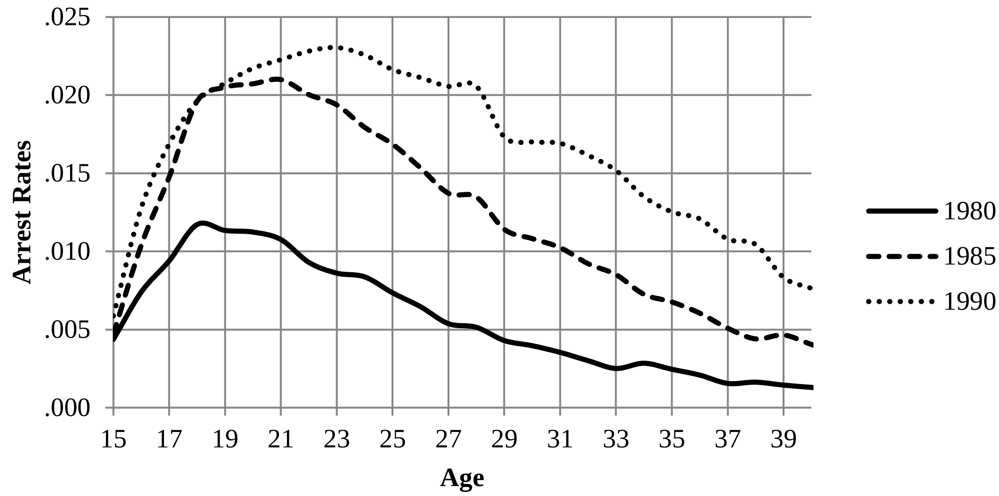
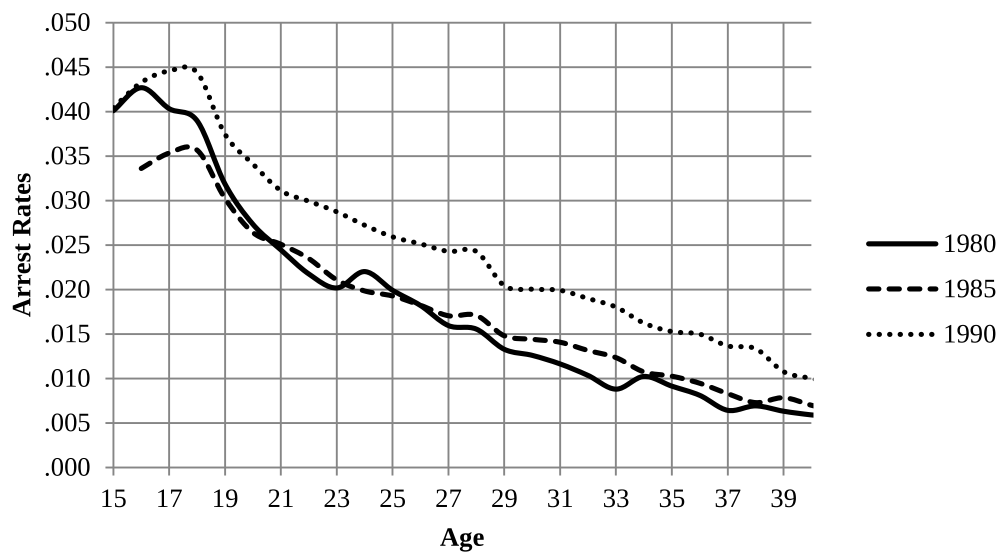


Figure 1d. NY Age-Crime Curves for property offenses, 1980, 1985, and 1990



ii. Data

The data we used to test the robustness of recidivism and redemption times consist of the criminal history of three cohorts of first-time adult arrestees in 1980, 1985, and 1990 in New York State, with approximately 70,000, 63,000, and 65,000 individuals in the three cohorts respectively.[9] We focus on individuals whose age at first arrest (denoted A_1) is between 19 and 30 and who were convicted and whose crime type of arrest (denoted C_1) were categorized as violent, property, drug, and public-order crimes, and a remaining group of "others."[10, 11]

Table 1 provides for each sampling year the distribution of the sample by age (three groups: 19-20, 21-24, and 25-30, which are of similar sizes) and C_1. The difference between the total number of individuals for each of the three years in the table and the cohort sizes above is due to the fact that the table displays the distribution of those who were convicted, whose initial arrest record in 1980, 1985, and 1990 respectively is unsealed, and whose age at first arrest is between 19 and 30.[12, 13] One can see that larger proportions of the convictees were arrested for drug offenses in more recent years. Also, the convictees tend to be older in more recent years.[14]

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[9] BN 2009 report that 88,000 individuals were arrested in 1980 in NY for the first time. The number of 1980 first-time arrestees reported here is different because it does not include those whose criminal history consists only of driving under the influence (DUI) offenses. The rationale for excluding DUI arrestees draws from discussion in BN 2009.

[10] Violent crimes are designated to include robbery, aggravated assault, forcible rape, and simple assault. Murder and non negligent manslaughter are not included as C_1 because special conditions are likely to apply to their redemption. Property crimes are designated to include burglary, larceny, motor vehicle theft, stolen property, forgery, fraud, and embezzlement. Drug crimes include both possession and sales of any controlled substance. Public-order crimes include such crimes as prostitution, gambling, weapon-related offenses, criminal mischief, and disorderly conduct.

[11] Although we show the hazard estimates for only violent, property, and drugs, in a regression-based analysis (i.e., Cox regression) in the following section, all five categories are used.

[12] The reason to focus on the 19-30 age range is that the arrestees whose ages are between 16 and 18 are considered "youthful offenders" in NY and their criminal records are often sealed. Also, although first-time arrestees in our data may have records as juveniles, given that juvenile records are not accessible to most employers, it is reasonable to focus on adult records. The examination of national records from the

Table 1. Initial sample size of those who were convicted, by age at first arrest (A_1) and first arrest offense (C_1) in 1980, 1985, and 1990 in NY (marginal % in brackets)

		C_1					
Year	A_1	Violent	Property	Drugs	Pub Ord	Others	Total
1980	19,20	971	2,510	546	824	522	5,373 (33.7)
	21-24	1,066	2,558	729	904	641	5,898 (37.0)
	25-30	871	1,945	627	716	518	4,677 (29.3)
	Total	2,908 (18.2)	7,013 (44.0)	1,902 (11.9)	2,444 (15.3)	1,681 (10.5)	15,948
1985	19,20	887	1,814	761	728	430	4,620 (27.6)
	21-24	1,154	2,090	1,390	1,097	620	6,351 (38.0)
	25-30	957	1,919	1,379	926	571	5,752 (34.4)
	Total	2,998 (17.9)	5,823 (34.8)	3,530 (21.2)	2,751 (16.5)	1,621 (9.7)	16,723
1990	19,20	931	1,820	1,089	745	423	5,008 (27.3)
	21-24	1,108	2,072	1,858	948	604	6,590 (36.0)
	25-30	1,058	1,923	2,266	874	608	6,729 (36.7)
	Total	3,097 (16.9)	5,815 (31.7)	5,213 (28.4)	2,567 (14.0)	1,635 (8.9)	18,327

iii. Approaches and Results

Comparison of empirical hazard estimates across the three sampling years

FBI indicates that a number of those with older values of A_1 (especially over 30) often had an adult arrest record prior to 1980 in NY, a recording anomaly that would disqualify them as "first-time arrestees" in 1980. In order to minimize these problems while retaining a large enough sample size for the precision in the estimation of hazards, we focus here more narrowly on those with A_1 in the 19-30 range.

[13] The percentages of those convicted are 60% in 1980, 65% in 1985, and 71% in 1990. Eighteen percent of the 1980 arrest records, 24% of the 1985 arrest records, and 25% of the 1990 arrest records are sealed. Those with A_1 = 19-30 constitute 43% of the 1980 arrestee cohort, 50% of the 1985 arrestee cohort, and 51% of the 1990 arrestee cohort.

[14] The arrest offenses are not necessarily the same as the conviction offenses. The conviction offenses are generally not available in the New York rap-sheet data, so we categorize C_1 of the convictees by their arrest offense.

Our first approach to testing robustness of recidivism patterns involves estimating empirical hazards of a new arrest across the three sampling years and visually examining them.[15] This allows us to understand the overall patterns of the recidivism across the three sampling years and to identify any important similarities and differences at different values of *t*, the time since the first arrest.

Figure 2a shows the hazards for A_1 = 19-30 from the three sampling years 1980, 1985, 1990, in NY.[16] During the first year or two, the 1990 and 1985 hazards are higher than 1980, likely reflecting the higher arrest rates seen in Fig. 1a. They are still reasonably close to one another, especially after about 6.5 years. Figure 2b depicts the same hazards on a logarithm scale, which allows us to better observe the hazard differences at larger values of *t*. It shows more clearly the convergence after about 6.5 years, and it also shows some divergence after about 8.5 years, which we will investigate more closely next by looking at C_1-specific hazards. Nevertheless, the simple plots of the hazards suggest that the overall patterns of recidivism after the first few years are reasonably similar across the sampling years, especially at the larger values of *t*, when the issue of redemption is most relevant.

[15] The hazard, *h(t)*, represents the conditional probability of a new arrest at time *t*, given survival to *t* without an arrest (Hess et al., 1999, Wooldridge, 2002).

[16] In order to reduce random fluctuations that prevent capturing the overall trend of the hazard, the hazard estimates are smoothed using kernel smoothing with the Epanechnikov kernel (Klein and Moeschberger, 2005; Wang, 2005).

Figure 2a. Hazards for arrest for any crime type for those convicted across three arrest-sampling years (1980, 85, 90) in NY, A_1 = 19-30

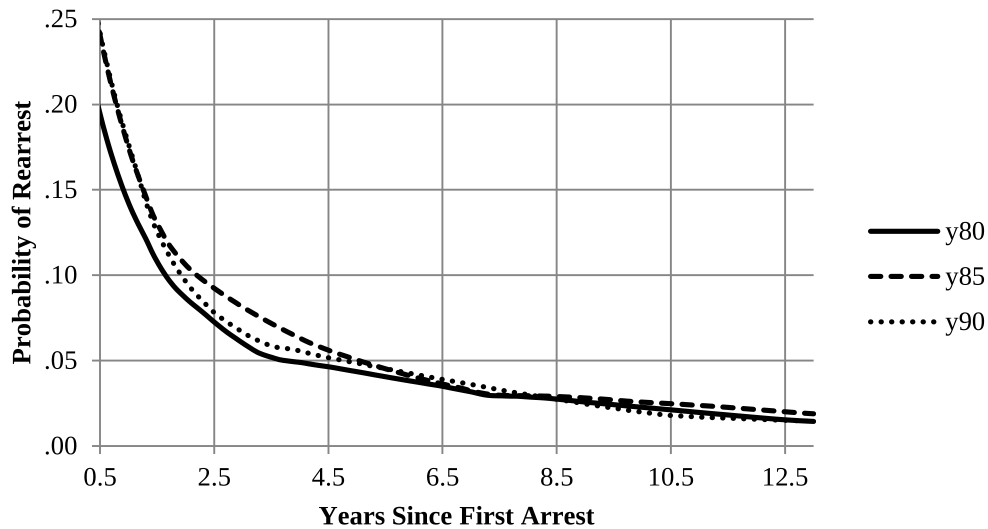
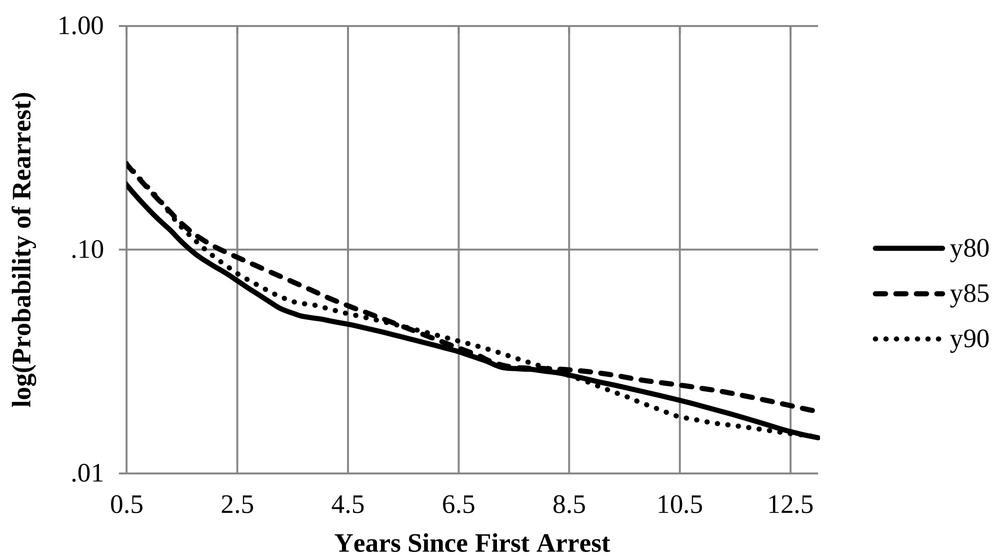


Figure 2b. Logarithm of hazards for arrest for any crime type for those convicted across three arrest-sampling years (1980, 85, 90) in NY, A_1 = 19-30



Figures 3a-3c show the hazards for the three sampling years for A_1 = 19-20 for each of the three crime-type groupings, C_1 = Violent, Property, and Drugs.[17] Initially, for each of the three crime types, the 1980 hazard is consistently lower than the hazards for 1985 and 1990.[18] For C_1 = Violent, the three hazards cross at about $t = 6.5$. For C_1 = Property, the 1980 and 1990 hazards seem to follow one another closely after $t = 2$, while the 1985 hazard seems to be consistently higher than the other two.

For C_1 = Drugs (Fig. 3c), after the three hazards cross at about $t = 5$, the 1985 hazard goes below the other two until $t = 10$ and then goes up rather steeply, surpassing the 1980 and 1990 hazards. This abrupt increase in the 1985 hazard for drugs basically explains the fact that the 1985 aggregated hazard seems to depart from the other two in Fig. 2a-2b. It is possible that this is simply a data artifact that could be explained by the stochastic nature of the hazard. However, the trend of the drug arrest rates (Figure 4 from UCR arrest data) might provide an explanation for the seemingly anomalous pattern. Fig. 4 shows that after the peak in the late 80s (crack cocaine), the drug arrest rate experienced a gradual increase, mostly due to the increased arrests for marijuana. The drug arrest rate's peak in the late 80s, the trough around the early 90s, and the following increase could possibly have pushed the 1985 hazard upward.

[17] The differences across the sampling years are larger once A_1 and C_1 are disaggregated, possibly in part because the disaggregated hazard estimates might be noisier with smaller samples that are used for the estimation (for example, n = 15,948 was used for the estimation of the 1980 hazard for A_1 = 19-30, C_1 = Any offense in Figure 2a, and n = 971 was used for the estimation of the 1980 hazard for A_1 = 19-20, C_1 = Violent in Figure 3a).

[18] For C_1 = Drugs, the highest hazard (1990) is about 1.9 times higher than the lowest (1980), while for C_1 = Property, the highest (1985) is 1.3 times higher than the lowest (1980), which are quite consistent with the difference observed in the crime-type-specific age-crime curves for the three years. Thus, the early differences in the redemption candidates' hazards across the three sampling years reflect the differences in the prevalence of arrests in the three years.

Figure 3a. Hazards for those convicted across three arrest-sampling years (1980, 85, 90) in NY, A_1 = 19-20, C_1 = Violent

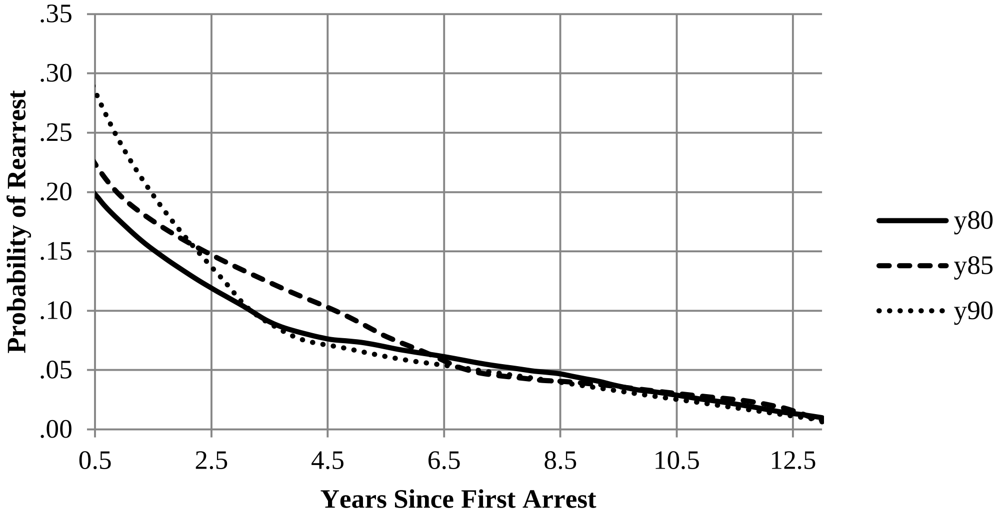


Figure 3b. Hazards for those convicted across three arrest-sampling years (1980, 85, 90) in NY, A_1 = 19-20, C_1 = Property

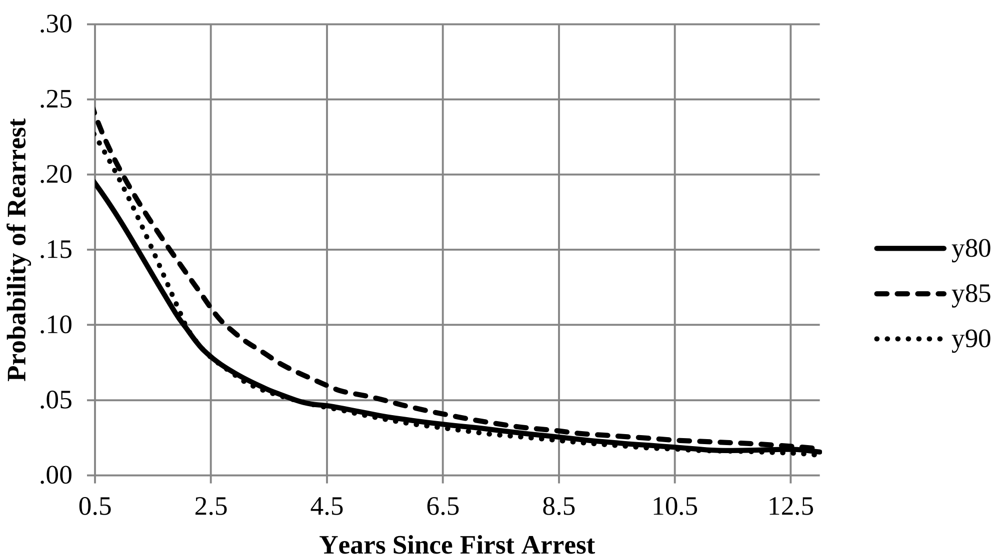


Figure 3c. Hazards for those convicted across three arrest-sampling years (1980, 85, 90) in NY, A_1 = 19-20, C_1 = Drugs

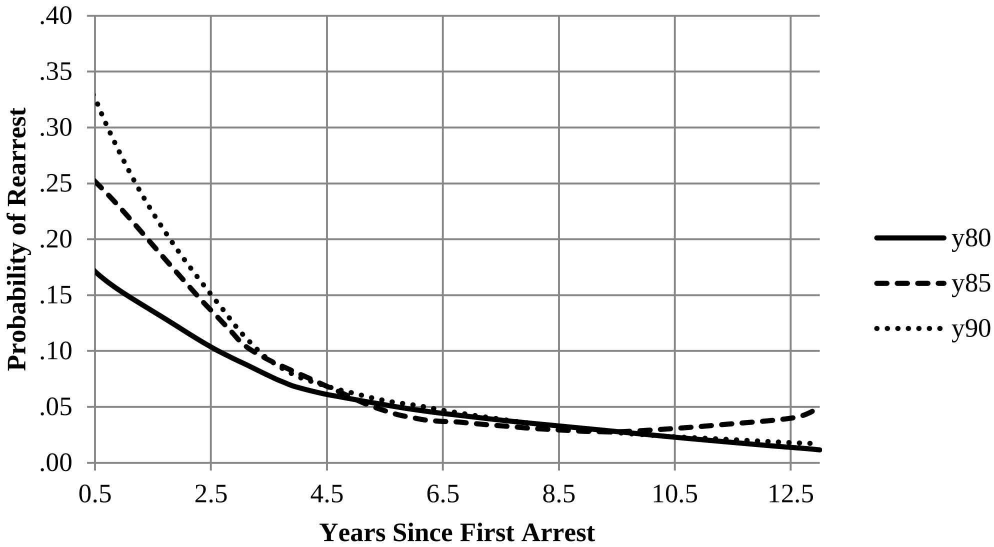
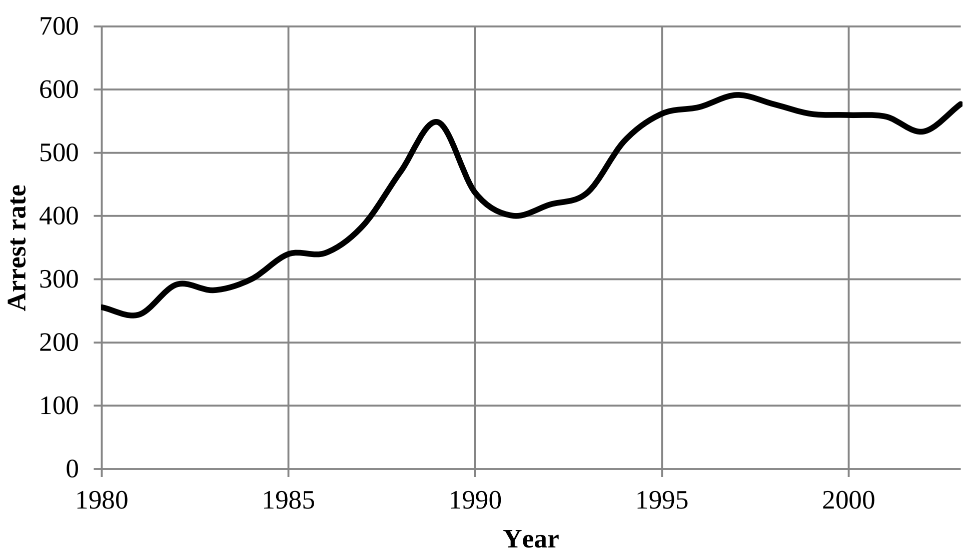


Figure 4. Drug arrest rates (per 100,000 population), 1980-2003



The hazard estimates are visually very close, especially after t = 6.5, but it would be desirable to introduce further statistical tests to appreciate the degree to which they differ as a result of statistical variation and to generate more precise estimates of their proximity, and the regions where they are close and where they are different. To address this, we introduce estimation of time-varying effects of sampling years based on Cox regression models.

