Scarlet Letters and Recidivism: Does An Old Criminal Record Predict Future Offending?

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ABSTRACT

Research Summary: This research explores the issue of old prior records and their ability to predict future offending. In particular, we are interested in the question of whether, after a given period of time, the risk of recidivism for a person who has been arrested in the distant past is ever indistinguishable from that of a population of persons with no prior arrests. Two well-documented empirical facts guide our investigation: (1) individuals who have offended in the past are relatively more likely to offend in the future; and (2) the risk of recidivism declines as the time since the last criminal act increases. Using hazard rates and posterior distribution analysis, we find that immediately following an arrest, the knowledge of this prior record does significantly differentiate this population from a population of nonoffenders. However, these differences weaken dramatically and quickly over time so that a person who offended 6 or 7 years in the past looks very similar in regard to risk of new offending to a person who never offended at all.

Policy Implications: Individuals with official records of past offending behavior encounter a number of barriers when they try to obtain employment, acquire housing, meet certification requirements, access student loans, adopt children, or vote in elections. Even if a person's most recent offense occurred in the distant past, a criminal record can block access to opportunities. There are many reasons for such obstacles but they are at least partially premised on the concern that individuals with arrest records - even from the distant past - are more likely to offend in the future than persons with no criminal history. Our analysis bring into question the logic of such practices and suggests that after a given period of remaining crime free it may be prudent to wash away the brand of "offender" and open up more legitimate opportunities to this population.

Keywords: Collateral consequences, recidivism, desistance.

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INTRODUCTION

The commission of a criminal offense carries a multitude of consequences for the perpetrator. While the most well known and immediate include the chance for arrest, conviction and possible incarceration, there also exists an array of less well known collateral consequences. These additional consequences include loss of public office—and/or the right to run for public office--loss of the right to vote, loss of the right to carry a firearm, and restricted access to public housing and other government aid programs, just to name a few. In addition, once the label of "offender" or "felon" is affixed, a person assumes a life-long stigma that restricts or even prohibits a multitude of future employment opportunities. These civil restrictions persist long after the offender has "paid his/her debt to society" (Uggen, Manza, and Behrens, 2004).

While many question the inherent fairness of such civil restrictions, the practice of imposing civil consequences like those noted above has a long history dating at least as far back to the practice of "infamy" in ancient Greece under which an offender lost all rights to influence public affairs such as the right to attend public meetings, hold public offices and vote (Damaska, 1968; Cromwell et al, 2004). The Roman practice of "outlawry" took this notion even further denying the offender the rights to his family (e.g. his children could be declared orphans and his wife a widow), to all his possessions and placing the individual fully outside the protection of the law.

The imposition of such lasting social consequences after conviction is generally supported by an abundance of criminological research showing that people who have offended in the past are more likely to offend in the future than those who have not offended in the past (Wolfgang, Thornberry and Figlio, 1987; Blumstein, Cohen, Roth and Visher, 1986). Indeed, the most recent statistics from the U.S. Department of Justice indicate that over two-thirds of parole releasees commit a new offense or violate parole within two years of release (Langan and Levine, 2004). Civil restrictions are, therefore, seen not only as additional punishment but perhaps more importantly as a way of protecting the public from further harm (Buckler and Travis, 2003).

However, recidivism statistics such as those noted above are predominantly based on relatively short follow-up periods with most tracking offenders for 6 months to 2 years from initial offense or prison release. Thus, they do not provide us with any insight into the future outcomes of those ex-offenders who survive this relatively short follow-up period without a new criminal event. Also, they do not provide for a comparison of new criminal activity between this population of offenders and heretofore nonoffenders.

These omissions of prior research raise several pertinent and important considerations for the field. First, if an offender survives an immediate or short follow-up period without a new criminal event, does this imply continued success as a law-abiding citizen in the future? More specifically, if the ex-offender survives without a new offense for a given time period, does his/her risk of re-offending ever become similar or equal to the risk for someone who has never offended at all? If so, what then is the rationale for the continued imposition of civil disenfranchisement and other “invisible punishments” (Travis, 2002) on this population of now law-abiding citizens? These are the questions addressed by the current study.

LITERATURE REVIEW

The notion that past behavior is one of the best predictors of future behavior has been accepted as fact in a variety of fields. For example, in the field of education entrance to college depends on past academic performance in high school and on standardized tests to predict future success. In personal finance matters, creditors rely on an individual's past reliability in paying bills on time and meeting financial obligations to assign a credit score. This score is then used to determine future lending opportunities. Similarly, when applying for auto insurance one is almost always asked a question such as: "Have you had any traffic violations in the past 3 years?" The answer to this all-important question directly impacts the rate one is asked to pay for insurance.