Time-varying effects of sampling years based on Cox models

Although the above graphs provide a general sense of the degree to which the hazards from different sampling years are distinguishable over the entire follow up, it is not clear whether any effect of sampling years (period effect and cohort effect) changes over time. Moreover, if the effect of sampling years diminishes over *t*, it is of most interest to know *when* the effect practically disappears.

One way to examine statistically the possibly diminishing effect of sampling year is to use Cox's proportional-hazard model (Cox, 1972). For simplicity, let us consider a Cox model with a single covariate x:

$$h(t \mid x) = h_0(t) \exp(\beta x) .$$

The function $h_0(t)$ is the baseline hazard function, and it is the hazard function for an individual for whom the value of the covariate x is zero.[19] The fundamental assumption of the Cox model is that the hazard ratio of two groups is constant *in time*, and so the hazard rates are proportional. In other words, the effect of a change in a covariate is to shift the hazard by a factor of proportionality, and the magnitude of the shift remains the same over time. As an illustration, if we look at two groups with covariate values x_1 and x_2, the ratio of their hazards is

$$\text{hazard ratio} = \frac{h(t \mid x = x_1)}{h(t \mid x = x_2)} = \frac{h_0(t)\exp(\beta x_1)}{h_0(t)\exp(\beta x_2)} = \exp[\beta(x_1 - x_2)].$$

[19] The baseline hazard is treated nonparametrically. The Cox model is called a semi-parametric model because a parametric form is only assumed for the covariate effect (exp(βx)).

and so the hazard *ratio* is constant with regard to time. In the case of binary covariates (i.e., x_1 = 1 and x_2 = 0), the hazard ratio is $\exp(\beta)$. Thus, the hazard ratio, $h(t \mid x = 1) / h(t \mid x = 0)$, can be estimated by exponentiating the parameter estimate from the Cox regression, $\hat{\beta}$.

Since we are interested in examining the possibility that the effect of sampling years could vary with time clean, we include interactions between sampling year dummies (y85, y90) and the indicator functions for the two-year time intervals in the Cox regression model where we use 1980 (i.e., y80) as the reference year (Klein and Moeschberger, 2005). In this model, the y85-to-y80 and y90-to-y80 hazard ratios can vary across the two-year intervals of time clean.[20]

In addition to A_1 and C_1, we control for race (*Black*: 1 if black, 0 otherwise) and sex (*Male*: 1 if male, 0 if female).[21] The proportionality assumption of the Cox model was tested using the Schoenfeld residuals (Grambsch and Therneau, 1994; Schoenfeld, 1982). We found that A_1 and C_1 violate the proportionality assumption (i.e., the effects of A_1 and C_1 on recidivism hazard are not constant over time). One way of accommodating non-proportional hazards is to stratify on the covariates that violate the assumption and employ the proportional-hazard model within each stratum for the other covariates, and each stratum has its own baseline hazard function (Klein and Moeschberger, 2005).[22] Following this strategy, we fit the Cox model stratified by A_1 and C_1, which can be written as follows:

[20] Similar results for the models were obtained with varying interval widths (e.g., one-year interval).

[21] Prior criminal history is an important predictor of recidivism and is associated with a higher risk of recidivism. In our regression model, since our data are of first-time adult arrestees, prior criminal history is held constant.

[22] One consequence of the stratified model is that the effects of the stratifying covariates cannot be estimated. However, since our main interest is in estimating the effects of sampling years, this does not limit our analysis.

$$h(t)_{ij} = h_{0ij}(t)\exp[\beta_1 Male + \beta_2 Black + (\beta_3 I_{(0,2]}(t) + \beta_4 I_{(2,4]}(t) + ... + \beta_{10} I_{(14,+\infty)}(t))y85$$
$$+ (\beta_{11} I_{(0,2]}(t) + \beta_{12} I_{(2,4]}(t) + ... + \beta_{18} I_{(14,+\infty)}(t))y90],$$
$$i = Age\ 19\text{-}20, 21\text{-}24, 25\text{-}30;\ j = Violent, Property, Drugs, Public\ Order, Others.$$

The subscripts *i* and *j* represent the stratification by A_1 and C_1 respectively. Table 2 shows the point estimates of the hazard ratios from the model and the confidence intervals.[23]

Table 2. Hazard Ratio Estimates from the Stratified Cox Proportional-Hazard Model (Time-Varying Sampling-Year Effects)

	Hazard Ratio	Std. Err.	95% Confidence Interval	
Male	1.277	.019	1.241	1.315
Black	1.717	.022	1.675	1.761
Y85				
0-2 yrs	1.212	.026	1.162	1.263
2-4 yrs	1.300	.047	1.211	1.395
4-6 yrs	1.137	.054	1.037	1.247
6-8 yrs	1.027	.062	.913	1.155
8-10 yrs	1.038	.068	.914	1.180
10-12 yrs	1.215	.093	1.045	1.412
12-14 yrs	1.228	.109	1.031	1.462
14- yrs	1.044	.078	.901	1.209
Y90				
0-2 yrs	1.200	.025	1.151	1.250
2-4 yrs	1.073	.040	.998	1.154
4-6 yrs	1.100	.051	1.004	1.205
6-8 yrs	1.150	.066	1.028	1.286
8-10 yrs	.868	.058	.762	.989
10-12 yrs	.865	.070	.737	1.014
12-14 yrs	.876	.082	.729	1.053
14- yrs	.836	.064	.719	.973

Note: Stratified by A_1 (19-20, 21-24, 25-30), C_1 (Violent, Property, Drugs, Public Order, Others)

[23] The confidence interval for the hazard ratio is based on the exponentiated endpoints of the confidence interval for the original coefficient of the Cox model. Thus, for example, the confidence interval for the y85-to-y80 hazard ratio in the first two-year interval would be:

$$\{\exp[\hat{\beta}_3 - z_{1-\alpha/2} se(\hat{\beta}_3)], \exp[\hat{\beta}_3 + z_{1-\alpha/2} se(\hat{\beta}_3)]\}.$$

This is preferable to an alternative way, which is based on the standard error of the hazard ratio directly, because this alternative method can lead to negative values of the confidence intervals. Both methods are asymptotically equivalent (Klein and Moeschberger, 2003).

As expected, blacks and males have significantly higher hazards than non-blacks and females respectively, indicated by the confidence interval estimates of their hazard ratios being higher than unity. The hazards are deemed robust across sampling years if the hazards converge (or the hazard ratio becomes unity).[24] The confidence intervals of the y85-to-y80 hazard ratios over the intervals indicates that the 1985 hazard gradually approaches the 1980 hazard, and remains relatively close to it (i.e., the hazard ratio remains close to 1.0).[25] The confidence intervals of the y90-to-80 hazard ratios indicate that the 1990 hazard quickly closes in on that of 1980, and stays quite close. The 1990 hazard point estimate is lower than the 1980 hazard for the later years, but they are marginally distinguishable from each other. Thus, once the uncertainty of the hazard is taken into account, the difference we observe between the 1990 and 1980 hazards in Fig. 2b is only marginally statistically significant.[26]

iv. Robustness of Redemption Times across Sampling Years

The robustness of the redemption process against variation in sampling years can be tested by examining the convergence of recidivism hazards over time and the similarity in the estimates of redemption times. In the previous section, we observed the convergence of hazards and also

[24] We determine whether the hazards from different sampling years are deemed robust by examining how often the confidence intervals of the hazard ratio contain unity. In statistical inference terms, this is equivalent to setting a null hypothesis that the hazards are the same. We retain the null hypothesis if the data do not provide sufficient evidence to reject it. This logic applies to the robustness test of hazards across states in the following section.

[25] Although between t = 10 and 14, the 1985 hazard estimate goes above the 1980 hazard, which we observe also in Fig. 2b, the confidence intervals indicate that the ratio of 1985/1980 hazard during t = 10-14 is only marginally different from unity.

[26] The results do not change in any important manner if the time interval is for 1 year or 2 years.

some variation in hazards (i.e. fluctuations in hazard ratios) across sampling years. It is important to recognize that the fluctuations may not affect the robustness of the redemption-time estimates because redemption occurs when the declining hazard crosses some benchmark, and some variation in hazard after the point of redemption would not be relevant to the robustness of redemption times.

In this section, we examine how robust the estimates of redemption times are against variation in sampling years. The estimation of redemption times requires benchmarks, which determine when the hazards are sufficiently low so that a person with a prior criminal record is considered redeemed. The choice of benchmarks in BN 2009 was relatively straightforward since the redemption candidates all have their first arrest in the same year (1980). Determining appropriate benchmarks for redemption candidates who have their first arrests in different years involves more choices.

One approach is to use sampling-year-specific benchmarks such as age-crime curves from years that correspond to the years of redemption candidates' first arrests. Taking this approach, redemption times are estimated at time points when the 1980 redemption candidate's hazard crosses the 1980 age-crime curve, and the 1985 redemption candidate's hazard crosses the 1985 age-crime curve, and so forth. Another approach is to use a more general benchmark such as the average age-crime curve over the sampling years (80, 85, and 90). With this approach, redemption times are estimated at time points when the hazards from different sampling years cross a general age-crime curve. Yet another approach is to set a risk threshold in terms of probability of arrest, say .1, which is the probability of arrest at the redemption time in relation with the general population for the 1980 cohort, discussed in BN 2009 or .03, which is the benchmark probability of arrest for the never-arrested with a risk tolerance of 2%, and then to estimate redemption times when the hazards fall below the respective benchmark thresholds.[27, 28] This last approach has the virtue of the benchmark being not directly influenced by period effects, and we have shown some evidence that the hazards from different sampling years are reasonably close to one another, whereas the benchmarks (age-crime curves) from different years could be very different (see Fig. 1a). Table 3 shows the redemption time estimates for A_1 = 19-20, C_1 = Violent, Property, and Drugs using the threshold of .1 and .03. The estimates are calculated by computing time points when the *upper* confidence bound of the hazard crosses the two thresholds. The use of upper bound provides a statistically appropriate approach to answering the question of when the hazard of those with a prior record is "low enough" in relation with some benchmarks (BN 2009).[29] Within about 1.5 years from one another, the hazards from the three different sampling years fall below 0.1. Similarly, within 2 years from one another, the hazards from the three years fall below .03.

Table 3 also reports the average and standard deviation of redemption time estimates for each of the C_1's. The small standard deviations (consistently about 1.0 or less) highlight the similarity of the estimates across the three years, and given that similarity, we are reasonably confident in the appropriateness of the average of the redemption-time estimates for NY, regardless of in which of the three years the prior crime was committed. Thus, the redemption times fall within

[27] The concept of risk tolerance draws on discussion from BN 2009.

[28] The arrest probability of .03 is also reasonably close to the probability of arrest for the never arrested in other studies (Kurlychek et al., 2006, 2007); thus, it serves as a good representation of the risk of arrest for the never arrested.

[29] The lower bound is often used in determining when a declining hazard becomes "indistinguishable" from some benchmark, which represents a sufficiently low risk. However, the use of the lower bound is problematic in the sense that smaller sample sizes inevitably make confidence intervals wider, and the lower confidence bound would inappropriately make it easier to conclude that the hazard drops to the benchmark level of risk.

the intervals of 3-5 years for p=0.1 and 8-12 years for p=0.03; there is variation within those ranges depending C_1, with violent C_1 at the upper end and property C_1 at the lower end.

Table 3. Values of redemption time estimates for A_1 = 19-20, C_1 = Violent, Property, Drugs by sampling years, using the upper CI with the thresholds of .1 and .03

		Thresholds (probability of a new arrest)	
C_1	Year	.1	.03
Violent	1980	4.66	12.33
	1985	5.07	13.40
	1990	3.88	11.07
Average		4.5	12.3
Std. Dev.		.6	1.2
Property	1980	2.94	8.16
	1985	3.66	9.87
	1990	2.73	7.71
Average		3.1	8.6
Std. Dev.		.5	1.1
Drugs	1980	3.67	11.87
	1985	4.39	12.68
	1990	3.87	10.30
Average		4.0	11.6
Std. Dev.		.4	1.2

B. Robustness across States

We can perform similar robustness tests with data from different states. There is a possibility that conditions in New York, from which our 1980 data came, are different from that in other states. A recent study by Pew found a large variation across states in recidivism rates of those released from state prisons in 1999 and 2004 (Pew Center on the States, 2011).[30] It is likely that various factors that may affect arrest rates such as policing policies and labor market

[30] A variation in recidivism rates across states is observed also in the BJS's 1994 prison-release cohort data (U.S. Department of Justice - Bureau of Justice Statistics, 2011).

opportunities differ from one state to another, and so it is desirable that we test the robustness across states of the hazard patterns and of the estimates of redemption times. To the extent that we find similar patterns, that would be encouraging in terms of the generalizability of our results.

i. Data

The data used for the test of robustness across states consist of rap-sheet data of 1980 arrest cohorts from two additional states, Florida (FL) and Illinois (IL), that are similar to the NY data. The data from the two states both contain information about the arrests (particularly the dates and crime types of the arrests) and demographic information about the arrestees (e.g., the date of birth, gender, and race). Our comparison across the three states focuses on those arrestees who were convicted and were 19 to 30 years old at the time of their arrest.

The distribution of dispositions in the three states is shown in Table 4. The fact that the percentage convicted varies considerably across the states suggests a possibility that the court processes and thus the characteristics of those convicted in the three states could be different.[31] In order to assure that any difference across the states is not completely driven by differences in the disposition process, the cross-state comparison will be based on the convicted as well as those who were arrested (including the convicted, the non-convicted, and those with unknown dispositions).

[31] The ways in which court dispositions are categorized differ across states. That could contribute to the different proportions of arrestees who were convicted. In addition to the fact that employers are usually allowed to consider only conviction records, the rationale for focusing our attention on those who were convicted lies in our efforts to make the three states comparable in terms of the extent to which the data contain the recidivism events. In Florida, those who are convicted are not eligible for sealing of their criminal records (the conviction record and the record of any subsequent arrest/conviction); thus, we should be able to capture any subsequent arrests of the convictees. In Illinois, we were told that sealing in the face of conviction is very unlikely, and the situation is similar in New York. Thus, these divergent policies regarding sealing encouraged us to focus specifically on those who were convicted among the 1980 arrestees.

Table 4. Dispositions in NY, FL, and IL in 1980 (for A_1 = 19-30)

State	Disposition: Conviction	Disposition: Non-conviction	Disposition: Unknown disposition	Total number of arrestees
NY	15,948 (59.48%)	6,266 (23.37%)	4,600 (17.16%)	26,814
FL	13,812 (26.53%)	23,411 (44.96%)	14,843 (28.51%)	52,066
IL	8,537 (19.10%)	23,098 (51.67%)	13,065 (29.23%)	44,700
Total	38,297	52,775	32,508	123,580

ii. Approaches and Results

The approach will be similar to the ones discussed in the examination of robustness across sampling years. We first compare the hazard estimates across the three states and then investigate further whether the hazard ratio of different states becomes statistically indistinguishable from unity using the estimates of the interactions between the dummy variables for the states (FL and IL) and time from Cox regression models.

Comparison of hazard estimates across the three states

Figure 5a presents the hazards for the three states. It is clear that the FL cohort has a higher initial recidivism risk, but that all three converge very quickly so that the hazards at about t = 2.5 are almost the same. Then the hazard for IL drops somewhat below the other two for t about 4-8 and the three seem to be very close after t > 8. The log-transformed hazards in Figure 5b show more clearly that the IL hazard stays below the NY and FL hazards for about 5 years in the middle and that after about t = 8 years, the FL hazard is lower than the other two.

Figure 5a. h(t) of NY, FL, and IL for those convicted (A_1 = 19-30)

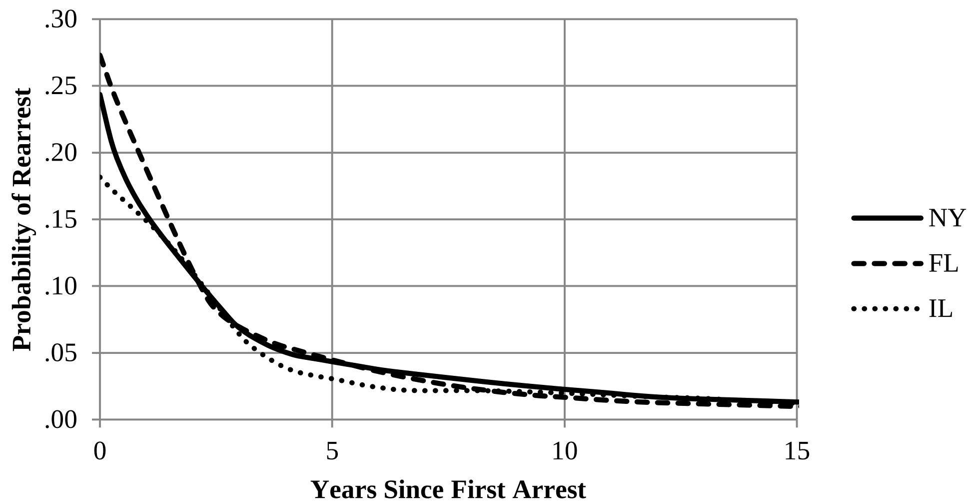
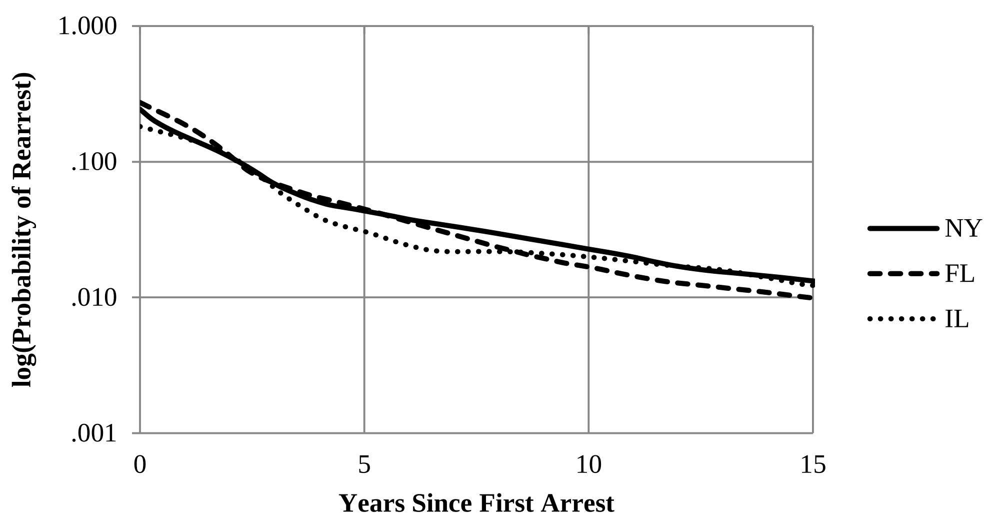


Figure 5b. Logarithm of h(t) of NY, FL, and IL for those convicted (A_1 = 19-30)



Figures 6a-6b compare the hazards and log-transformed hazards for those who were arrested in each of the three states. They show that the NY and FL arrestee cohorts are very similar, while the hazard for the IL arrestee cohort is lower than the other two states until about t = 10. In order to develop better estimates of their proximity, we also examine the hazard ratios using the interaction terms between state dummies and time in Cox models.

Figure 6a. h(t) of NY, FL, and IL for those who were arrested (A_1 = 19-30)

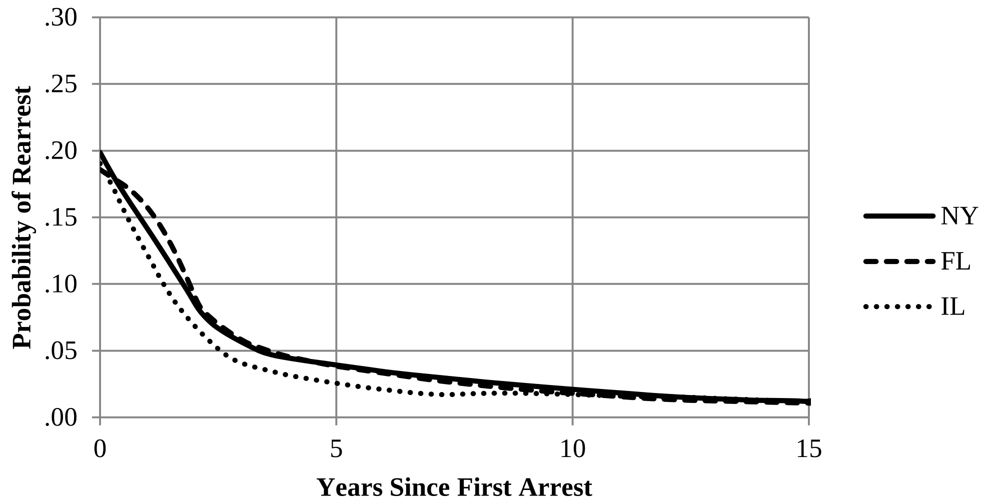
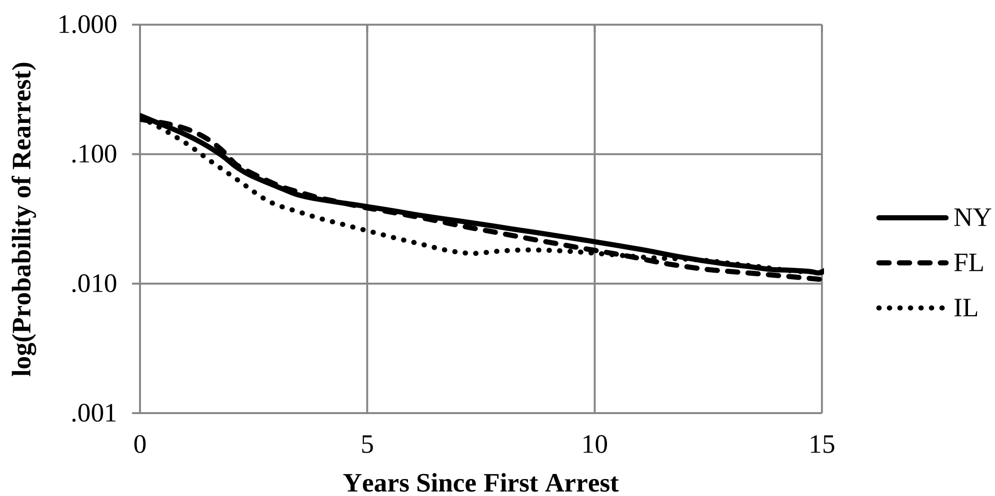


Figure 6b. Logarithm of h(t) of NY, FL, and IL for those who were arrested (A_1 = 19-30)



<u>Time-varying effects of states based on Cox models</u>

Similar to the analysis of sampling-year effects above, a proportional-hazard model that allows the state effects to vary over time was estimated, and the results are shown in Table 5.[32] Consistent with the model for the time-varying sampling-year effects, this model controls for A_1, C_1, race, and sex. The estimates are based on a model that is stratified by two covariates, C_1 and *Black*, which are shown to violate the proportionality assumption based on the Schoenfeld residual test. As expected, A_1 is negatively related to the recidivism hazard, which indicates that older offenders have a lower likelihood of recidivism. By examining the confidence intervals of the hazard-ratio estimates for the states (FL/NY, IL/NY), it is clear that in relation to the NY hazard, the hazard of FL is higher initially, crosses NY within 5-7 years, stays somewhat lower than NY for a while, and approaches or crosses NY after 14 years. The IL hazard seems to cross the NY hazard faster than FL hazard, which can be seen in the log-transformed hazards in Figure 6b as well. The IL and NY hazards seem to converge within 10 years after the initial arrest.

Table 6 displays the Cox model estimates based on the arrestee cohorts. Besides the fact that the confidence intervals are narrower for a given confidence level due to larger samples sizes, the hazard ratio estimates based on the arrestee cohorts are generally similar to the results based on the convictee cohorts. When the specifics are examined by using the criminal history of arrestee cohorts, the ratio of FL to NY seems to change less with time clean and is closer to unity than the ratio based on conviction cohorts. Together with the observation from Figure 6b that the FL hazard is more similar to the hazards for the other two states when the hazard is based on arrests, it is possible that the process of conviction in FL could be different than that of NY and IL. On the other hand, the finding that the hazard of IL is lower than the hazard of NY or FL holds whether the observation is based on arrests or convictions.

[32] NY is the reference state.

Table 5. Hazard Ratio Estimates from the Stratified Cox Proportional-Hazard Model (Time-Varying State Effects) based on conviction data

	Hazard Ratio	Std. Err.	95% Confidence Interval	
Male	1.432	.028	1.378	1.488
Age 21-24	.827	.014	.800	.855
Age 25-30	.733	.014	.706	.760
FL				
0-2 yrs	1.257	.018	1.202	1.314
2-4 yrs	1.125	.029	1.039	1.218
4-6 yrs	1.143	.036	1.033	1.265
6-8 yrs	.991	.043	.869	1.129
8-10 yrs	.746	.042	.640	.870
10-12 yrs	.815	.051	.680	.976
12-14 yrs	.734	.063	.592	.910
14- yrs	.819	.081	.610	1.100
IL				
0-2 yrs	1.068	.017	1.014	1.126
2-4 yrs	.839	.024	.762	.925
4-6 yrs	.729	.026	.641	.828
6-8 yrs	.660	.029	.561	.776
8-10 yrs	.812	.035	.690	.957
10-12 yrs	1.033	.054	.860	1.241
12-14 yrs	1.042	.071	.841	1.291
14- yrs	.981	.087	.722	1.334

Note: Stratified by C_1 (Violent, Property, Drugs, Public Order, Others), Black

Table 6. Hazard Ratio Estimates from the Stratified Cox Proportional-Hazard Model (Time-Varying State Effects) based on arrest data

	Hazard Ratio	Std. Err.	95% Confidence Interval	
Male	1.525	.017	1.492	1.558
Age 21-24	.818	.008	.802	.834
Age 25-30	.712	.008	.697	.727
FL				
0-2 yrs	1.177	.018	1.142	1.214
2-4 yrs	1.093	.029	1.038	1.152
4-6 yrs	1.055	.036	.986	1.128
6-8 yrs	1.053	.043	.972	1.141
8-10 yrs	.887	.042	.809	.973
10-12 yrs	.919	.051	.825	1.025
12-14 yrs	.959	.063	.844	1.091
14- yrs	.897	.081	.750	1.071
IL				
0-2 yrs	1.043	.017	1.010	1.076
2-4 yrs	.827	.024	.782	.875
4-6 yrs	.685	.026	.636	.737
6-8 yrs	.626	.029	.572	.685
8-10 yrs	.710	.035	.644	.782
10-12 yrs	.973	.054	.873	1.084
12-14 yrs	1.091	.071	.961	1.239
14- yrs	.961	.087	.805	1.147

Note: Stratified by C_1 (Violent, Property, Drugs, Public Order, Others), Black

We can begin to explain the patterns of differences between the hazards of the three states by looking at the age-crime curves from the three states. Figures 7a-7b show the age-crime curves of NY, FL, and IL in 1985 and 1992, 5 years and 12 years after their initial arrest in 1980.[33] Those who were 19-20 years old in 1980 are 24-25 years old in 1985. The arrest rate for 24-25 year olds in IL is the lowest (Figure 7a). Those 19-20 year olds become 31-32 year olds in 1992.

[33] We were unable to construct 1990 age-crime curves due to the fact that the 1990 IL UCR data from the National Consortium on Violence Research Data Center seem anomalous.

The state with the lowest arrest rate for 31-32 is now FL, which is somewhat lower than IL. This switch of FL and IL are consistent with the patterns of hazards we observe in Figure 6b.

This finding suggests that the arrest prevalence (represented by age-crime curves) in different states is useful in understanding the long-term patterns of recidivism for those who stay clean for a long period of time. It is important to note that the magnitude is very different between the hazard for redemption candidates and the age-crime curves (for example, the hazards at t = 12 for FL and IL are in the range of .013-.017, whereas the arrest rates at ages 31-32 in FL and IL are appreciably higher, in the range of .06-.08).

Figure 7a. 1985 Age-Crime Curves for NY, FL, and IL

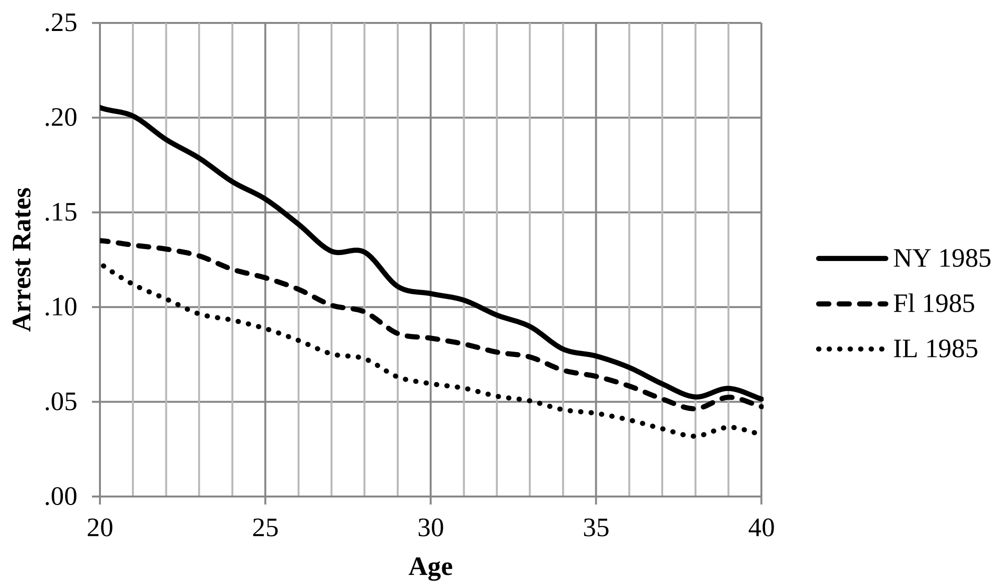
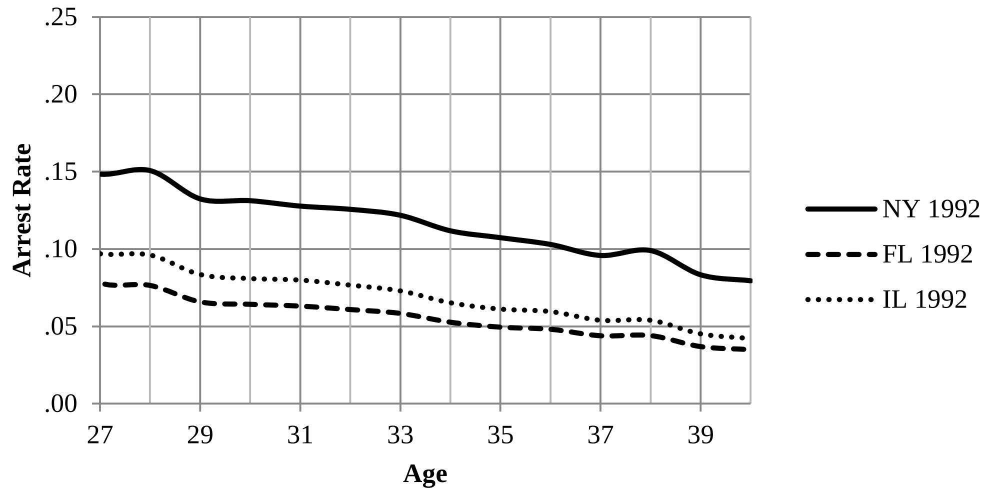


Figure 7b. 1992 Age-Crime Curves for NY, FL, and IL



C. Robustness of Redemption Times across States

Finally, it is important to examine how much the difference in the hazards across states affects the estimates of redemption times. For the reasons discussed in the robustness of redemption times across sampling years, the choice of benchmarks to estimate redemption times could require considering different approaches. One way is to use the age-crime curves from the different states. Another approach is to apply one universal benchmark to all states. A natural choice of such a universal benchmark is the national age-crime curve. As discussed above in the context of robustness across sampling years, setting a risk threshold would be useful here. As shown in Table 7a, using the value of 0.1, which is the probability of arrest at the redemption time for the 1980 NY cohort in relation to the general population, as the threshold, the hazards of those who were convicted in the three states (A_1 = 19-20, C_1 = Violent, Property, Drugs) fall below the threshold on average after about 6 years for Violent and 4 years for Property and Drugs. Especially for C_1 = Drugs, the redemption time estimates are very close. For the .03 threshold, the redemption times are on average about 14 years for Violent, 9 years for Property, and 11 years for Drugs. There is more variation in the redemption times across the three states, partly because the estimation of redemption times uses the upper confidence intervals. The sizes of the samples that are used to produce the confidence intervals are different across the states, and these sample-size differences affect the widths of the confidence intervals (especially at later times), and in turn affect the estimates of redemption times. Table 7b shows redemption times that are similar to Table 7a, but uses those who were arrested instead of those who were convicted. Because of the larger samples sizes based on the arrests, the variation in the estimated redemption times across the states is smaller.

There is larger variation in the estimates of redemption times across the states than across sampling years, indicated by larger standard deviations in Table 7a. Yet, except for C_1 = Drugs, the estimates from the three states are on average within 2 years of each other, which provides reasonable evidence for the robustness of the estimates.

Table 7a. Estimates of Redemption times for A_1 = 19-20, C_1 = Violent, Property, Drugs (convictees) by states, using the upper CI with the thresholds of .1 and .03

	Threshold (probability of a new arrest)					
	0.1			0.03		
	C_1			C_1		
	Violent	Property	Drugs	Violent	Property	Drugs
NY	4.66	2.94	3.67	12.33	8.16	11.87
FL	6.99	3.76	3.57	13.89	7.99	7.58
IL	5.56	3.68	3.54	15.00	11.31	14.13
Average	5.7	3.5	3.6	13.7	9.2	11.2
Std. Dev.	1.2	.5	.1	1.3	1.9	3.3

Table 7b. Values of T^* for A_1 = 19-20, C_1 = Violent, Property, Drugs (arrestees) by states, using the upper CI with the thresholds of .1 and .03

	Threshold (probability of a new arrest)					
	.1			.03		
	C_1			C_1		
	Violent	Property	Drugs	Violent	Property	Drugs
NY	3.81	2.59	2.82	11.10	7.45	10.13
FL	4.75	2.90	2.43	10.60	8.16	6.81
IL	3.71	2.86	2.66	12.32	6.28	6.59
Average	4.1	2.8	2.6	11.3	7.3	7.8
Std. Dev.	.6	.2	.2	.9	.9	2.0

D. Conclusion

As an increasing number of people looking for employment are turned down because of stale criminal records, the concept of redemption has attracted media attention as well as interests from policy makers who are concerned about the handicap imposed by widespread criminal background checks by employers. BN 2009 estimated when the recidivism risk of individuals with a criminal record falls to appropriate benchmarks based on data of the 1980 first-time arrestee cohort in NY. Given the potential influence of such estimates on policies concerning redemption, it is important to test robustness of the estimates. In this section, we tested the robustness of redemption time estimates in terms of two variations: sampling year and jurisdiction, using data from two additional sampling years (1985 and 1990) in NY and 1980 data from two additional states (Florida and Illinois).

Despite major shifts in the levels of arrest rates during the period of 1980 through 1990, the patterns of recidivism risk across the three sampling years are found to be very similar. In estimating redemption times across sampling years and across states, two threshold probabilities (0.1 and .03) of incurring a second arrest are used. For the higher threshold probability (0.1), the average estimates of redemption times of the three sampling years are about 5 years, 4 years, and

3 years for C_1 = Violent, Drugs, and Property respectively. For the lower threshold probability (.03), the averages are about 12 years, 12 years, and 9 years for the three C_1's. These estimates are robust, to the degree that the estimates are on average within a year of the estimate from each of the sampling years.

The risk patterns and the associated estimates of redemption times vary more across the states than across sampling years, but they appear to converge after 10 years. However, even that variation may not be operationally significant since the estimates across the three states differ by an average of only two years except for drugs. For drugs, the estimates differ, on average, just over 3 years. For the higher threshold probability (0.1), the average estimates of redemption times of the three years are about 6 years, 4 years, and 4 years for C_1 = Violent, Drugs, and Property respectively. For the lower threshold probability (.03), the averages are about 14 years, 11 years, and 9 years for the three C_1's.

It is important to recognize that there is considerable variation in the arrest rates across years and states for the first few years after the initial arrest that gave rise to the criminal record. The observed differences in those recidivism hazards clearly reflect differences in the factors contributing to the variation in current arrest rates. However, the tendency for the hazards to converge after several years suggests that those who survive those first several years are more similar regardless of where and when their first crime occurred, and this tendency is what makes the redemption process reasonably robust across time and place.[34] Lastly, Table 8 displays the

[34] The convergence may be explained by a mixture of interacting processes. Offender heterogeneity results in those with high criminal propensity recidivating quickly, whereas those with lower criminal propensity display resilience against the variations in the environment that contribute to differences in arrest prevalence. Then, staying rearrest-free for a longer period of time further lowers the risk of recidivism, suggesting that life without criminal involvement has taken root and strengthens the commitment to stay clean. This process corresponds to the two explanations for the positive correlation between past and present criminality: population heterogeneity and state dependence (Nagin and

range of redemption time estimates by C_1 for the two threshold probabilities. The estimates for C_1 = Violent tends to be the largest, the estimates for C_1 = Property tend to be the smallest, and the estimates for C_1 = Drugs are in between the other two.

Table 8. Range of redemption time estimates (years) for C_1 = {Violent, Drugs, Property} based on the estimates across three sampling years and three states

	Thresholds (probability of a new arrest)	
C_1	.1	.03
Violent	4-7	11-15
Drugs	4	10-14
Property	3-4	8-11

Thus, we believe that, despite the concern that the results from BN 2009 would be of limited generalizability beyond those individuals first arrested in New York in 1980, we are reasonably confident that those results apply more broadly, especially to a population that would be strong candidates for consideration for redemption. We find reasonable differences in time and state in the first 5-10 years after their first arrest, but there is appreciably more consistency across time and location for those who have avoided contact with the criminal justice system for a period beyond those first years,. While further testing and verification is always desirable, we have seen sufficient consistency in that period that we believe our estimates provide useful starting points for consideration of redemption currently and in many other jurisdictions.

Paternoster, 1991, 2000). Further exploration of the factors contributing to the convergence is an important question and warrants further research, but it is beyond the scope of the current report.

3. Concern about the "Next Crime"

Employers and other stakeholders may find those redemption times to be of considerable interest. However, the recidivism risk that has been addressed by the recent studies on redemption is for *any* type of next offense, including offenses as serious as homicide and rape as well as offenses as minor as disorderly conduct (BN 2009; Bushway et al., 2011; Kurlychek et al., 2006, 2007; Soothill and Francis, 2009). Employers are usually concerned, not so much about the risk of *any* types of crime, but are more likely to be concerned about certain specific types of crime, such as violent or property crime. Employers are also legally bound to consider the criminal record only if the type of offense is relevant to the job position (EEOC, 1990). Thus, the question that employers would be most interested in is: what are the redemption times for particular crime types that they are most concerned about? Is information about the type of prior crime contained in a criminal record, relevant in determining the redemption time for particular crime types of future concern? This section addresses these particular questions.

A. Employer's Concern about Particular Crime Types

The estimates of redemption times provide crucial information to employers in determining how far back in time they need to consider the criminal record of prospective employees to reduce the risk of negligent-hiring liability as well as to demonstrate the second factor of business necessity set forth by the EEOC.[35] However, since the prior studies have all examined the hazard of recidivism for *any* crime type, and since many employers are more likely to be concerned about a job applicant's risk of committing a particular type of crime, they are more likely to be interested in the hazard for that particular kind of crime For example, employers who

[35] The studies on redemption provide grounds for relief to individuals who are blocked for an unreasonably long time from employment opportunities because of a stale criminal record.

are looking for someone to work as a cashier are probably concerned mostly about an applicant's risk of committing a property crime, whereas if they are looking for someone to drive a paratransit vehicle for children or the elderly, the crime of most concern is more likely to be a violent crime.[36] Suppose there is a job position that is sensitive to the risk of violent crimes, and the employer has a pool of job applicants with criminal records of a variety of crime types. Then, the employer would be interested in comparing the applicants based on their risk of committing a violent crime, and that risk will depend on the crime types associated with their criminal records.