The field of criminal justice has also relied heavily on this basic knowledge. For example, it is known that about 30 to 60% of juvenile delinquents go on to have at least one adult offense (McCord, 1978; Shannon, 1982; Farrington, 1987; Brame, Bushway, and Paternoster, 2003). Analysis of recidivism data in several cohorts reported by Blumstein et al. (1985) reveals that the majority of individuals with multiple past official records of offending accumulate new official records of offending in the future (see also, Greenberg 1991). Figure 1 illustrates this point with data from the 1958 Philadelphia birth cohort used in this study (where individuals are followed through age 26). Knowledge of an offender's prior record is, therefore, used as a general indicator of dangerousness and propensity to re-offend at all key decision-making points in the criminal justice process from the police decision to arrest, to the prosecutor's charging decision, to the final sentence handed down by the criminal court judge (Gottfredson and Gottfredson, 1985; Blumstein et al., 1986:75-76).

Insert Figure 1 About Here

An important counterweight to this finding, however, is that only about 5 to 10% of young offenders actually become “chronic” criminals (see e.g., Moffitt, 1993; Wolfgang, Figlio and Sellin, 1972; Shannon, 1982; Dunford and Elliott, 1984). This indicates that the majority of people with a criminal justice contact at some point early in life pose little or no risk of active, long-term criminal careers. The challenge then becomes how to distinguish between the one time or “temporary” offender from his/her persistently criminal counterpart.

Existing research suggests that the time lapsing between criminal events might be one key distinguishing factor between these two populations. For example, in an analysis of a sample of the original 1945 Philadelphia birth cohort, Raskin (1987) found the hazard rate for re-offending to decrease steadily with time since last incident. The hazard rate for a new police contact was the greatest during the first six months following a previous contact, after which time it continually decreased. In fact, during the last month of the study he found that none of the prior offenders who had “survived” to this point were rearrested. These findings lead Raskin to conclude that, “the longer an individual is able to survive without committing his next offense, the better his chances of desisting from crime” (p. 63).

There is considerable ambiguity about why individuals who have refrained from offending for an extended period of time tend to recidivate at lower rates than individuals who last offended recently. One possibility is that the actual experience of offending abstinence has a causal effect on risk of re-offending; the more a life is lived crime-free, the more one comes to see the benefits of desistance. Another possibility is that individuals with a high risk of recidivism tend to recidivate quickly while others who sincerely try to avoid new offenses tend to dominate the population of lower-risk individuals. Regardless of the reason, however, it is clear that individuals who have offended in the distant past appear less likely to recidivate than individuals who have offended in the recent past.

Classic volumes on recidivism by Maltz (1984) and Schmidt and Witte (1988) are especially emphatic in pointing out that parametric models of time to the next recidivism event should be chosen with typical features of recidivism data in mind, the most prominent of which is a highly skewed time-to-recidivism distribution. For example, Schmidt and Witte (1988) followed two cohorts of North Carolina prison releasees to estimate the percentage of released inmates who return to prison. Their analysis shows that the percentage of inmates returning to prison peaked before those inmates had been in the community for ten months. At the twenty-month mark, the percentage dropped to half of the peak level. By the 40-month mark, the estimated percentage returning to prison was half of its 20-month level. These results imply that risk of recidivism for a cohort of offenders returning to the community peaks fairly quickly and then diminishes considerably with the passage of time. While we are aware of many studies that exhibit this same time-to-recidivism pattern (see e.g., Carr-Hill & Carr-Hill, 1972; Greenberg, 1978; Harris and Moitra, 1978; Harris et al., 1981; Maltz, 1984; Schmidt and Witte, 1988; Visher et al., 1991; Lattimore and Baker, 1992), we are not aware of any studies finding patterns that vary greatly from the Schmidt and Witte benchmark. In addition, most of the studies of which we are aware indicate that the percentage of the population recidivating begins to approach zero after several years of follow-up (see e.g., Schmidt and Witte, 1988:50).

Figure 2 summarizes the five-year time-to-recidivism distribution for adult male offenders arrested for the first time between ages 18 and 20 in the 1958 Philadelphia cohort data examined later in this paper. Over the five-year follow-up period a total of 47.4% of these young adult arrestees were re-arrested. But, as Figure 2 indicates, the risk of re-arrest is not evenly distributed over the five-year follow-up period. The hazard rate plotted in Figure 2 represents the probability that an individual who successfully makes it to a particular time point in the follow-up period is arrested at that time point. This analysis indicates that time-to-recidivism patterns in the Philadelphia data are broadly congruent with those in other recidivism studies.