More importantly, the third factor of business necessity requires employers to determine how the nature of the job position is related to the nature and the level of the risk of crime that the job applicants with criminal records are likely to commit. As Harris and Keller (2005) point out, the assumption underlying the third factor is that the offense type of the prior crime event, about which employers learn from the background checks, has a predictive relationship with the type of crime that the employers are concerned about. When evaluating applicants with criminal records, employers consider the applicants' risk of future crime, but they can only observe the record of crimes that already occurred. Thus, it is important to consider the relationship between the crime types of both the prior criminal event and the potential recidivism event and probabilistically quantify the extent to which the offense type of the prior record (known to employers) is likely to lead to a particular offense type of a future crime - unknown to employers, but of specific concern to them.

[36] A survey suggests that employers are strongly averse to hiring those with prior violent offenses, and less averse to those with prior property and drug offenses (Holzer et al. 2007). The strong aversion toward the record of violence is probably the reflection of employers' assumption that prior violence indicates higher likelihood of future violence. In general, employers seem to assume that there is a direct connection between the crime type of a prior record in a potential employee's background and the type of crime that the employee is most like to commit in the future (e.g., employers representing financial services tend to avoid those with a record of embezzlement) (Fahey et al., 2006).

Given that there is evidence that a prior record of a specific type of offense has a significant, yet time-varying-effect on the recidivism risk of some future offense (Lattimore et al., 1995), we investigate, employing multiple approaches, the extent to which the offense type in the prior record is relevant to the longer-term recidivism and redemption from concern over a specific offense type. We consider factors other than the offense type, such as the age when the prior crime was committed, that are relevant in understanding the risk of recidivism of certain specific crime types.

B. Data

The data we use to examine the relationship between the crime type of the prior criminal record and the risk of recidivism of the type of offense that employers are concerned about consist of the arrest history of a cohort of approximately 70,000 first-time adult arrestees in 1980 in New York State, a subset of data used for the robustness testing.

We focus specifically on those who were convicted because use of an arrest without conviction is often prohibited. We categorize the crime type of arrest, denoted as C_1, as violent, property, drug, and public-order crimes, and a remaining group of "others." The crime type of conviction is not necessarily the same as the crime type of the arrest,[37] but it is difficult to infer the crime type of conviction from the arrest histories available from NY, so we use the crime type of arrest to designate C_1. The size of this convicted population is approximately 16,000. In addition to A_1 and C_1, we consider possible crime types of a second arrest, denoted here as C_2.

[37] This difference is often the result of a plea bargain, and so the crime type of conviction is not necessarily a better indicator of the crime that actually occurred.

We focus particularly on violent and property crimes as C_2, often an employer's primary concern (Fahey et al., 2006; Holzer et al., 2007).[38]

C. Approaches and Results

i. Crime-switch matrix

One way to examine how C_1 is related to C_2 is to construct a "crime-switch matrix" (Blumstein et al., 1988). A crime-switch matrix displays the combination of the crime type of first arrest (the rows) and the probability of different crime types in a second arrest (including the possibility of no second arrest). This allows us to examine what proportion of those who were arrested for each of the five C_1 categories in 1980 were rearrested for the same crime category or for a different category. The values in the diagonals of the matrix represent the proportion recidivating to the same crime type, while the values in the off-diagonals represent the proportion expected to commit different crime types than their first one.

Since redemption time is based on the length of time clean that it takes for recidivism probability to decline to a sufficiently low level, it is important to examine the crime-switch matrices that are conditional on time clean. Such conditional crime-switch matrices allow us to investigate how the strength of relationship between C_1 and C_2 varies over time clean.[39] Tables

[38] Although it is likely that a large number of individuals with records of drug offenses (C_1 = Drugs) are handicapped in finding employment, our analysis focuses on the risk of future violent and property crimes (C_2 = Violent, Property) based on the heightened concern for those crimes expressed by employers (Fahey et al., 2006; Holzer et al., 2007).

[39] The crime-switch matrices inform only about the probability of switching from the crime type of the first arrest to different crime types of the second arrest. The matrices take no account of the crime types of the third and later arrests for those who have more than two arrests. In this sense, the information that the matrices contain is consistent with the original conception of redemption, which reflects long-held public sentiment that first-time offenders deserve a second chance (Nussbaum, 1974). The use of C_1-to-C_2 crime-switch matrices is also consistent with the use of hazard of having a second arrest in the previous research on redemption (BN 2009; Kurlychek et al., 2006, 2007).

9a-9c display conditional crime-switch matrices for A_1 = 19-20 by the timing of their second arrest (the number of years since the first arrest is denoted as t):

- T1) those who have a second arrest within the first 5 years ($0 < t <= 5$) (Table 9a),
- T2) those who stay clean in the first 5 years and have a second arrest between 5 and 10 years ($5 < t <= 10$) (Table 9b), and
- T3) those who stay clean for the first 10 years and have a second arrest after 10 years ($t > 10$) (Table 9c).

By this construction, each one of the convictees with a second arrest belongs to one and only one of the disjoint groups (T1, T2, T3) depending on the timing of their second arrest. We also consider similar crime-switch matrices for A_1 = 25-30 in Tables 10a-10c. By comparing the two A_1 groups, we examine how the relationship between C_1 and C_2 could depend on A_1. [40]

The last column contains the Forward Specialization Coefficients (FSC) for the diagonal entries, which is a measure of the tendency to be rearrested for the same offense type as the first arrest (Farrington, 1986; Farrington et al., 1988). Based on the diagonal cells of crime-switch matrices, FSC for crime type i can be calculated as

$$FSC_i = \frac{Observed\ Frequency_i - Expected\ Frequency_i}{Row\ Total_i - Expected\ Frequency_i}$$

where *Observed Frequency*$_i$ is the observed count in the diagonal cell for crime type i, *Expected Frequency*$_i$ is the count in the diagonal cell for crime type i expected by chance alone, and *Row Total*$_i$ is the total row counts for crime type i.[41] The value of FSC is 0 if crime switching is independent of C_1, and the observed frequency is equal to the expected C_2 frequency. The value

[40] Here, two A_1 groups (19-20, 25-30) are used to contrast younger A_1 with older A_1.

[41] *Expected Frequency*$_i$ is calculated by (*Row Total*$_i$)(*Column Total*$_i$) / *Grand Total*.

is 1 if C_2 is always equal to C_1. Thus, FSC serve as an index of the degree to which C_2 is driven by C_1.[42]

For A_1 = 19-20, it is not surprising that T1 (Table 9a) shows a relatively strong propensity to recidivate to the same crime type because the interval between the first and second arrests is rather short.[43] Among the five crime types, those with C_1 = Drugs show the strongest propensity to repeat the same crime for the second arrest, consistent with the analysis based on a similar adult arrest-history data set (Blumstein et al., 1988).[44]

The propensity to commit the same crime types tends to be much lower for T2 than T1 as the time between the first and second arrests increases. This is consistent with the literature on offending specialization, which shows that as the time span increases, the tendency towards specialization declines (McGloin et al., 2009; Sullivan et al., 2006). One exception is for those with C_1 = Drugs, who continue the strongest inclination to be rearrested for drugs. This could be due to the growing crack market during the period of mid to late 80s (Johnson et al., 2000). Those who have a history of involvement in drugs (C_1 = Drugs) could have been particularly vulnerable to re-engaging in and being arrested for drugs despite the fact that they remained arrest-free for at least 5 years. In Table 9c, similar patterns are found in the crime-switch matrix

[42] It can also take negative values if there is a systematic tendency for C_2 to be different from C_1.

[43] In some cases, we find that an arrest is followed quickly by another arrest. We are concerned that what seems to be a “new arrest” might be related to the same crime event as the prior arrest (e.g., transfer to a different jurisdiction), so we count an arrest as a new arrest only if it occurs at least 30 days after the prior arrest.

[44] The values of FSC are not dictated by the relative prevalence of different crime types, while the entries of the crime-switch matrices are influenced by the relative prevalence (Blumstein et al., 1988).

of T3.[45] The propensity to commit the same crime types is relatively weak, again except for drug offenders who show even a stronger propensity to be rearrested for the same crime type.[46]

For those with A_1 = 25-30, their propensity to commit the same crime types tends to be larger than the younger offenders for C_1 = Violent and Property. Older offenders who are initially arrested for violent or property offenses are more likely to return to the same crime type than younger offenders, possibly reflecting the association between the age and the tendency to specialize (Nieuwbeerta et al., 2011; Piquero et al., 1999).[47] Among those with C_1 = Drugs who stay clean at least 5 years, older offenders do not show as strong a tendency to repeat a drug offense as younger offenders. Again, considering the period where there was an increasing effect of the crack market, older drug offenders might have been less involved in crack than their younger counterparts (Blumstein, 1995).

[45] Although not shown in the crime-switch matrix, the probability of no subsequent arrest is about 45%. For those who stayed clean for at least 10 years, the probability of no subsequent arrest is rather high (80-85%). For those who stay clean longer than 5 years, the probability is just over 70% except for C_1 = Violent, which is 61%. Thus, staying clean for an additional 5 years is associated with about a 10 percentage-point increase in the probability of no subsequent arrest.

[46] Those with C_1 = Public Order also show a stronger tendency to repeat the same crime type for T2 than T3.

[47] It is important to note that despite the older offenders' increased tendency to repeat the same crime types, their probability of having a subsequent arrest for any crime is lower than their younger counterparts (about 60% for A_1 = 19-20 and 50% for A_1 = 25-30); this is consistent with the criminological research that an earlier age of onset is a good predictor of a serious criminal career characterized by a larger number of offenses and a longer career duration (Blumstein et al., 1986; Farrington et al., 1990; Farrington et al., 2003; Piquero et al., 2007).

Table 9a. Crime-switch matrix for T1 (0 < *t* <= 5), A_1 = 19-20 (*n* is in brackets)

	C_2					
C_1	Violent	Property	Drugs	Public Order	Others	FSC
Violent (439)	35.8	30.1	10.3	12.5	11.4	.18
Property (958)	19.1	51.8	8.7	12.8	7.6	.23
Drugs (218)	15.6	24.3	43.6	12.8	3.7	.35
Public Order (383)	18.3	19.6	11.0	42.3	8.9	.29
Others (189)	20.6	28.0	13.8	16.9	20.6	.12
						Avg = .23

Table 9b. Crime-switch matrix for T2 (5 < *t* <= 10), A_1 = 19-20 (*n* is in brackets)

	C_2					
C_1	Violent	Property	Drugs	Public Order	Others	FSC
Violent (126)	32.5	17.5	19.8	18.3	11.9	.11
Property (217)	19.4	32.7	19.4	14.3	14.3	.12
Drugs (53)	13.2	22.6	47.2	9.4	7.6	.32
Public Order (70)	30.0	15.7	20.0	20.0	14.3	.05
Others (45)	24.4	13.3	17.8	15.6	28.9	.17
						Avg = .15

Table 9c. Crime-switch matrix for T3 (*t* > 10), A_1 = 19-20 (*n* is in brackets)

	C_2					
C_1	Violent	Property	Drugs	Public Order	Others	FSC
Violent (406)	6.4	3.9	4.4	3.0	3.0	.09
Property (1335)	3.2	4.3	2.9	1.3	3.4	.15
Drugs (275)	3.3	1.5	6.6	0.7	3.6	.48
Public Order (371)	4.9	3.2	1.9	1.4	2.7	.19
Others (288)	3.1	4.5	2.1	1.7	5.2	.07
						Avg = .20

Table 10a. Crime-switch matrix for T1 ($0 < t <= 5$), A_1 = 25-30 (*n* is in brackets)

	C_2					
C_1	Violent	Property	Drugs	Public Order	Others	FSC
Violent (267)	36.3	25.1	9.7	16.9	12.0	.23
Property (652)	12.3	61.5	8.1	9.5	8.6	.37
Drugs (207)	10.1	17.9	52.7	11.6	7.7	.44
Public Order (248)	13.7	15.7	8.1	55.2	7.3	.45
Others (143)	20.3	30.1	12.6	8.4	28.7	.20
						Avg = .34

Table 10b. Crime-switch matrix for T2 ($5 < t <= 10$), A_1 = 25-30 (*n* is in brackets)

	C_2					
C_1	Violent	Property	Drugs	Public Order	Others	FSC
Violent (91)	30.8	19.8	22.0	14.3	13.2	.12
Property (152)	13.2	46.1	17.8	10.5	12.5	.21
Drugs (52)	19.2	23.1	44.2	5.8	7.7	.28
Public Order (65)	30.8	24.6	20.0	21.5	3.1	.11
Others (43)	18.6	30.2	14.0	7.0	30.2	.20
						Avg = .18

Table 10c. Crime-switch matrix for T3 ($t > 10$), A_1 = 25-30 (*n* is in brackets)

	C_2					
C_1	Violent	Property	Drugs	Public Order	Others	FSC
Violent (513)	6.0	2.9	2.7	2.3	1.6	.20
Property (1141)	2.4	5.7	2.1	1.3	2.5	.17
Drugs (368)	1.9	2.7	5.4	1.6	2.7	.23
Public Order (403)	3.5	1.0	2.7	0.7	3.5	-.04
Others (332)	3.6	4.8	0.9	1.2	3.9	.10
						Avg = .13

ii. Crime-type specific hazard

While a crime-switch matrix is informative in characterizing the crime types to which the 1980 arrestees recidivate, and by breaking it into three T's, the matrices inform us about the temporal patterns of C_1-C_2 interactions, we are interested in more explicitly examining how the risk of recidivism to certain C_2's changes over time. In order to estimate the hazard for recidivism to a particular crime type, we use type-specific hazard (Allison, 2010; Kalbfleisch and Prentice, 2002). Type-specific hazard approximates the conditional probability of having a new arrest for a particular crime type at time *t* given surviving without a new arrest until time *t*. In the context of our study, once an individual experiences his first rearrest for a particular C_2 crime type, the individual is censored for the hazard of rearrest for all the other crime types.[48]

As in the robustness testing, we can examine the effect of C_1 on C_2-specific hazards and the extent to which the effect changes over time using Cox's proportional-hazard model (Cox, 1972). In the Cox model of the type-specific hazards, the type-specific hazard of type *k*, $h_{ik}(t)$, can be modeled as

$$h_{ik}(t \mid X_i) = h_{k0}(t)\exp(X_i \beta_k)$$

where $h_{k0}(t)$ is now the type-specific baseline hazard function of type *k*, and β_k represents the coefficients of type *k*.[49] Here, the type *k* corresponds to two types of C_2 (*k* = Violent, Property), which are often of most concern to employers. Since we are most interested in examining how the effects of C_1 on C_2-specific hazards could vary with time clean, we include interactions

[48] The concept of type-specific hazard has been used in the competing-risks analysis in criminology (e.g., Escarela et al., 2000; Fagan, 1996; Lattimore et al., 1995)

[49] In order to estimate the time-varying effects of C_1 on C_2-specific hazards, one can either fit two separate Cox regressions, one for C_2 = Violent and the other for C_2 = Property, or fit both regressions simultaneously (Cleves et al., 2010; Putter et al., 2007). Using either method, the same estimates will be obtained.

between C_1 and the indicator functions for the two-year time intervals in the Cox regression model where we use "Others" as the reference C_1 category (Klein and Moeschberger, 2005).[50] Thus, in this model, for each C_2 (Violent, Property), the hazard ratios – the ratios of hazards for the four C_1's (Violent, Property, Drugs, Public Order) to the reference C_1 (Others) – can vary across the two-year intervals of time clean.[51]

In addition to C_1, we control for A_1, race (*Black*: 1 if black, 0 otherwise), and sex (*Male*: 1 if male, 0 if female).[52] Table 11 shows the estimates of the hazard ratios from the model. As expected, older individuals tend to have lower hazards, indicated by the hazard ratios of A_1 = 21-24, 25-30 to A_1 = 19-20 (reference category) being lower than unity. Blacks have higher hazards than non-blacks, and males have higher hazards of rearrest for a violent crime than females. It is interesting that the effect of A_1 on the hazard of C_2 = Violent is more pronounced than the hazard of C_2 = Property: the hazard ratios for C_2 = Violent seem to decline faster as A_1 increases. The effects of being male and black are also stronger for the hazards of C_2 = Violent than the hazard of C_2 = Property. For the hazard of C_2 = Violent, the effect of C_1 = Violent is positive and significant during the first 10 years. No other C_1 has a significant effect on the hazard of C_2 = Violent across all intervals.

For the hazard of C_2 = Property, on the other hand, the effect of C_1 = Property seems to last slightly shorter, for the first 8 years. Although there are several intervals of time clean during

[50] The indicator functions are defined as: $I_{(0,2]}(t), I_{(2,4]}(t) \ldots I_{(18,20]}(t), I_{(20,+\infty)}(t)$, where the function $I_{(\,)}$ is equal to 1 if the condition is true and 0 otherwise (e.g., $I_{(0,2]}$ = 1 if $0 < t \leq 2$ and 0 otherwise).

[51] Similar results for the models were obtained with varying interval widths.

[52] The proportionality assumption of the Cox model was tested using the Schoenfeld residuals (Grambsch and Therneau, 1994; Schoenfeld, 1982). None of the covariates in the model was found to be violating the proportionality assumption.

which C_1 = Drugs and C_1 = Violent have significant effects on the hazard of C_2 = Property, there are no systematic patterns of C_1 effects other than C_1 = Property.[53]

Table 11. Hazard-Ratio Estimates from the C_2-Specific Cox Proportional-Hazard Model (Time-Varying C_1 Effects) based on conviction data

	C_2 = Violent	C_2 = Property
Age 21-24	.853*	.953
Age 25-30	.626*	.869*
Male	2.590*	1.084
Black	2.374*	1.741*
C_1 = Violent		
0-2 yrs	2.031*	.859
2-4 yrs	1.875*	1.139
4-6 yrs	1.680*	1.223
6-8 yrs	2.610*	4.016*
8-10 yrs	3.086*	.683
10-12 yrs	1.463	.700
12-14 yrs	1.615	1.406
14-16 yrs	6.033*	.418
16-18 yrs	2.546	1.209
18-20 yrs	1.165	2.011
20- yrs	1.944	1.711
C_1 = Property		
0-2 yrs	1.029	2.080*
2-4 yrs	1.087	1.705*
4-6 yrs	.832	1.709*
6-8 yrs	.786	4.620*
8-10 yrs	1.054	1.135
10-12 yrs	.617	1.022
12-14 yrs	.765	1.500
14-16 yrs	1.370	1.066
16-18 yrs	2.708	0.993
18-20 yrs	.540	4.448
20- yrs	1.046	1.986

Note: * indicates $p < .05$ (two tailed).

[53] Very few estimates of the effect on C_2=Violence or C_2 = Property of C_1 = Drugs and none of the estimates for C_1 = Public Order are significant at the .05 level, thus they are not shown in the Table 11.

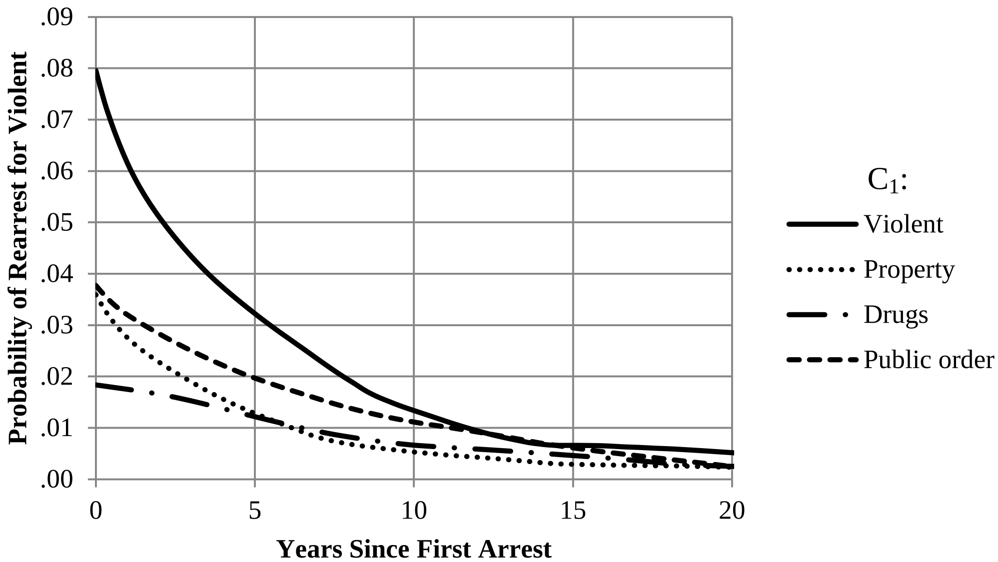
D. Redemption-Time Estimates

In this section, C_2-specific redemption times are estimated using C_2-specific hazard estimates. Figure 8a shows the hazards of rearrest for a violent offense for each of four C_1's.[54] First, based on the previous findings (BN 2009), we find that the hazard of rearrest for violence is much lower (less than half) than the hazard of rearrest for *any* crime (not shown here). Thus, employers should be aware that the risk of a particular kind of future crime of concern (e.g., violence) by a potential employee with a prior record is inherently less than that of *any* crime.

As implied by the crime-switch matrixes and the hazard ratio estimates from the C_2-specific Cox models above, those whose first arrest in 1980 was for violence tend to have a higher risk of violence for about 10 years than those whose first arrest was for any of the other four crimes. This suggests that for the employers who are particularly concerned about the potential employee's risk of violence, a prior record of violence, which could be as old as 10 years, indicates at most a probability of .015 if C_1 = Violent and 20% less, or .012, if C_1 = Property.

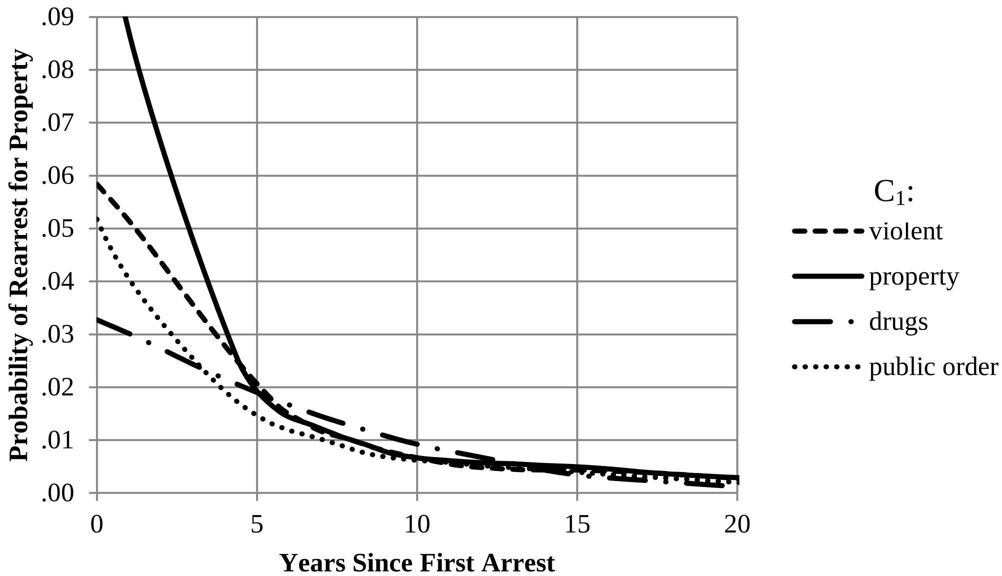
[54] In order to reduce random fluctuations that prevent capturing the overall trend of the hazard, the hazard estimates are smoothed using kernel smoothing with the Epanechnikov kernel (Klein and Moeschberger, 2005; Wang, 2005).

Figure 8a. h(t) of C_2 = Violent, A_1 = 19-20, for Four C_1's



Similarly, as shown in Figure 8b, those with C_1 = Property have a higher hazard of rearrest for property offenses than those with other C_1's. In contrast to Violent, where those with C_1 = Violent have the highest hazard for C_2 = Violent for about 10 years, the hazards for those with C_1 = Property seem to converge to the same rearrest probability as the other four crime types at about $t = 5$. Thus, a prior record of a property offense seems to lose its relevance in predicting a subsequent property crime faster than a prior violent crime in predicting a subsequent future violent crime.

Figure 8b. h(t) of C_2 = Property, A_1 = 19-20, for 4 C_1's



Figures 9a-9b show the same hazards (for C_2 = Violent and Property) for A_1 = 25-30. Again, for C_2 = Violent, a prior record of violence is associated with a higher risk of violent recidivism than the prior records of other crime types. However, the magnitude of the risk of rearrest for violence is about half that of those with A_1 = 19-20, which is consistent with the previous findings that older ages at first arrest is associated with lower hazards of rearrest (BN 2009; Bushway et al., 2011).

For C_2 = Property, a prior record of a property crime is not only associated with the highest hazard, but its magnitude is about the same as its younger counterparts (A_1 = 19-20). Considering the general tendency that those with older A_1's to have lower hazards, this result could suggest a particularly strong propensity of recidivating to the same crime for older property offenders. This is consistent with the finding from the crime switch matrix for A_1 = 25-30 (Tables 10).

Figure 9a. h(t) of C_2 = Violent, A_1 = 25-30, for 4 C_1's

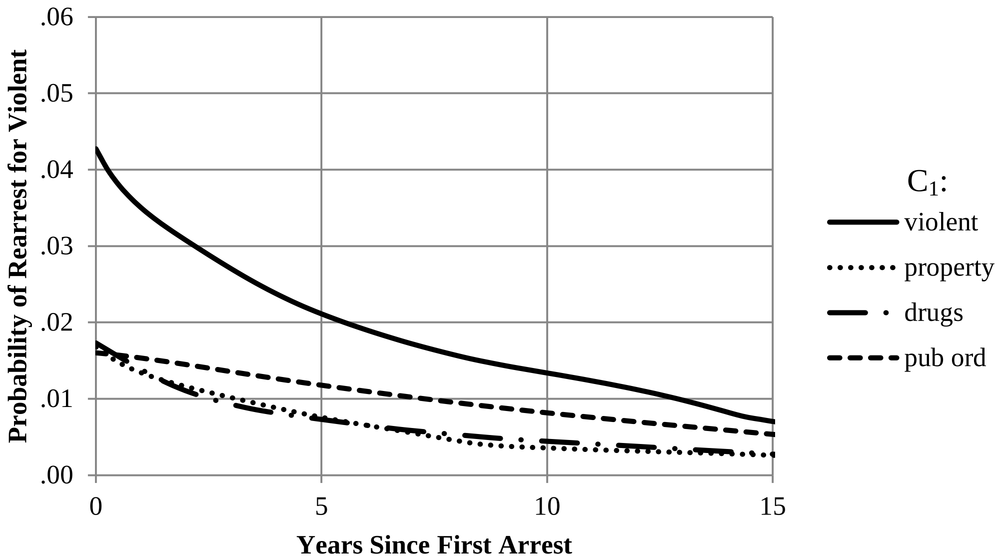
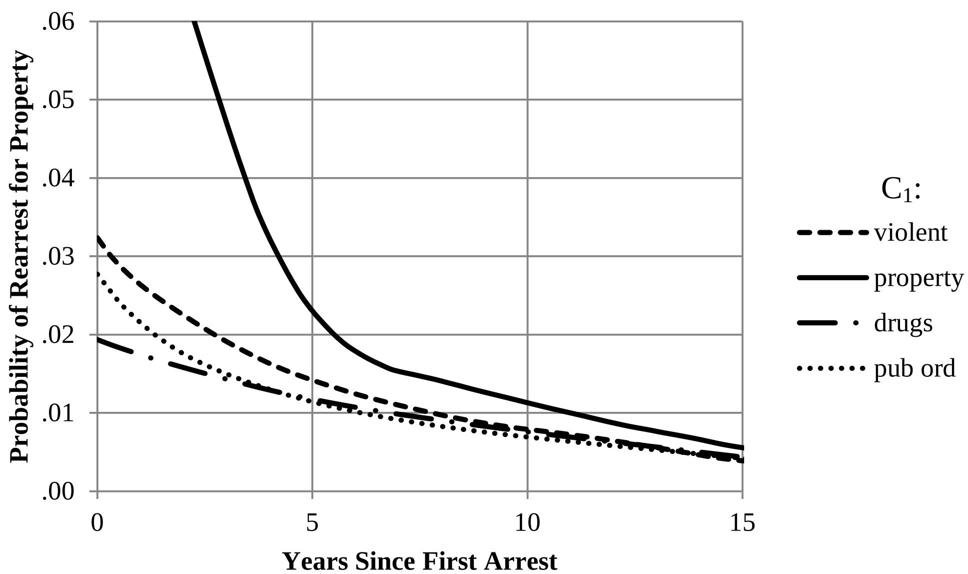


Figure 9b. h(t) of C_2 = Property, A_1 = 25-30, for 4 C_1's



i. Redemption benchmarks

In order to estimate redemption times, which represent the time points where the risk of rearrest is considered sufficiently low, we need appropriate benchmarks to compare against the risk of rearrest. Determining the appropriate benchmarks could involve considering different approaches. The most straightforward way is to use a benchmark that reflects the acceptable level of risk for an employer. Suppose an employer considers the value of .01 (or 1 chance in 100) as an acceptable probability of arrest. Then, a redemption time can be estimated as the time point when the *upper* bound of the confidence interval of the hazard crosses this benchmark of .01. The use of the upper bound provides a more conservative approach to answering the redemption question (BN 2009).[55]

Table 12 shows the estimates of redemption times by C_1, A_1, and C_2, using this benchmark. In almost all cases, the redemption-time estimates are larger for younger A_1's, which is consistent with the fact that the hazards for younger offenders tend to be higher than the hazards for older offenders. However, when $C_1 = C_2$ for Property, the estimates are higher for older offenders because the hazard for older property offenders declines more slowly than for their younger counterparts. This result is a striking contrast to the redemption-time estimates in the context of C_2 = Any (BN 2009; Bushway et al., 2011), which are consistently shorter for older A_1's for all C_1's.

Although the redemption time for C_2 = Property is highest for C_1 = Property, the redemption times are relatively similar across four different C_1's (the average is about 10 years) for the younger A_1 because the hazards for the different C_1's converge relatively early. In contrast, for

[55] The use of upper bound also provides a more statistically appropriate approach. The lower bound is often used in determining when a declining hazard becomes "indistinguishable" from some benchmark, which represents a sufficiently low risk. However, the use of the lower bound is problematic in the sense that smaller sample sizes inevitably make confidence intervals wider, and the lower confidence bound would inappropriately make it easier to conclude that the hazard drops to the benchmark level of risk.

the older A_1, C_1 = Property is associated with a longer redemption time than the other C_1's. For C_2 = Violent, C_1 = Violent is clearly an indication of longer redemption times for both categories of A_1.[56] This is attributable to the higher hazards for C_1 = Violent, as shown in Figures 8a-8b and Table 11. Clearly, this is not the only appropriate benchmark that can be used to estimate redemption times. See Appendix B for an additional approach that sets a C_2-specific benchmark using age-crime curves and the resulting redemption times. Although the estimates are somewhat different using the alternative benchmark, within each A_1-C_1-C_2 combination, the relative magnitude of the estimates are similar.

Table 12. Estimates of Redemption Times by C_1, A_1, and C_2 (for benchmark probability = .01)

		A_1	
C_2	C_1	19-20	25-30
Violent	Violent	14.7	13.9
	Property	7.3	4.3
	Drugs	8.8	4.7
	Public Order	13.3	9.9
Property	Violent	11.1	9.1
	Property	9.2	12.5
	Drugs	11.6	8.8
	Public Order	9.8	8.0

E. Discussion

[56] It is interesting that for C_2=Violent, A_1 = 19-20, C_1 = Public Order is associated with a relatively long redemption time. This suggests that it is likely that young offenders with C_1 = weapon-related offenses (included in Public Order crime) are similar to young offenders with C_1 = Violent in terms of their propensity to have a second arrest for a violent crime.

As an increasing number of people who are seeking employment are turned down because of their stale criminal records, the concept of redemption has attracted interest of policy makers concerned about the handicap resulting from widespread criminal background checks by employers. While research on redemption has helped identify when the prior criminal record loses relevance in predicting any future crime, research has not yet reflected employers' different concerns about different kinds of future crimes. Some may be concerned primarily about violence because the job position involves interactions with vulnerable populations, while others may be more concerned about crimes of theft, and both may be more tolerant about disorderly conduct outside of the workplace.[57] In addition, the EEOC has recently been increasing its pressure on employers to demonstrate the relevance of an employee's prior record to the nature of the demands of the job position. Despite these differences in employer preferences, there has been little known about the extent to which a particular prior record is predictive of the risk of different kinds of future crimes, and perhaps more important, to the estimation of redemption times associated with specific crime types of concern.

The results here can provide some guidance on those issues. Employers should be aware that if they are primarily concerned about violence, a prior record of violence is associated with the highest risk of recidivism and the longest redemption times. This pattern holds for both A_1 groups. For those who are concerned about property crimes, a prior record of property crime is less predictive. For younger offenders (A_1 = 19-20), the redemption times are similar across different C_1 groups because the rearrest risks for property crimes converge relatively quickly. For older offenders (A_1 = 25-30), a prior property crime has a risk pattern similar to that of the

[57] The distinction of workplace offenses was not included in our data, so we were not able to estimate recidivism risk specifically for workplace crimes. Although such distinction may be useful, it is important to recognize that employers are likely to be concerned about potential negative publicity as a result of their employee's crime (especially of violent nature) outside of their workplace.

younger offender, but the redemption times for the other C_1's are appreciably shorter. Results from analysis of the crime-switch matrices and the Cox regressions corroborate the finding that the connection between the prior crime type and the crime type of recidivism diminishes as time clean increases. Thus, employers should recognize that beyond redemption times, the information about C_1 becomes less relevant over time regardless of the C_2 that they are concerned about. Employers should also recognize that the risk of rearrest for a particular crime type is very low after $t > 10$, much lower than the risk of rearrest for any crime type. For example, the hazard of rearrest for *any* crime type at $t = 10$ for A_1 = 19-20 and C_1 = Violent is about .05, whereas the hazard of rearrest for violent offenses at $t = 10$ for the same A_1 and C_1 is close to .01. This implies that, although C_1 provides meaningful information about relative risk until redemption times, the predicted level of C_2-specific rearrest risk after that is rather low.

The results and insights developed in this report should be helpful in providing reasonable guidance on determining redemption times based on a prospective employee's prior criminal record and also helpful for the EEOC in developing guidelines on redemption policies that reflect the crime types of concern to particular employers seeking to hire employees for particular positions.

4. Race and Recidivism Risk in the Context of Redemption

A. Concern over the Role of Race in Criminal Background Checking

The issue of redemption is particularly important for African-Americans compared to whites. It is widely recognized that their arrest experience is considerably greater than that of whites, and therefore it is reasonable to assume that this higher prevalence of arrest would lead to further handicaps beyond those based on racial discrimination alone. This difference has been shown rather dramatically by Pager (2003) in her experimental audit study, which shows both a race effect and a prior-record effect, so that a white job applicant with a criminal record was 3.4 times more likely to receive a call back from an employer than a black applicant with a criminal record. The race effect was somewhat larger than the prior-record effect, so that a white applicant with no criminal record was 2.4 times more likely to be called back than a similarly situated black applicant.[58] The difference in the likelihoods implies a considerable additional disadvantage that African-Americans with criminal records face in employment opportunities.

The concern about this racial difference in criminal-history background has been an important focus of the EEOC, which is committed to finding means of enhancing employment opportunities for minorities, and especially African-Americans. The EEOC issued a guideline in 1990 that employers' decisions to screen out job applicants with criminal records would cause a disparate impact of race or ethnicity under Title VII of the Civil Rights Act of 1964 (EEOC, 1990). Title VII prohibits employers from denying employment to job applicants based on their race, sex, religion, or national origin. Individuals with criminal records are not part of the "protected classes" under Title VII. However, given the racial/ethnic disparity in the rates of having criminal records, blacks, Hispanics, and other racial/ethnic minorities could be affected adversely by the employers' screening out those with criminal records.

B. Relative Arrest Experience of Blacks and Whites

It is widely recognized that blacks experience higher arrest rates than do whites. This disparity is represented by a black-to-white arrest rate ratio. This ratio *R* is calculated for each

[58] These race-based differences combine to give rise to her oft-cited observation that a white applicant with a criminal record is more likely to receive a call-back than a black with no criminal record.

offense type by the reported ratios of black-arrests-to-black-population divided by the ratio of white-arrests-to-white-population:

$$R = B/W \text{ Arrest - Rate Ratio} = \frac{A_B / P_B}{A_W / P_W}$$

where:

R = black-to-white arrest rate ratio

A_B and A_W = number of arrests of blacks and whites respectively

P_B and P_W = population of blacks and whites respectively.

The data for the arrest numbers are available for each year in the Uniform Crime Reports (UCR) published by the FBI (2010).[59, 60] Table 13 presents the B/W arrest-rate ratios for 2009 for the variety of crime types enumerated in the UCR.[61, 62] The crime types are listed in the order of their ratios and are grouped as high ($R > 4$), medium ($3 < R < 4$), moderate ($1 < R < 3$), and reverse ($R < 1$).

The highest ratios are for robbery ($R = 8.0$) and murder ($R = 6.2$) (probably the two offenses seen as most serious) as well as involvement in prostitution ($R = 4.5$) and weapons offenses ($R = 4.4$, primarily for carrying unlicensed weapons). The reverse ratios occur for liquor-law

[59] These measures of relative arrest prevalence are based on national arrest numbers based on the reports of police departments to the UCR. The number of departments reporting represents only about 75% of the total US population, and to the extent that they might be a less-than-representative sample, that could lead to some distortions in the values of *R*.

[60] In the UCR arrest data, there are four categories for race: White, Black, American Indian or Alaskan Native, and Asian or Pacific Islander. In the Census population data, in addition to a question on race, there is a separate binary question on Hispanic origin. To be consistent with A_W and A_B, P_W and P_B both include Hispanic and non-Hispanic.

[61] We do not include in Table 13 crime types that are applicable only to juveniles (curfew and loitering violations and runaways) and crime types for which fewer than 10,000 arrests were reported: suspicion ($R = 7.54$) and gambling ($R = 14.85$), which had the largest value of *R*.

[62] The values of *R* for the previous two years, 2008 and 2007, are very close to those for 2009.

violations (R = .83, primarily involving juveniles in possession of alcoholic beverages) and driving under the influence of alcohol (R = .79).

Table 13. B/W arrest-rate ratios in 2009

	Offense	B/W arrest-rate ratios
High (> 4)	Robbery	7.98
	Murder	6.24
	Vagrancy	4.66
	Prostitution	4.48
	Weapons	4.39
Medium (3-4)	Motor vehicle theft	3.66
	Stolen property	3.48
	Disorderly conduct	3.32
	Aggravated assault	3.29
	Drug abuse	3.19
	Forcible rape	3.08
	Other assaults	3.04
Low (1-3)	Embezzlement	2.96
	Burglary	2.94
	Forgery and counterfeiting	2.93
	All other offenses (except traffic)	2.90
	Fraud	2.87
	Offenses against the family and children	2.85
	Larceny-theft	2.62
	Other sex offenses	2.00
	Vandalism	1.90
	Arson	1.87
	Drunkenness	1.13
Reverse (< 1)	Liquor laws	.83
	Driving under the influence	.79

Blacks tend to be from lower socioeconomic status (SES) groups disproportionately compared to whites, and it has been demonstrated (.e.g., Bjerk, 2007) that there is potentially a strong interaction between the SES and likelihood of involvement in many of the serious crimes. It is also the case that differences in police patrol patterns, which are more densely located in minority and high-crime areas, could be important factors affecting differential involvement in crimes like vagrancy and disorderly conduct (whites might confine their disorderliness to their homes and backyards whereas blacks without those refuges are more likely to do so in the street where they are visible to patrolling police). It could well be that other factors distinguish blacks and whites, especially in different neighborhoods, and could contribute further to their differences.

C. Long-Term Patterns of Recidivism by Blacks and Whites

The differences in arrest rates between blacks and whites displayed in Table 13 represent the racial difference in the prevalence of arrests, how commonly an arrest occurs in each of the two populations. The prevalence difference is explained by the fact that blacks are more likely than whites to penetrate the participation "filter" between the general population and those who participate in crimes (Blumstein and Graddy, 1982; Blumstein and Cohen, 1987; Blumstein et al., 1986). It is clear that there are important differences between the two races in their participation in the various kinds of criminal activity – or at least in their likelihood of being apprehended for doing so. However, it is reasonable to anticipate that there is much less difference between blacks and whites in the arrest frequency of those who have already been identified as being criminally active (i.e., those who passed through the participation filter) (Blumstein and Graddy, 1982; Blumstein and Cohen, 1987); This suggests that race may play less of a role in predicting their propensity to commit another crime.

Studies of recidivism provide additional insight into this phenomenon. Recidivism studies of released prisoners conducted by the BJS have shown that there is racial disparity in the recidivism rates; blacks are more likely, but only somewhat so, to recidivate (Beck and Shipley, 1997; Langan and Levin, 2002). Among the sample of prisoners released in 1983, the rearrest rate within 3 years is about 8 percentage points higher (67% compared to 59%) for blacks than whites (Beck and Shipley, 1997). Among a similar sample of prisoners released in 1994, blacks' reaarrest rate within 3 years was 10 percentage points higher (73% compared to 63%) than whites' rearrest rate (Langan and Levin, 2002). These differences in recidivism rates among the released prisoners are much smaller than the race difference in the prevalence rates. The released prisoners were more similar in terms of their propensity to commit a new crime regardless of race because they all passed through the participation filters of arrest and conviction, and they were all given an incarceration sentence.[63] Thus, racial selection effects are likely to be different in the general population compared to those arrested or convicted.

It is quite possible that the large arrest-prevalence difference between blacks and whites, which is widely known, could play a role in shaping employers' perception of applicants' risk of future crime. However, in the context of redemption, where job applicants with a prior record have stayed clean for a substantial length of time, we might anticipate that the racial difference in the recidivism risk, which is what employers should be concerned about, will be less than the difference in arrest prevalence. Employers should be able to make more informed evaluations

[63] It is interesting to note that the BJS recidivism studies also show that the race difference in rearrest rates declines with the number of prior arrests. Thus, the more prior arrests the released prisoners have, the less important race is as an indicator of recidivism.

regarding the risk associated with white and black applicants if they had the information about the racial difference in the risk of recidivism *conditional on the length of time clean*.