Insert Figure 2 About Here

We are, therefore, led to the basis for a useful policy implication: individuals who have official records of past offending are relatively more likely to offend in the future but individuals who have managed to refrain from offending for a long period of time - even though they too offended in the past - consistently exhibit much lower risk of future offending than individuals who have offended in the recent past. This implies that the length of time that has passed since the last record of offending should accompany information about prior offending records. However, this information cannot be properly interpreted in a vacuum. Even individuals whose last offense record occurred years ago will - as a group - generally exhibit some non-zero risk of re-offending in the future. A logical point of comparison is needed. One possible point of comparison is the likelihood that an individual who has no record will offend can serve as a comparative benchmark. For example, an individual whose last offense record was seven years ago may have much lower objective risk of new offenses now than six years ago. But such an analysis cannot, on its own, tell us anything about whether that person presents a substantially greater risk to the community than someone who has no record of offending.

In this paper, we use data from the Second Philadelphia Birth Cohort Study to examine recidivism patterns for people who have a record of past offending in comparison to onset patterns for people who have no record of past offending. In Section 2, we describe the data while Section 3 presents our analysis results. We offer some concluding thoughts and priorities for future research in Section 4.

DATA DESCRIPTION

All males born in the city of Philadelphia in 1958 and who resided in the city between the ages of 10 and 17 years old were included in the study (N = 13,160). The dates of juvenile police contacts for criminal events were collected on all subjects through age 17. After age 17, arrest dates were collected on all subjects through age 26. Our reliance on arrest data implies that our analysis will be less relevant for the type of collateral consequences that are explicitly tied to convictions, such as voter disenfranchisement and more relevant in areas, like employment, where decision makers have more discretion about how to evaluate a criminal history record. The data also include information about the offense that led to each contact or arrest. A potential weakness of our analysis is that some individuals may have moved out of the city after age 17. Moreover, some arrests and contacts may have occurred outside the jurisdictional limits of Philadelphia; these events are not recorded in the database. Finally, the results are unadjusted for periods of incarceration. The likely consequence of this problem is that our estimated risks of re-arrest among those arrested in the past are too low. However, this data has the advantage of being very similar to the data used by employers to conduct background checks which tend to come from local courts.

We rely on two different but complementary analytic frameworks to study the Philadelphia data. First, we use the concept of a hazard rate. Since our data are arrayed in discrete time, the hazard rate definition used in this paper is quite straightforward. For any given group, G, comprised of $i = 1, 2, ..., N$ individuals observed at discrete time points, $t = 1, 2, ... T$, we estimate the hazard rate by:

$$h\left(t \mid G\right) = \frac{\#\ \text{of Individuals in Group } G \text{ Arrested at Time } t}{\#\ \text{of Individuals in Group } G \text{ Avoiding Arrest Prior to Time } t}$$

This means that individuals who are arrested at time t - 1 are no longer considered to be at risk for experiencing a new arrest at time t. That is, once they are rearrested they are removed from the at-risk population. The hazard rate as defined above is particularly useful for policy purposes because it represents the case with which a decision maker is often faced. Someone with a criminal record at some point in the past who has avoided new criminal activities for a particular period of time seeks a favorable decision. In this situation, an estimate of the hazard rate would provide helpful information above and beyond simply knowing that an individual had offended at some point in the past. Our hazard rate analysis divides the adult follow-up period into four-month periods through age 26.

Next we calculate the conditional probability that an individual is arrested during the two year period of ages 25 and 26. We denote this probability by $p(a|G)$ which implies that we condition our estimate of the probability on membership in a particular group G:

$$p\left(a \mid G\right) = \frac{\text{\# of Individuals in Group } G \text{ Arrested at } A\text{ge 25 - 26}}{\text{\# of Individuals in Group } G}$$

Our objective here is to determine whether different groups of individuals can be distinguished by their probability of experiencing new arrests during the 25-26 age period.

ANALYSIS RESULTS

In this section, we present several analyses based on records of juvenile police contacts for criminal offenses and adult arrests in the Philadelphia data. As noted above, we first estimate the probability that an arrest occurs at a particular time, conditional on no arrest having occurred prior to that time (i.e., the hazard rate). We then estimate the probability that an arrest occurs during the age 25-26 time period for various groups of past offenders and non-offenders. Combined these analysis provide both a parametric and nonparametric examination of the effects of time since last arrest on the risk of future offending.