The evidence of racial difference in recidivism rates in the BJS studies is short term, since their follow-up time was limited to 3 years, and there is little known about the extent to which the racial difference in recidivism rates persists in the long run. Thus, it is important to investigate the possibility that the risk of recidivism for blacks with a prior record will be greater than that of whites, if at all, but because of the different selection effect, we would anticipate that the difference between the two will be much less than the difference in their prevalence. Also, among those who stay clean for a considerable length of time after their first arrest or conviction, the racial difference in recidivism probability could be smaller not only than the difference in arrest prevalence, but even in the hazard shortly after their prior arrest. That warrants examination of how those hazard differences vary over time clean.

D. Data

We continue to use the criminal history data of the cohort of about first-time arrestees in 1980 in New York State. This provided a large enough population to disaggregate by important factors that could affect the likelihood of recidivism and still have an adequate number of individuals who have remained clean of crime 10, 20, and even 25 years later.

In addition to A_1 and C_1, we now consider race differences. The NY data record four race categories: white, black, Hispanic, and other, but in order to examine the most relevant racial differences in recidivism and redemption, we focus specifically on only white and black offenders.[64]

[64] In the data we received from the NY State repository, there is one column for race (white, black, Hispanic, other) and another column for "Ever Hispanic". Among the 1980 NY arrestees (A_1 = 19-30),

In order to maintain sample sizes large enough for more precise statistical estimation, we base our analyses on all the arrestees, including those who were not necessarily convicted for their first crime. The conviction probabilities are very similar between blacks and whites, as shown in Table 14, which depicts the fraction of arrestees who were convicted for each of the five C_1's and for all crime types. For property offenses, whites are only slightly more likely to be convicted than blacks, and vice versa for drug offenses and public order offenses; however, overall, there is not much difference between whites and blacks in their probability of being convicted after having been arrested. Table 15 provides the distribution of the 1980 arrestee sample by crime type at first arrest.

Table 14. Percent of 1980 arrestees who were convicted

	C_1					
Race	Violent	Property	Drugs	Public Order	Others	All
White	64.6%	75.6%	72.1%	70.5%	68.4%	71.5%
Black	64.4%	71.2%	76.9%	74.8%	66.6%	70.6%

Table 15. Initial Sample Size of Arrestees, by First Offense (C_1) in 1980*

	C_1					
Race	Violent	Property	Drugs	Public Order	Others	All
White	3,053 (18.0)	7,268 (42.9)	1,904 (11.25)	2,375 (14.0)	2,324 (13.7)	16,924 (71.3)
Black	1,556 (22.8)	2,801 (41.1)	827 (12.1)	1,125 (16.5)	508 (7.5)	6,817 (28.7)

* The distribution for the five C_1's are contained in parentheses.
The distribution by race is provided in parentheses in the column for C_1 = All.

11% are recorded as Hispanic in the race column. In order to focus on the contrast between white and black, we do not treat those whose race is recorded as Hispanic. 96% of black arrestees and 97% of white arrestees are recorded as Non-Hispanic in the "Ever Hispanic" column.

E. Approach and Results

We are interested in contrasting the arrest prevalence between blacks and whites in the general population and then comparing that to the relative hazard or risk of arrest between blacks and whites in the population of those with a prior criminal arrest who have stayed clean for a time t since the arrest.

i. Relative Arrest Experience of Blacks and Whites

The relative experience of arrest between blacks and whites in the general population is represented by the prevalence ratio, *R*, discussed earlier. The *R* values are calculated as the number of arrests of blacks and whites in New York State for the violent, property, and drug offenses from the UCR, each divided by their respective NY populations. We estimated these values for 1985, 1990, and 1995, representing 5-year intervals for the 1980 arrestee cohort. These values of *R* are tabulated in Table 16. We note that the prevalence ratios are reasonably close for the three sampling years, and that they show a slight decline over that interval. We also note that the average of the ratios is appreciably larger for violence (4.7) than for property (3.3) and that violence and drugs (4.4) are reasonably close. This suggests that although the racial disparity in arrest prevalence may be declining somewhat over time, it is still the case that arrest is about 4 times more common for blacks than for whites in the NY general population.

Table16. Black-to-White Arrest Prevalence Ratios for Violent, Property, Drugs in 1985, 1990, 1995

	C_1			
Year	Violent	Property	Drugs	All
1985	5.0	3.5	4.7	5.0
1990	4.7	3.0	4.6	3.9
1995	4.3	3.3	4.1	3.5
Average	4.7	3.3	4.4	4.1

ii. Relative Rearrest Experience of Blacks and Whites

As a contrast to the prevalence of arrests, we now turn to examine the hazard of a rearrest, *h(t)*. We first estimate *h(t)* separately for blacks and whites for three C_1's (Violent, Property, Drugs), shown in Figures 10a-10c. For the three crime types, blacks have consistently higher hazards than whites. Initially, the ratios of hazards for blacks to whites are higher for C_1 = Violent and Drugs than for C_1 = Property. This is consistent with what we found above (Table 16) in the arrest-prevalence ratios for the three crime types: the black-to-white arrest-prevalence ratio is higher for violent offenses and drug offenses, than for property offenses. But, most strikingly, for drug offenses, the hazard for blacks within the first several years is more than 3 times the hazard for whites; this results from the fact that drugs represents blacks' highest hazard and whites' lowest. During the early 1980s, crack started to be marketed, primarily by blacks, and crack certainly was a major contributor to the differences in the hazards.

Figure 10a. *h(t)* for black and white arrestees, C_1 = Violent

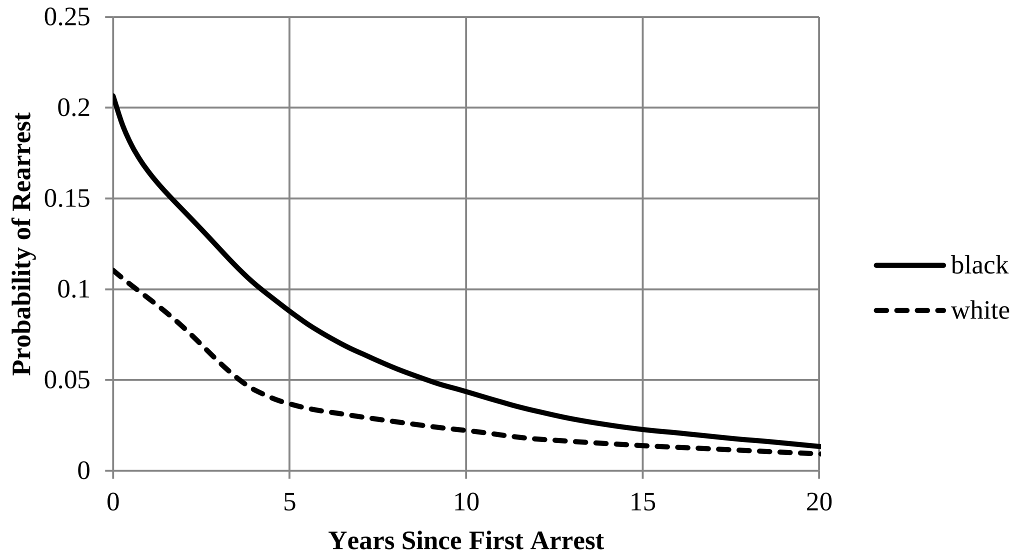


Figure 10b. *h(t)* for black and white arrestees, C_1 = Property

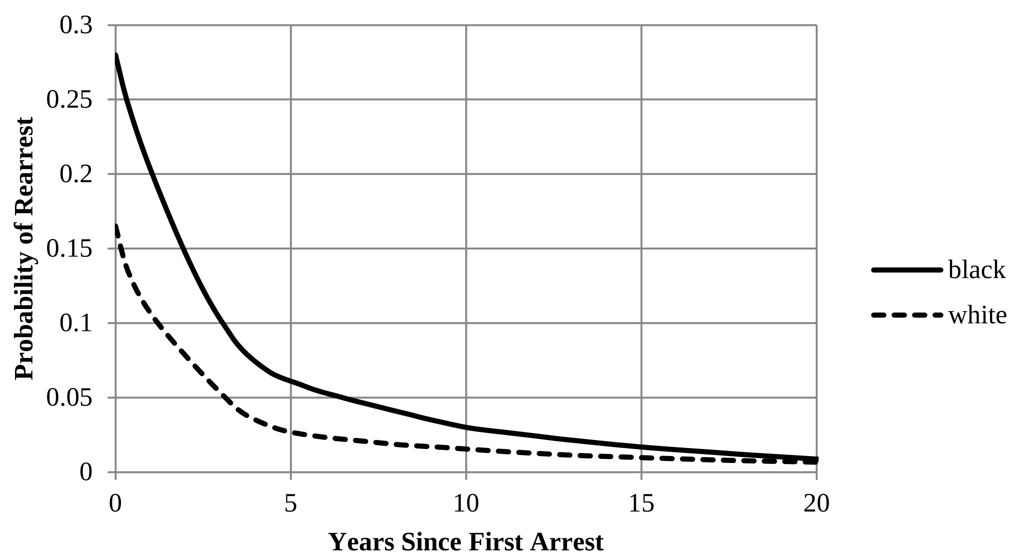
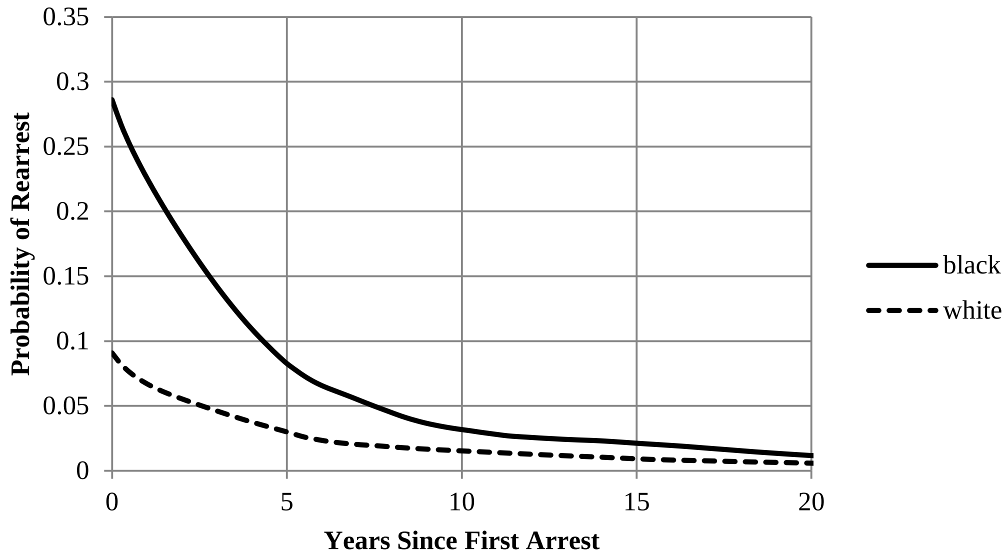


Figure 10c. *h(t)* for black and white arrestees, C_1 = Drugs



<u>Examining racial differences in the rearrest risk as a function of time clean</u>

Since we are interested in examining the possibility that the effect of the binary covariate, race (white or black), on the rearrest hazard could vary with time clean, we use proportional hazards models with interactions between the binary variable for blacks, *Black* (1 if black, 0 if white) and the indicator functions for the five-year time intervals in the Cox regression model (Klein and Moeschberger, 2003). The Cox model with the interaction terms can be expressed as follows:[65]

---

[65] The general form of an indicator function is:

$$I_A(t) = \begin{cases} 1 & \text{if } t \in A \\ 0 & \text{if } t \in A. \end{cases}$$

So, for example, the indicator function for the first five-year interval can be expressed as:

$$I_{(0,5]}(t) = \begin{cases} 1 & \text{if } 0 < t \leq 5 \\ 0 & \text{otherwise}. \end{cases}$$

$$
\begin{aligned}
&h(t \mid Black(t)) \\
&= h_0(t)\exp[(\beta_1 I_{(0,5]}(t) + \beta_2 I_{(5,10]}(t) + \beta_3 I_{(10,15]}(t) + \beta_4 I_{(15,20]}(t) + \beta_5 I_{(20,+\infty)}(t))Black]. \qquad (1)
\end{aligned}
$$

In this model (1), the black-to-white hazard ratio can vary across the five five-year intervals of time clean (0 to 5 years, 5 to 10 years, 10 to 15 years, 15 to 20 years, and longer than 20 years).[66]

In order to control for A_1 and C_1, we stratify (1) by A_1, and fit a separate model by C_1. The estimates of hazard ratio (B/W) from these stratified Cox models with confidence intervals can be plotted against time to examine whether and how the ratio changes with arrest-free time.[67]

Figures 11a-11c show the estimated hazard ratios, (B/W) for C_1 = Violent, Property, and Drugs, with confidence intervals using the Cox model with the interactions between *Black* and time (5-year time intervals). The hazard ratios for C_1 = Violent and Property start at about 2 and increase slightly for the first 10 years, and after that the ratios decline steadily toward 1. In contrast, for C_1 = Drugs, the ratio shows a different pattern. First, it is much higher than the other two crime types: the initial ratio for drugs is about 3.5, while for violent and property offenses, the ratios are about 2. Second, the Drug ratio gradually declines in the first 15 years, but it is sill over 2 during that period. After t = 15, the ratio seems to increase somewhat, but since the confidence intervals are very wide, it could well be that it doesn't change much and remains at

[66] Alternatively, the model can be parameterized as:

$$h(t \mid Black(t)) = h_0(t)\exp[(\theta_1 + \theta_2 I_{(5,+\infty)}(t) + \theta_3 I_{(10,+\infty)}(t) + \theta_4 I_{(15,+\infty)}(t) + \theta_5 I_{(20,+\infty)}(t))Black]. \qquad (2)$$

The two models ((1) and (2)) will have an identical likelihood function with β_1 in (1) to θ_1 in (2), β_2 in (1) to $\theta_1 + \theta_2$ in (2), β_3 in (1) to $\theta_1 + \theta_2 + \theta_3$ in (2), and so forth.

[67] The confidence interval for the hazard ratio is based on the exponentiated endpoints of the confidence interval for the original coefficient of the Cox model. So, for example, the confidence interval for the black-to-white hazard ratio in the first five-year interval would be:

$$\{\exp[\hat{\beta}_1 - z_{1-\alpha/2}se(\hat{\beta}_1)], \exp[\hat{\beta}_1 + z_{1-\alpha/2}se(\hat{\beta}_1)]\}.$$

This is preferable to an alternative way, which is based on the standard error of the hazard ratio directly, because this alternative method can lead to negative values of the confidence intervals. Both methods are asymptotically equivalent (Klein and Moeschberger, 2003).

about 2. Table 17 indicates the values of the hazard ratio for the 1980 arrestee cohort at the five-year points. Again, it highlights the overall downward trend for the hazard ratios as those with a prior stay clean.

Figure 11a. Hazard ratio estimates (B/W) with confidence intervals, C_1 = Violent

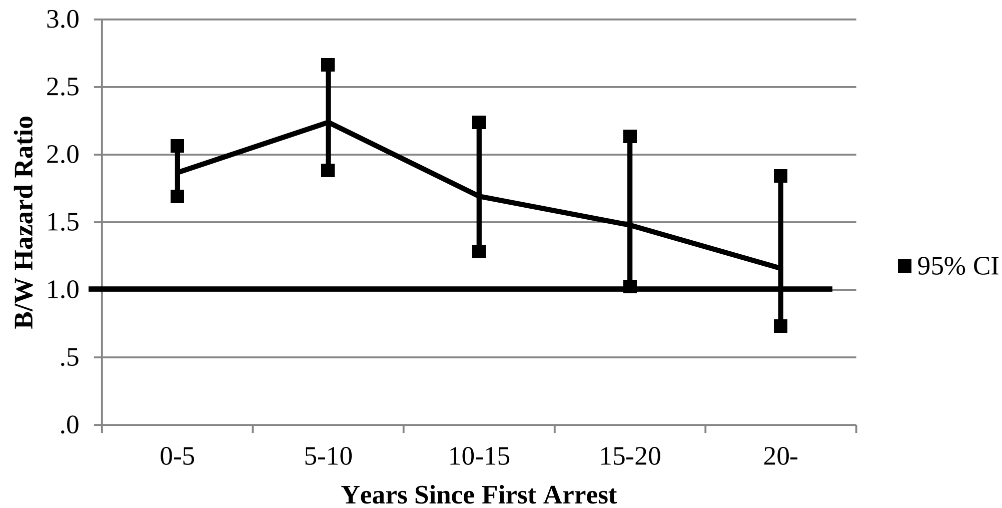


Figure 11b. Hazard ratio estimates (B/W) with confidence intervals, C_1 = Property

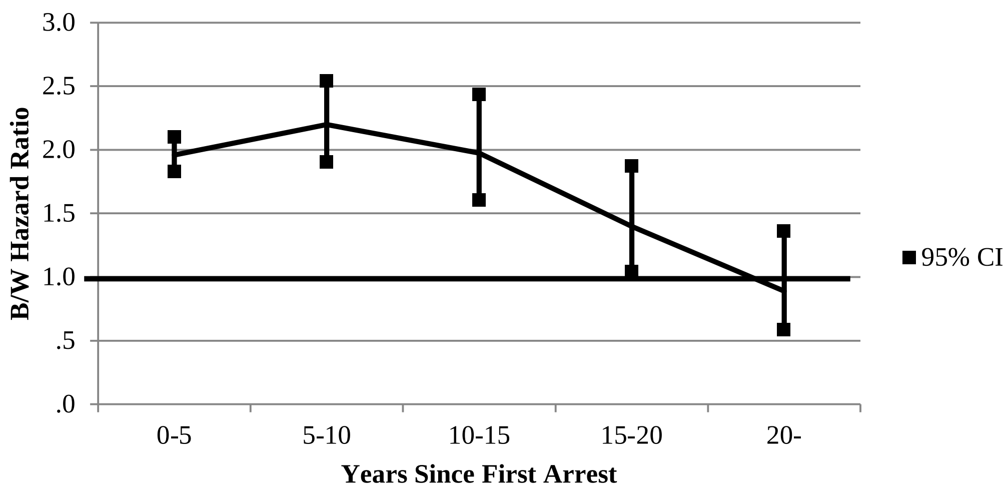


Figure 11c. Hazard ratio estimates (B/W) with confidence intervals, C_1 = Drugs

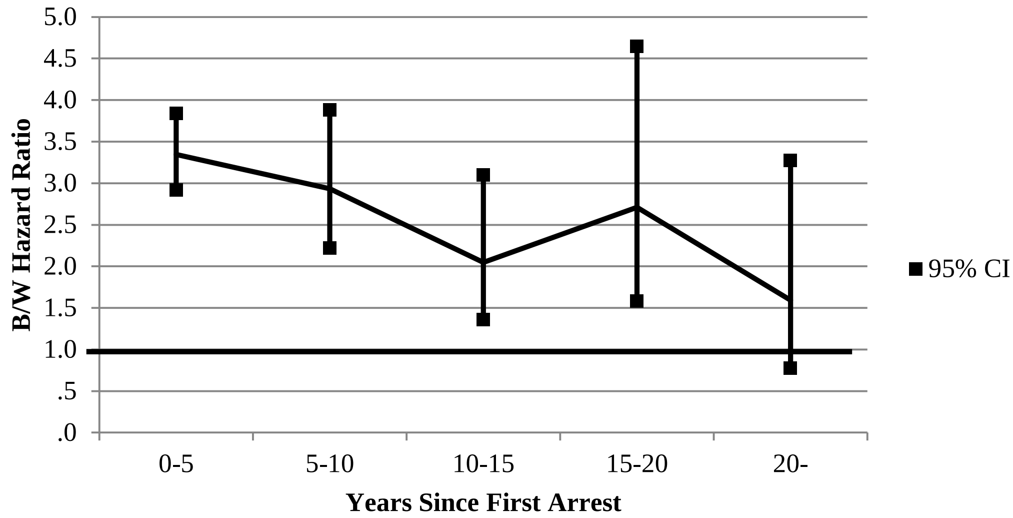
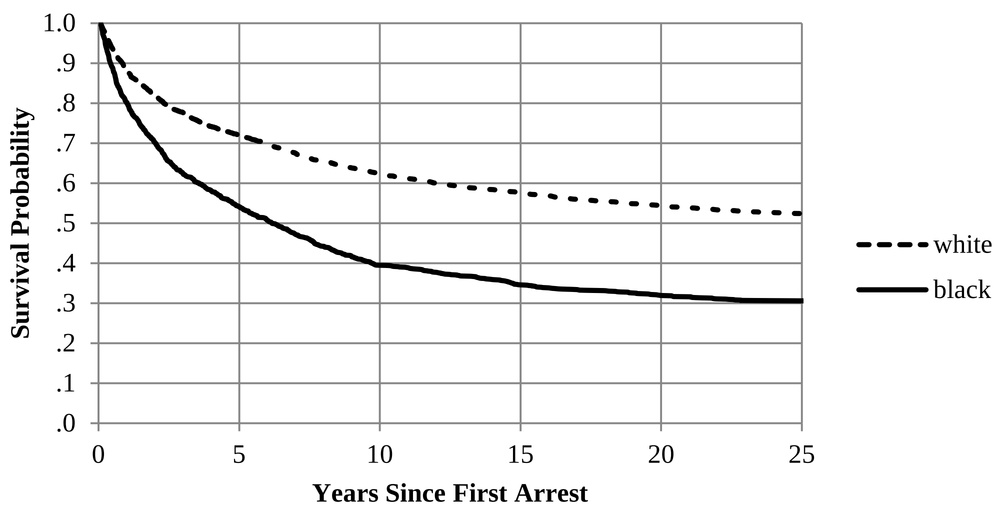


Table 17. Black-to-white hazard ratios for C_1 = Violent, Property, Drugs, All at 5 year intervals for the 1980 Cohort

	C_1			
t	Violent	Property	Drugs	All
0-5	1.9	2.0	3.3	2.1
5-10	2.2	2.2	2.9	2.2
10-15	1.7	2.0	2.0	1.8
15-20	1.5	1.4	2.7	1.5

The analysis of the survival probabilities for whites and blacks shown in Figures 12a-12c also illustrates the point that the risk of recidivism for blacks becomes similar to the risk for whites. It is clear that the survival probabilities for blacks are substantially lower than for whites: at t = 20, about 20% lower for C_1 = Violent and Property and about 35% lower for C_1 = Drugs. However, these large differences are mostly due to the differences that occur in the first 10 years and the fact that the survival probabilities for blacks fall much faster than for whites in that period. This is consistent with the relatively large black-to-white hazard ratio in that period. While hazard function is informative about the instantaneous rearrest risk at *t*, survival probability, which is 1 – *F(t)*, the cumulative distribution function, is informative about the probability of rearrest in a certain time interval. Table 18 shows the proportions of blacks and whites being rearrested in the first 10 years and after 10 years, which are calculated by the differences of survival probabilities, $S(t = 0) - S(t = 10)$ and $S(t = 10) - S(t = 25)$, respectively. In the first 10 years, much larger proportions of blacks experience re-arrests than whites. On the other hand, after 10 years, there is virtually no difference between whites and blacks in their probabilities of being rearrested. This suggests that although blacks may have a higher hazard than whites at $t = 10$, blacks who stay clean for 10 years have about the same probability as whites of ever being rearrested in the future.[68]

Figure 12a. Survival probabilities, C_1 = Violent



[68] This anticipates that, after staying clean for 25 years, very few would experience re-arrests.

Figure 12b. Survival probabilities, C_1 = Property

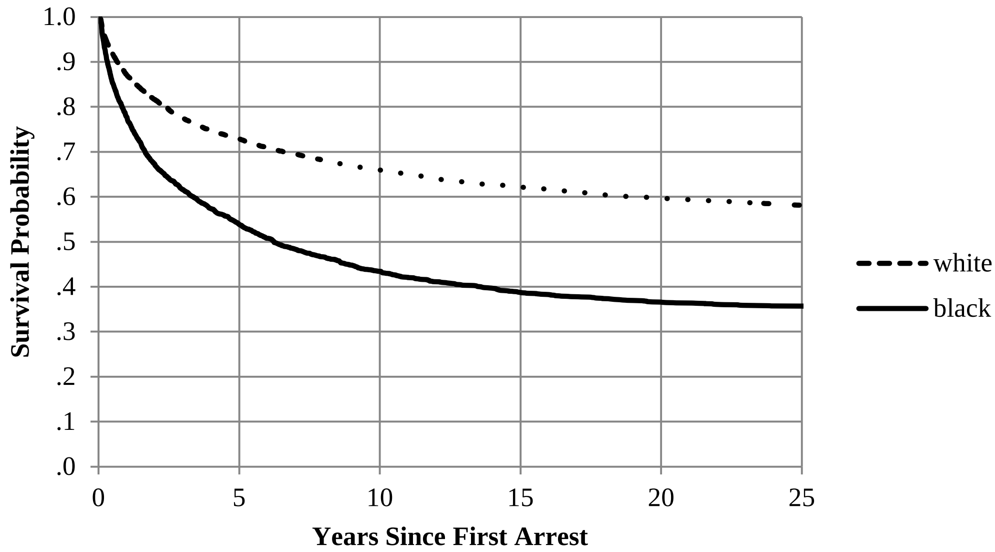


Figure 12c. Survival probabilities, C_1 = Drugs

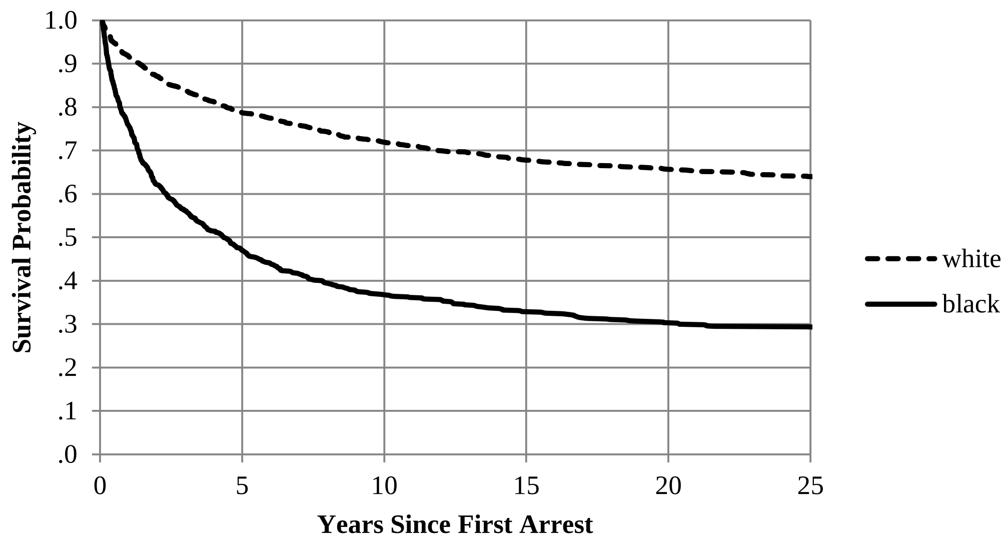


Table 18. Proportions rearrested between t = 0 and 10 and between t = 10 and 25

		C_1		
		Violent	Property	Drugs
1 - $S(t = 10)$	white	.38	.34	.28
	black	.61	.57	.63
$S(10) - S(25)$	white	.10	.08	.08
	black	.09	.08	.08

F. The Effect of "The Crack Epidemic"

Despite the overall trend of decreasing black-to-white hazard, it is important to explore further the possible explanations for the fact that blacks have a higher hazard than whites for more than 10 years, and the hazard for the 1980 drug arrestees seems particularly high. One possible interpretation of this large black-to-white difference could be that during the mid to late 1980s, through which the 1980 cohort arrestees went, the "crack epidemic" swept through African-American neighborhoods in major cities, and in New York City in particular.[69] The crack market and the aggressive policing that followed might have put the relatively few African-Americans who were arrested for drugs in 1980 - before the introduction of crack - in a particularly vulnerable situation for recidivism.[70, 71] The introduction of crack and the drug war

[69] In New York City in particular, crack cocaine began to be distributed in 1984, and its market grew considerably in 1985-86, mostly in minority neighborhoods (Johnson, Golub, and Dunlap, 2000).

[70] In the 1980 cohort, 827 blacks were arrested for drugs. The number of first-time black drug offenders increased to 1,400 in the 1985 cohort and over 2,300 in the 1990 cohort.

[71] As a response to the growing crack problem in the city, the New York Police Department launched Tactical Narcotics Teams (TNT) in 1988, reassigned about one-fourth of the department to the teams, and began mass drug arrests (Johnson, Golub, and Dunlap, 2000), and the open street transactions made the sellers particularly vulnerable to the arrests. African-American sellers of crack tended to operate in the streets, whereas sellers of powder cocaine, primarily whites and Hispanics, tended to operate indoors, thereby contributing to the disproportionate arrests of African-Americans.

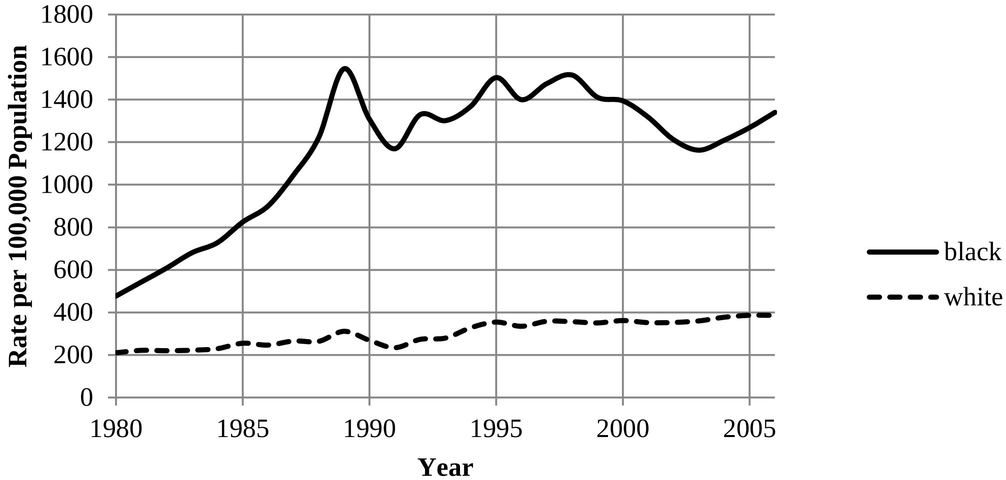
resulted in a large racial disparity in the arrest rates for drug offenses in the late 1980s (Blumstein, 1995). As shown in Figure 13, which is based on the UCR national arrest data, drug arrests for blacks increased rather sharply after 1980, while drug arrests for whites, remained reasonably stable (National Consortium on Violence Research, n.d.). The arrest rates for blacks rose to 4-5 times that of whites in the late 1980s.[72]

Since 1990, intense policing forced the crack market to move from outdoor curbside locations to closed-door locations (Johnson, Dunlap, and Tourigny, 2000). At the same time, in the early 1990s, the drug of choice for the youths began to shift from crack to marijuana, which could be largely attributed to a growing realization of the negative impact of crack on its users (Johnson, Dunlap, and Tourigny, 2000). This transition in the market location and the drug of choice possibly contributed to the end of the previous sharp rise to a peak in 1989, and then a leveling until about 2000, as seen in Figure 13. However, those changes did not lead to any significant closing of the gap between whites and blacks. As seen in Figure 13, even as marijuana replaced crack as the drug of choice, African-Americans continued to be disproportionately arrested for drug offenses.[73, 74]

[72] The disproportionate impact of the drug war on African-Americans has profound lasting effects. Collateral consequences of acquiring criminal records can limit the access to services and opportunities that are essential for offenders to reintegrate into society (Travis, 2002). Compared to other types of crimes, drug offenders are often subjected to additional layers of collateral consequences. For example, those with drug convictions may be denied access to public housing or be ineligible for other housing assistance programs (e.g., Section 8). According to a report by the Government Accountability Office (2005), 15 large public housing agencies reported that about 5 percent of applications for admission were denied because of drug-related convictions. People with certain drug convictions are also ineligible for Temporary Aid to Needy Families and Food Stamps, federally-funded health care programs, and federal student loans.

[73] At least in New York City, the use of marijuana became the most common misdemeanor arrest (15% of all NYC adult arrests) by 2000. Golub et al. (2007) reports that in 2000, the black-to-white ratio of misdemeanor marijuana arrest rates in NYC was about 6. For marijuana sale, the ratio was over 26. Although these numbers are limited to NYC, they provide some evidence for the continuing racial disproportionality in drug arrests into the 1990s.

Figure 13. Drug arrest rates for blacks and whites (national)



One way to understand the impact of racial disproportionality in drug arrests on the recidivism risk of whites and blacks in our 1980 NY cohort is to investigate the crime types for which the rearrest is made (C_2). We have been treating recidivism here as the rearrest for any crime. However, considering the possibility of the differential impact of the drug arrests on whites and blacks, examining the distribution of C_2 may help us understand why blacks have a higher hazard.

Tables 14a-14d show the crime switch matrices, which display the combination of crime type of first arrest (the rows) and the probability of different crime types of second arrest (the columns), for those who have a second arrest and stay clean for the first 5 years, 5 to 10 years, 10

[74] It is informative to follow over time the fraction of total drug re-arrests for the 1980 black arrestees in our data which are for marijuana. Among the drug re-arrests, 56% are marijuana in the period $0 < t <= 5$, 14% in $5< t <=10$, 4% in $10 < t <= 15$, and 21% in $t > 15$. Thus, it appears that marijuana was the main drug type for their re-arrests until 1985, non-marijuana (most likely crack) was the major drug for the next 10 years, and marijuana returned as the more common drug after the mid-90s.

to 15 years, and more than 15 years.[75] This allows us to examine the proportion of those who were arrested for each of the five C_1 categories in 1980 were rearrested for the same crime category, or for a different category. The values in the diagonals of the matrix represent the proportion recidivating to the same crime type as their first arrest. The values in the off-diagonals represent the proportion committing different crime types than their first one. The last row is the average of the probabilities of each C_2. Since an important concern is the repetition of the initial crime type (C_1), the last column contains the ratio of the diagonal values (the probability of repeating C_1) to the average of the off-diagonal values.

For both whites and blacks who were rearrested within the first 5 years (Table 19a), the diagonal values (in bold in the table) tend to be higher than off-diagonal values, indicating a propensity to repeat the first crime type in the second arrest, and especially so for property crimes. It is important to note that for C_1 = Drugs, the diagonals are appreciably larger for blacks than whites, which could suggest the growing influence of the crack market on African-Americans of our 1980 cohort.[76]

For the next interval, $5< t <= 10$ (Table 19b), the overall propensity to repeat the same crimes is lower for both whites and blacks, reflecting a weaker connection between C_1 and C_2, undoubtedly a result of the longer interval. More importantly, a clear pattern emerging from Table 19b is that blacks' recidivism to drug offenses is much more salient than for whites. The average of the conditional probabilities of drug rearrest (average of the values in the column

[75] The crime-switch matrices display the distribution of the crime types of the second arrests conditional on the crime type of the first arrest.. It is important to note that the matrices take no account for the crime types of the third and later arrests for those who have more than two arrests. In this sense, the information that the matrices contain is consistent with the hazard, which is the risk of having a second arrest.

[76] The diagonals are also larger for blacks than whites for C_1 = Public Order, which could reflect different patrol patterns.

Drugs) is 28.9% for blacks and 17.5% for whites. Similar 1.5:1 disparities are seen in Table 19c (for 10 < *t*<= 15) and 19d (for *t* > 15).

The fact that the drug offenses are such a dominant crime type for the rearrest of black offenders who stay clean for 10 years is clearly in accord with the explanation that African-Americans were disproportionately caught up in the intensive drug battles of the 1980s and 1990s.

Table 19a. Crime switch matrix for arrestees 0 < *t* <= 5

		C_2					
	C_1	Violent	Property	Drugs	Public Order	Others	Diag/Avg of Off-Diags
white	Violent	**37.5**	23.6	8.2	15.6	15.1	2.4
	Property	13.3	**57.4**	7.0	11.6	10.7	5.4
	Drugs	14.4	26.2	**35.9**	12.9	10.6	2.2
	Public Order	22.1	23.3	9.5	**33.1**	12.0	2.0
	Others	18.3	32.4	8.5	14.8	**26.1**	1.4
	Avg	21.1	32.6	13.8	17.6	14.9	2.7
black	Violent	**37.0**	28.4	12.2	11.8	10.6	2.3
	Property	20.1	**53.0**	9.1	10.7	7.2	4.5
	Drugs	15.1	16.9	**52.5**	11.4	4.1	4.4
	Public Order	19.3	19.8	9.9	**45.5**	5.5	3.3
	Others	24.4	36.1	12.6	11.7	**15.2**	0.7
	Avg	23.2	30.8	19.3	18.2	8.5	3.1

Table 19b. Crime switch matrix for arrestees 5 < *t* <= 10

	C_1	C_2 Violent	Property	Drugs	Public Order	Others	Diag/Avg of Off-Diags
white	Violent	**33.7**	20.8	15.3	16.3	14.0	2.0
	Property	15.2	**44.9**	12.2	11.0	16.8	3.3
	Drugs	20.2	29.5	**27.9**	9.3	13.2	1.5
	Public Order	36.0	18.8	15.2	**15.7**	14.2	0.7
	Others	19.7	24.9	16.8	8.7	**30.1**	1.7
	Avg	25.0	27.8	17.5	12.2	17.7	1.9
black	Violent	**41.0**	20.3	23.4	8.4	7.1	2.8
	Property	19.5	**38.7**	25.0	10.6	6.2	2.5
	Drugs	17.9	25.0	**46.4**	6.0	4.8	3.5
	Public Order	27.3	23.2	27.3	**19.2**	3.0	1.0
	Others	31.5	22.2	22.2	3.7	**20.4**	1.0
	Avg	27.4	25.9	28.9	9.6	8.3	2.1

Table 19c. Crime switch matrix for arrestees 10 < *t* <= 15

	C_1	C_2 Violent	Property	Drugs	Public Order	Others	Diag/Avg of Off-Diags
white	Violent	**24.3**	25.0	13.9	16.0	20.8	1.3
	Property	12.1	**45.6**	8.5	12.9	21.0	3.4
	Drugs	21.5	17.7	**26.6**	11.4	22.8	1.4
	Public Order	32.6	24.7	16.9	**10.1**	15.7	0.4
	Others	15.2	34.3	14.1	9.1	**27.3**	1.5
	Avg	21.1	29.5	16.0	11.9	21.5	1.6
black	Violent	**31.6**	29.0	27.6	7.9	4.0	1.8
	Property	14.4	**39.4**	29.6	6.1	10.6	2.6
	Drugs	24.2	18.2	**27.3**	12.1	18.2	1.5
	Public Order	20.0	22.9	34.3	**14.3**	8.6	0.7
	Others	28.0	48.0	8.0	8.0	**8.0**	0.3
	Avg	23.6	31.5	25.4	9.7	9.9	1.4

Table 19d. Crime switch matrix for arrestees 15 < *t*

	C_1	C_2 Violent	Property	Drugs	Public Order	Others	Diag/Avg of Off-Diags
White	Violent	**32.5**	17.8	15.4	10.7	23.7	1.9
	Property	18.1	**32.0**	12.3	9.1	28.5	1.9
	Drugs	23.0	16.2	**29.7**	8.1	23.0	1.7
	Public Order	17.1	15.9	18.3	**9.8**	39.0	0.4
	Others	25.4	14.0	8.8	11.4	**40.4**	2.7
	Avg	23.2	19.2	16.9	9.8	30.9	1.7
Black	Violent	**33.9**	26.2	23.1	7.7	9.2	2.0
	Property	25.6	**29.1**	37.2	3.5	4.7	1.6
	Drugs	22.6	16.1	**41.9**	6.5	12.9	2.9
	Public Order	27.6	13.8	27.6	**13.8**	17.2	0.6
	Others	31.6	36.8	26.3	.00	**5.3**	0.2
	Avg	28.3	24.4	31.2	6.3	9.9	1.5

If this period-specific drug involvement and enforcement in the 1980s are an important factor in explaining the observation that the probability of being rearrested for drug offenses is larger for blacks than for whites, it is possible that the disparity in the hazards between blacks and whites might not be as much as what we saw in Figures 11a-11c once we focus our attention on non-drug recidivism risk. Focusing on recidivism for crimes other than drugs may be reasonable, given that employers are more likely to be concerned about violence (assaults, rapes, etc.) against customers and co-workers, or property crimes, which could involve stealing property or money from the business entity.

Figures 15a-15b show the black-to-white ratio of hazards for non-drug offenses for C_1 = Violent, Property.[77] Compared to Figures 11a-11c, the ratio declines and approaches unity faster,

[77] The confidence intervals of the hazard ratio for C_1 = Drugs are too wide to make reasonable interpretations.

especially for C_1 = Property. This indicates that at least part of the explanation for the blacks' higher hazard is due to the period effect of the 1980s when blacks were disproportionately arrested for drugs. After taking into account that period effect, those blacks who succeed in remaining arrest free for over 10-15 years are much more similar to whites in terms of their future recidivism risk.