HAZARD RATE ANALYSIS

Although there are many ways of dividing a population like the Philadelphia cohort, several are of particular interest to us and we will be referring to them throughout our presentation of the results. Table 1 presents a summary of three different groups used in our hazard rate analysis. Each of these groups can be described in terms of their age-18 arrest records. Our analysis will compare the post-age-18 arrest experiences of the first two groups; in a supplementary analysis, we will also study the post-age-18 arrest experiences of the violent arrestee group.

Insert Table 1 About Here

Our hazard rate analysis divides the entire period from age 19 to 26 into 24 different four-month periods. At the beginning of each of those time periods, we identify all individuals who have not yet been arrested and the subset of those individuals who are arrested during the time period. The hazard rate at any of these 24 time points is obtained by dividing the latter number by the former. Figure 3 presents the arrest hazard rate from age 19 through age 26 for those individuals who were not arrested at all when they were age 18. The hazard rate for this group declines in nearly monotonic fashion over this eight-year period. At age 19, for example, the hazard rate is approximately 1.5% - which implies that about 1.5% of individuals at risk to be arrested for the first time since turning age 19 actually are arrested. By age 25, however, the hazard rate has dropped to less than one-half of one percent.

Insert Figure 3 About Here

Despite the impressive decreasing trend in the hazard rate from Figure 3, the actual hazards are all very small. This point is best illustrated by comparing the hazard rate of these nonoffenders to those of the age 18 offenders (N = 1,009). Figure 4 presents this comparison. The analysis indicates that the hazard rate for the age-18 offenders is much higher than the age-18 nonoffender hazard rate during the early years of our follow-up period. Like the nonoffenders, the hazard rate for the age-18 offenders declines throughout the early twenties. However, unlike the nonoffenders the hazard rate decreases in a much more dramatic fashion so that by age 24 the hazard rate for the age-18 offenders drops below 2%. Although this hazard rate is still higher than the comparable hazard rate for the age-18 nonoffenders, the magnitude of the difference is substantively quite small.

Insert Figure 4 About Here

To explore the possibility that violent and non-violent age-18 offenders have different underlying hazard rate patterns, we created two groups: (1) individuals with at least one violent arrest at age 18 (N = 375); and (2) individuals with at least one arrest but no arrests for violence at age 18 (N = 634). As Figure 5 indicates, the hazard rate for the age-18 violent offenders tends to be somewhat higher than for the age-18 offender group. On the whole, however, they are hard to distinguish statistically.

Insert Figure 5 About Here

POSTERIOR DISTRIBUTION ANALSYIS

Next, we turn our attention to a comparison of age 25-26 arrest probabilities for several different groups of individuals. Table 2 provides a description of each of the groups used for this analysis. The first group includes individuals who have no record of any juvenile criminal contacts or adult arrests prior to age 25. This group of "clean record" individuals represents a logical point of comparison to groups with some type of juvenile police contact or adult arrest record. Another reasonable comparison group includes individuals in the first group as well as individuals who have a record of at least one juvenile contact for a criminal offense but no adult arrests through age 24. This group is relevant for policies excluding consideration of juvenile offense records.

Insert Table 2 About Here

We also consider a variety of groups defined by the type and last occurrence of officially recorded criminal activity. The first and largest of these groups is comprised of individuals with at least one juvenile police contact for a criminal offense but no adult arrests through age 24 (N = 2,197). In addition, we study the subset of this group with juvenile contacts for non-violent offenses only (N = 1,517). Next, we turn our attention to individuals who were arrested at least once at age 18 but had no new arrests through age 24 (N = 432). A subset of this group including those who were arrested exclusively for non-violent offenses at age 18 was also examined (N = 257). Finally, we identified individuals who were - prior to age 25 - last arrested at ages 19 (N = 341), 20 (N = 292), 21 (N = 361), 22 (N = 403), 23 (N = 497), and 24 (N = 594).

Our objective for each of these groups is to estimate the probability of an arrest during the two-year period of ages 25 and 26. This analysis framework maps onto the following policy problem: a 25-year old individual approaches a decision maker and seeks a favorable decision. The individual has an official record of some type (i.e., a juvenile record only, or an arrest at age 18). The question is whether the estimated probability of an arrest at age 25-26 ($p(a|G)$ as described in Section 2) differs between that individual compared to someone with no record at all. To develop inferences about the probability of an arrest at age 25 or 26, we calculate the full posterior probability distribution of this parameter for each of the groups described above. The posterior distribution is given by:

$$p\left(a \mid G\right) = \pi \times \binom{N_G}{r_G} p_j^{r_G} \left(1 - p_j\right)^{N_G - r_G}$$

where π represents our prior uninformed belief about the magnitude of *p*(*a*|*G*) which we assume to be identical for each value of *p*(*a*|*G*) between 0.0001 and 0.9999 (i.e., $\pi = \frac{1}{9999}$). Next, we allow *j* to index the binomial probability from 0.0001 to 0.9999; this allows us to calculate the full posterior probability distribution of *p*(*a*|*G*) conditional on N_G individuals in group *G* where a subset of the individuals in that group, r_G, are arrested at ages 25 or 26. With an uninformed or flat prior distribution (π), the value of p_j that maximizes the posterior probability of *p*(*a*|*G*) is simply $\frac{r_G}{N_G}$. But, as Table 2 indicates, the proportion of individuals arrested at age 25-26 is less than 0.08 for six of the groups in the analysis. In cases where p(a|G) lies close to the boundary of the parameter space (i.e., in this case, 0), standard confidence interval calculations can yield negative numbers at various confidence limits). Figure 6 displays the full posterior probability distribution for *p*(*a*|*G*) for these five different groups of individuals: those with no record at all; those with juvenile contacts only; and those whose last arrest occurred at ages 18, 19, and 20, respectively.

Insert Figure 6 About Here

The most salient feature of these distributions is the amount of separation between those with and without offending records and their close proximity to zero (i.e., the probability of an arrest at age 25-26 is quite low regardless of the group to which one belongs). Figure 7 summarizes the analysis results for all of the groups including the maximum posterior estimates, the posterior medians (i.e., the 50th percentile of the posterior distribution), and the 95% confidence limits (2.5th and 97.5th percentiles). Based on this information, we conclude that individuals with no record have a statistically lower risk of arrest at ages 25-26 than all of the other groups. We also conclude that individuals last arrested in the few years leading up to age 25 are much more likely to be arrested than individuals who were last contacted as juveniles or arrested as 18-year-olds. In other words, the groups included here represent a continuum of risk where those with no record at all have the lowest risk and those with recent records have much higher risk. Individuals in the middle - such as those who were last arrested at age 18 - occupy a position on the continuum that is much closer to the no-record group than the recent-record group.

Insert Figure 7 About Here

DISCUSSION AND CONCLUSIONS

We began our study with the basic knowledge that a person who has offended in the past has been found to have a high probability of future offending. We then further specify this notion by adding information gained from prior recidivism studies, which show the risk of recidivism to be highest in the time period immediately following arrest or release from custody and thereafter, to decrease dramatically. This marked and consistent decrease in the risk of future criminal activity then begged the question as to whether this risk ever becomes so small as to be indistinguishable from the risk of persons with no prior offending record. If so, we implied that current social practices of continued civil and social consequences of arrest and conviction may be ill informed.

Our answer to this question based on the current analysis of a cohort of young males from Philadelphia is two fold. First, statistically, we must conclude that persons with a prior police contact or arrest do not, at any time in the given follow-up period, become completely indistinguishable from those without a prior contact in regards to risk of offending. In Figure 4 we see that while the hazard rate for persons with a prior offense rapidly approaches the lower hazard rate of persons without a prior record, at five-years follow up, the two hazard rates are still separated by over 1% point: a difference that achieves statistical significance in this population. Using the alternative posterior distribution analysis to examine probability of arrest at ages 25 and 26 we again find that there is a statistically significant difference between those who have never been arrested and those who first and last arrest occurred at age 18.

Second, the difference is substantively small in magnitude and decreases with time since last criminal event. That is, after some period of time has passed, the risk of a new criminal event among a population of nonoffenders and a population of prior offenders becomes quite similar.

Third, the substantive size of the difference depends on the length of the reference period. In the hazard analysis, we used an exposure period of 4 months, and found a difference in the probability of an arrest between those with no records and those with an arrest at age 18 is about one percentage point (2% vs. 1%) at age 26. When we use the entire two year period of ages 25 and 26, the difference is almost 6 percentage points (7.2% vs, 1.3%). Although some of this difference can be explained by the fact that the hazard is continuing to decline somewhat rapidly as the individuals age, the main reason for the difference is that the non-offenders have an arrest probability that is close to zero.