Figure 15a. Hazard ratio estimates (B/W) for non-drug offenses with confidence intervals, C_1 = Violent

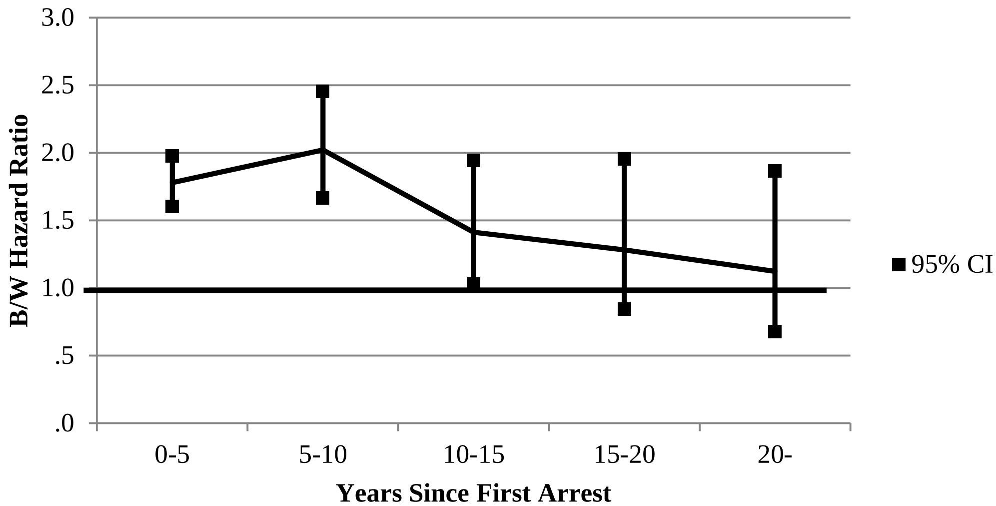
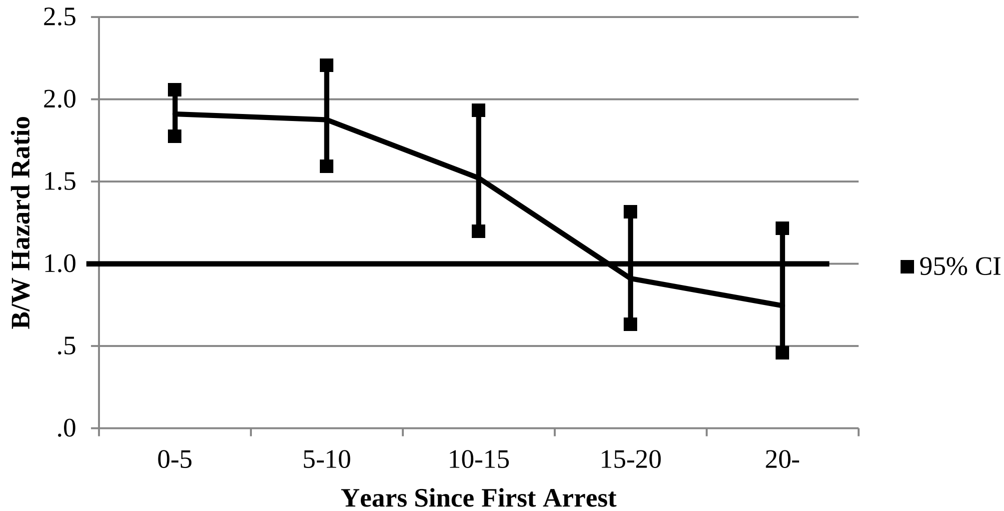


Figure 15b. Hazard ratio estimates (B/W) for non-drug offenses with confidence intervals, C_1 = Property



G. Comparison of Prevalence and Hazard Ratios

It is important to compare the black-to-white hazard ratios with the prevalence ratios shown in Table 16. First, it is seen that the hazard ratios – even at $t = 0$ - are appreciably smaller than the prevalence ratios. This undoubtedly reflects the difference of the two concepts: prevalence represents the fraction of people drawn from the total population who are arrested, whereas hazard represents the fraction of people with a prior record who are arrested. Thus, they represent the selection from two different base populations – prevalence: total population, hazard: those with a prior who have stayed clean so far. Thus, the selection differences associated with arrest could account for the fact that the black-to-white hazard ratios are roughly half the comparable prevalence ratios.

It is also important to consider the fact that the blacks' hazard becomes similar to whites' over time, as evidenced by the declining black-to-white hazard ratio. Thus, as the arrest-free period increases, the difference between the prevalence ratio and the hazard ratio becomes larger.

This could be due to a combination of many factors, but it can be speculated that staying clean for a substantial length of time is an important indication that those with a prior criminal record have made efforts to turn their life around and succeed in integrating into society by committing themselves to a stable marriage, gaining stable employment, and distancing themselves from environments that are highly susceptible to involvement in crime. Thus, those who stay clean for a long time are of comparably low risk of recidivism *regardless of race* because those are the ones who most surely managed to straighten their lives.[78]

These results have important implications for employers and for policy makers, such as the EEOC. There is reason to suspect that employers' perceived risk of future crime posed by white and black applicants is shaped by the racial difference in arrest prevalence. Arrest prevalence can easily be calculated using publicly available data from the UCR and the Census. It is also true that racial difference in arrest prevalence is often the statistic that is used to highlight blacks' higher likelihood of engaging in crime (or being involved in the criminal justice system). The results suggest that employers should be aware that the racial difference in arrest prevalence does not accurately reflect the risk difference of white and black applicants whose crime occurred long ago.

The possibility exists that employment discrimination against black applicants, which may well be caused by the employers' awareness of prevalence difference, further diminishes blacks' employment opportunities. Given this possibility and the finding that whites and blacks who stay crime free for a long period of time have a similar risk of future crime, it is important to develop empirically supported policies to encourage providing equal employment opportunities to people

[78] Evident in the large difference in survival probabilities, only a relatively smaller fraction of African-Americans with a prior arrest manage to stay clean. However, given that African-Americans are faced with disproportionate socioeconomic disadvantages and employment discrimination, those African-Americans who survive without subsequent involvement in crime for a long time might well have had to overcome more obstacles than their white counterparts.

with stale criminal records, regardless of race. The difference in the risks at some point diminishes appreciably, a point not recognized in short-time recidivism studies.

5. Conclusions and Next Steps

As information technology has increased the accessibility of criminal-history records, and concern for negligent hiring lawsuits has grown, there is no doubt that criminal background checking has become an important part of the hiring process for most employers. We have begun to understand the consequences of widespread criminal background checking through numerous stories covered in media about people being denied a job or losing a job, not because of a recent involvement in crime, but because of a criminal record from long ago. We have known from many studies on recidivism that the risk of recidivism declines monotonically as the time since the last crime lapses, and recent research on redemption has empirically shown how long it takes for the recidivism risk to decline to a level that is sufficiently low ("redemption time"). The current study extended the previous redemption research by examining the robustness of estimates of redemption times, and addressing several important, policy-relevant aspects of redemption such as race and the crime type of concern to employers.

Our original data used in BN 2009 were limited to those with their first arrests that occurred in New York State in 1980. Examination of robustness of redemption-time estimates is important to enable those estimates to be used for possible policy implementation. The period between 1980 and 1990 is characterized by changes in the levels of arrest rates; thus, the estimates may be sensitive to the sampling years from which the arrest cohort is drawn. Similarly, considering that there is variation across states in terms of factors such as law enforcement policies and labor market conditions that might affect recidivism, it is possible that the estimates may be sensitive to the state from which the arrest cohort is drawn. The robustness with regard to sampling years and states was tested using NY data from three different sampling years and additional data from Florida and Illinois. The results of the comparison across sampling years provide evidence for reasonable convergence in hazards across sampling years and that the redemption time estimates are robust. The results regarding the across-state comparison, on the other hand, show somewhat slower convergence of hazards and larger variation in the redemption time estimates, but are still reasonably close.

In estimating redemption times across sampling years and across states, we used two benchmark probabilities (0.1 and 0.03) of incurring a second arrest. The higher benchmark (0.1) represents the probability of arrest at the redemption time in relation to the general population for the 1980 cohort, discussed in BN 2009, and the lower benchmark (0.03) represents the benchmark probability of arrest for the never arrested with a risk tolerance of 2%. Table 20 below presents the range of redemption times by the crime type of the prior record for the two benchmark probabilities. The estimates for violent offenders tends to be the largest, the estimates for property offenders tend to be the smallest, and the estimates for drug offenders are in between the other two.

Table 20. Range of redemption time estimates (years) based on the estimates across three sampling years and three states

	Thresholds (probability of a new arrest)	
C_1	.1	.03
Violent	4-7	11-15
Drugs	4	10-14
Property	3-4	8-11

Because of racial differences in arrest rates, employers' use of criminal background checking as a screening tool is of great concern to the EEOC. The arrest prevalence for blacks is more than four times higher than the arrest prevalence for whites. In contrast, the risk of rearrest for blacks is about twice the risk of rearrest for whites shortly after their first arrest, so that racial rearrest-risk ratio is about half the arrest-prevalence ratio. Furthermore, the rearrest-risk ratio declines as the length of time clean increases and approaches unity after about 15 years. It is important that employers recognize that the arrest prevalence difference does not provide a meaningful estimate of risks posed by white and black applicants with a criminal record, and after a long period of time clean, their risks become similar.

The EEOC has ruled that in order for employers to use criminal records to screen job applicants, they need to demonstrate that the criminal record is "job related." That suggests that employers would need to understand whether the type of prior crime is a meaningful indicator of the type of crime that is of most concern in the context of what the job entails. In order to address this issue, we use crime-switch matrices to examine the probabilities of having a second arrest for a particular crime type, given the type of crime for the first arrest. We further analyze crime-type-specific hazards and estimate redemption times for different crime types depending on which crime is of most concern to employers. The results show that in general the type of prior crime tends to be related to a higher risk of rearrest for the same crime. The results provide support for employers, who are often concerned about a particular type of crime, to evaluate the predictive value of the prior record.

While the current study moves forward the research on redemption in a significant way, some important next steps should still be pursued. The estimates of redemption shown in this report are based on the length of time since the *first* arrest or conviction. In this sense, we only address redemption for *first-time* offenders. Although such first-time offenders can be viewed as most deserving of redemption, it is possible to extend the concept of redemption to people with more than one prior criminal event. Employers also routinely receive applications from individuals with multiple arrests or convictions who have stayed clean a reasonable length of time. How do the redemption estimates vary with the number of prior crime events?

Research on recidivism of released prisoners informs us that the presence of prior incarceration increases the likelihood of recidivism (Beck and Shipley, 1997; Harer, 1994; Hoffman and Stone-Meierhoefer, 1979; Kitchener, Schmidt, and Glaser, 1977; Langan and Levin, 2002). In general, criminal history is identified as one of the most powerful predictors of recidivism (Gendreau, Little, and Goggin, 1996). In evaluating the effectiveness of after-prison reentry programs, Rosenfeld (2008) points out an important but often ignored distinction among released prisoners, comparing first-timers, those who were released from prison for the first time and veterans, those who have a prior incarceration experience. The first-timers and the veterans are different in that the veterans have a higher chance of recidivism than the first-timers. Ezell (2007) empirically shows that the increased number of adult arrest charges is associated with a higher risk of reoffending, and more importantly that the duration of time since the last arrest is associated with a reduction in the reoffending risk, with the number of charges being fixed. As with first-time arrestees, this suggests the possibility that a long arrest-free duration should compensate for the effect of a number of prior arrest charges.

Importantly, Bushway et al. (2011) address the relationship between the number of prior convictions and redemption time, and future research should address the redemption-time relationship between the types of prior crimes for a specific type of future crime of concern. We find that most arrestees from the 1980 cohort were not incarcerated as a result of their first crime because it was their first arrest as adults. Thus, it was not necessary to account for the length of incarceration time in estimating the hazard of a new arrest.[79] As we pursue the consideration of those with multiple prior arrests, it is more likely that they would be incarcerated for a reasonable length of time following their last arrest. One approach to examine the effect of prior criminal history on redemption times without the complications of time served is to focus on a prison release cohort, in particular, those who are released from prison for the first time. With additional funding from the NIJ, we are pursuing data of a first-time prison release cohort that can be linked to arrest-history data as well as data on recidivism.

6. Outreach

We are committed to the dissemination of our findings, and so have presented the results at various meetings and conferences targeting a wide range of audiences from academics to practitioners, and to policy makers. We presented our findings at the Defendant Offender Workforce Development Conference in April, 2010 and also at the Middle Atlantic States Correctional Association Annual Conference in June, both of which were attended by a wide range of practitioners in the fields of corrections and in the organizations that facilitate employment for people with criminal records. We also presented our results to the representatives of the NY Division of Criminal Justice Services (DCJS), which provided us the initial data and other NY State agencies (e.g., Department of Correctional Services, Labor, and Health), to whom the issue of redemption is of great interest. Our presentation was well received by the representatives who are increasingly interested in the use of criminal history records for the purpose of background checks.

[79] For the discussion about the prevalence of incarceration in our NY cohort, see Blumstein and Nakamura (2010).

We presented our findings in the Ohio Ex-Offender Reentry Coalition meeting in September, 2010. The meeting was selected and funded by the NIJ to serve as a forum to introduce criminal justice research directly to policy makers and practitioners. We also presented at a symposium "Undoing Mass Incarceration" at George Mason University in January, 2011. The symposium was organized by the Center for Advancing Correctional Excellence and co-sponsored by Prison Fellowship and U.S. Senator Jim Webb's Office. The presentations were well received by correctional scholars, policy makers, and practitioners. We also presented at a workshop organized by the Job Opportunities Task Force in November, 2010 in Baltimore, and at a seminar organized by Optimal Solutions Group in February, 2011 in College Park, MD. In all the venues, there was a great interest in the issue of redemption and the policy implications of our research.

We also presented our findings in the conference organized by the National Employment Law Project and the Community Legal Services, titled "Taking on the Challenges Facing Workers with Criminal Records" in April, 2011. The conference was attended by advocates and organizations representing those with criminal records struggling to find employment and also attended by researchers and policy makers including the chair of the EEOC. We also delivered a plenary address at a conference of the International Community Corrections Association in September, 2011 for the audience of mostly community corrections (probation, parole) professionals. We also presented our research to the NIJ Community Corrections Research Topical Working Group in November, which is attended by state correctional agency representatives. In December, we presented our research results at the Netter Symposium organized by Cornell University School of Industrial and Labor Relations. The conference was attended by a wide range of organizations that facilitate the reentry of prisoners into the workforce, researchers, and lawyers, some of whom represent individuals with criminal records, while others represent firms that consider applicants with criminal records. In January, 2012, the *New York Times* published our Op-Ed article on redemption, titled “Paying a Price, Long After the Crime”. The article attracted significant attention and was at one point on the list of the *Times* “most emailed” articles and was on the *Atlantic* magazine’s “Five Best Columns”. Many responses to our article came from those who have a stale record and are frustrated by the wall of employment refusals they have experienced. Their experiences clearly highlight the importance of redemption and the need to move our research forward.

In communicating our findings to stakeholders, including employers, advocates, and policy makers, it is important to emphasize that the findings about redemption time estimates should not interfere with reentry efforts to encourage employment. Employment is likely to be one of the key factors in successful reentry and thus it should be facilitated as soon as possible, especially for jobs that involve group work environments where employees can supervise each other and minimize risk. However, our finding that the recidivism risk is relatively high initially and declines over time is important for risk-sensitive job positions that involve vulnerable populations such as children and the elderly. It is also important to recognize that this project’s findings suggest the limited usefulness of criminal records, and are inconsistent with employers’ “forever rules”, a blanket policy to exclude those with criminal records, regardless of how old the records are.

Appendix A: References

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Appendix B: Additional Approach for Setting a Benchmark

Another approach is to use the risk of arrest for the general population of the same age as the benchmark, which is represented by age-crime curves (BN 2009).[80] Since we are interested in the C_2-specific benchmark arrest risk, we can construct the age-crime curves for each particular C_2.

Figure A compares the age-crime curve covering all crime types (except DUI) and the C_2-specific age-crime curves (for Violent and Property).[81] Clearly, the likelihood of arrest for violent or property offenses in the general population is much smaller than the likelihood of arrest for any crime. This has important implications for estimating redemption times because if the hazards were stable, lowering benchmarks for redemption would increase the length of time to redemption.

[80] The age-crime curve has age (*A*) on the horizontal axis and the age-specific arrest rate on the vertical axis. The value of the age–crime curve in year *t* after the first arrest of persons of A_1 in 1980 is given by the number of arrests of people of age ($A_1 + t$) divided by the population of that age in 1980. The sample cohort is from New York, so the age–crime curve as a comparison is also from New York. The number of arrests by age in New York is from the 1980 Uniform Crime Reports (National Consortium on Violence Research, n.d.), and the population of New York State is from the census (U.S. Census Bureau, 1996).

[81] The number of arrests reported in the Uniform Crime Reports is greater than the number of individuals arrested because an individual can have multiple arrests in a year. As a result, the age-crime curve that is based on the number of arrests is an overestimate of the probability of arrest for a member of the general population. In order to adjust for these redundant arrests, we first calculate the ratio of the number of arrestees to the number of arrests as a function of A_1 in 1980, from the data of the 1980 NY arrestee cohort. We then estimate the number of arrestees by multiplying the A_1-specific ratio by the number of arrests from the UCR. In general, the ratio is smaller for younger ages (for example, for $A_1 = 16$, the ratio = .80, while for $A_1 = 40$, the ratio = .97), which is consistent with the fact that younger ages are associated with higher hazards and higher offending frequency. By accounting for the redundant arrests, the correction lowers the age-crime curve by 8-13% for A_1 = 19-20. The age-crime curves used here are corrected for the redundant arrests.

Figure A. Age-crime curves for Any, Violent, Property

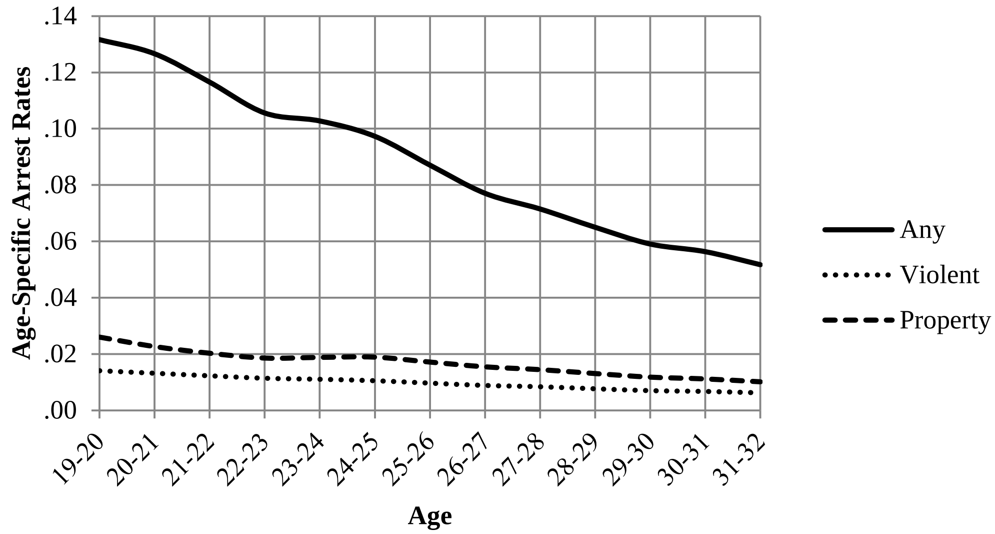

Table A shows the redemption time estimates for various C_1's for C_2 = Violent and for C_2 = Property for A_1 = 19-20 and 25-30. The redemption times are estimated as time points when the C_2-specific hazards are statistically "close enough" to the new benchmarks, the C_2-specific age-crime curves. The concept of "close enough" is invoked because the hazards tend to remain higher than C_2-specific age-crime curves. The determination of when the hazard is "close enough" to some benchmark involves the concept of risk tolerance, which is the additional risk of those with a prior record that employers can tolerate over the benchmark risk (i.e., arrest risk of the general population). In employment settings, the risk tolerance can be determined based on factors such as the risk sensitivity of the job position and qualifications of those with a prior record. The redemption times are estimated using the risk tolerance of .005 (more detailed discussion on risk tolerance can be found in BN 2009). We find that for C_2 = Property, the estimates for older and younger offenders are close, except for C_1 = Property, where the estimates are much larger for older offenders. This is attributable to the facts that: 1) the age-crime curve for the older offenders is much lower than that for the younger offenders, and 2) when $C_1 = C_2$ the hazards are similar for older and younger offenders. Because of the lower age-crime curves, although the redemption-time estimates are larger for older offenders, their probabilities of arrest at the redemption times are smaller. We also notice that for C_2 = Property, because the hazards for the different C_1's converge relatively early for A_1 = 19-20, the redemption times and the probability of arrest at the redemption times are similar across four different C_1's (the average redemption time is about 5 years and the average probability of arrest is about .02). For C_2 = Violent, older offenders have shorter redemption times except for those for C_1 = Violent, who have a much higher hazard than other C_1's, resulting in a longer redemption time.

Table A. Estimates of Redemption Times by C_1, A_1, and C_2 for C_2-specific age-crime curves (arrest probability at redemption times in brackets)

		A_1	
C_2	C_1	19-20	25-30
Violent	Violent	14.0 (.011)	15.9 (.008)
	Property	4.6 (.016)	3.4 (.011)
	Drugs	5.2 (.015)	3.8 (.011)
	Public Order	12.6 (.011)	10.3 (.010)
Property	Violent	6.1 (.022)	6.5 (.014)
	Property	5.2 (.024)	12.0 (.011)
	Drugs	4.8 (.024)	5.3 (.015)
	Public Order	4.2 (.024)	4.7 (.015)