As we watch the offenders for longer periods of time, we expect that they will acquire disproportionately higher numbers of arrests than will the nonoffenders.

Suppose for example that we have two groups, Group A with a starting probability of being arrested in the next month of .004 and Group B with the probability of being arrested in the next month of .01. At first glance, this does not seem like a large difference. However, let us consider what happens if we expand our time horizons (assuming a continued declining arrest rate for both populations). After 6 months about 2% of Group A will have an arrest as compared to 7% of Group B. After 1 year, about 3.5% of Group A will have an arrest as compared to 12% of Group B. Moreover, this cumulative difference in arrests will continue to increase until such time, if ever, that the two hazards completely converge—a feat that was not observed within the 7-year time-frame of this particular analysis.

This empirical pattern suggests that the answer to the policy questions concerning the level of elevated risk that is acceptable will depend in part on the decision maker's time horizon. An employer in an industry with high turnover will rationally expect to have relatively short term contact with the employee, and might therefore be more willing to tolerate the risk than an employer looking to hire individuals for longer time periods. In fact, the observed pattern of employer willingness to hire ex-offenders is consistent with this idea (Holzer et al. forthcoming).

There are of course other contextual factors that need to be taken into account when making a decision about how much risk to tolerate. Some include the ability to monitor the situation, the amount of potential harm that can be inflicted by the individual, and the alternatives. Consider the decision to adopt. There are many applicants, the time horizon is long, the ability to monitor is limited and the ability to harm is great. In this context, it is at least understandable why some adoption agencies are not willing to place children with ex-offenders regardless of the period of time since the last arrest. On the other hand, consider an urban construction firm. These firms often have a short job queue, anticipate a great deal of turnover, have much direct supervision and employees have little opportunity to inflict harm. It is not surprising that this type of firm might be willing to hire an ex-offender (Holzer et al. forthcoming).

We must also note that these findings are but a first look at this important question. Our analyses are limited to one cohort of individuals representing one location during one time period. To further understand patterns of desistance, we encourage further inquiry into this issue. Areas for future research include the examination of alternate populations from other locations and other time periods. We would also encourage a more detailed examination of patterns of desistance as they relate to type of prior offense and demographic characteristics of the population. For example, research suggests that certain statuses such as "being employed" and "being married" promote desistance (Sampson and Laub, 1993). We would also encourage studies designed to examine longer follow-up periods as our analyses clearly reveal a continued converging trend over time in the risk of new offending for non-offenders and one-time offenders. Our analysis is at best a first step towards creating the necessary information for informed discussion about the relative risks of offending presented by individuals with fading scarlet letters.

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Table 1. Groups of Individuals Used In Hazard Rate Analysis

Group Description	Number of Cases	Percent of Population
Exactly Zero Arrests at Age 18	12,151	92.3
At Least One Arrest at Age 18	1,009	7.7
At Least One Arrest for a Violent Crime at Age 18	375	2.8
At Least One Arrest at Age 18 But No Violence	634	4.8

Note: Violent Offenses include homicide/non-negligent manslaughter, rape, robbery, aggravated assault, and simple assault.

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Table 2. Conditional Posterior Probability of Arrest at Age 25-26

Group	N=	Proportion Offending at Age 25-26	Median of Distribution	Lower 95% Limit	Upper 95% Limit
No Record	8,043	0.0133	0.0134	0.0110	0.0160
No Record + Juvenile Contacts Only	10,240	0.0204	0.0204	0.0178	0.0233
Juvenile Contacts Only	2,197	0.0464	0.0467	0.0384	0.0560
Juvenile Non-VO Contacts Only	1,517	0.0435	0.0439	0.0343	0.0549
Last Arrested at Age 18	432	0.0718	0.0730	0.0511	0.1001
Last Arrested at Age 18 (No VO Record)	257	0.0623	0.0645	0.0388	0.0987
Last Arrested at Age 19	341	0.1085	0.1100	0.0798	0.1460
Last Arrested at Age 20	292	0.0890	0.0909	0.1091	0.1273
Last Arrested at Age 21	361	0.1413	0.1425	0.1091	0.1810
Last Arrested at Age 22	403	0.1861	0.1871	0.1511	0.2270
Last Arrested at Age 23	497	0.1871	0.1879	0.1553	0.2238
Last Arrested at Age 24	594	0.2963	0.2967	0.2609	0.3342

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Figure 1: Risk of New Offenses By Number of Prior Offenses
(1958 Philadelphia Birth Cohort Males, N = 13,160)

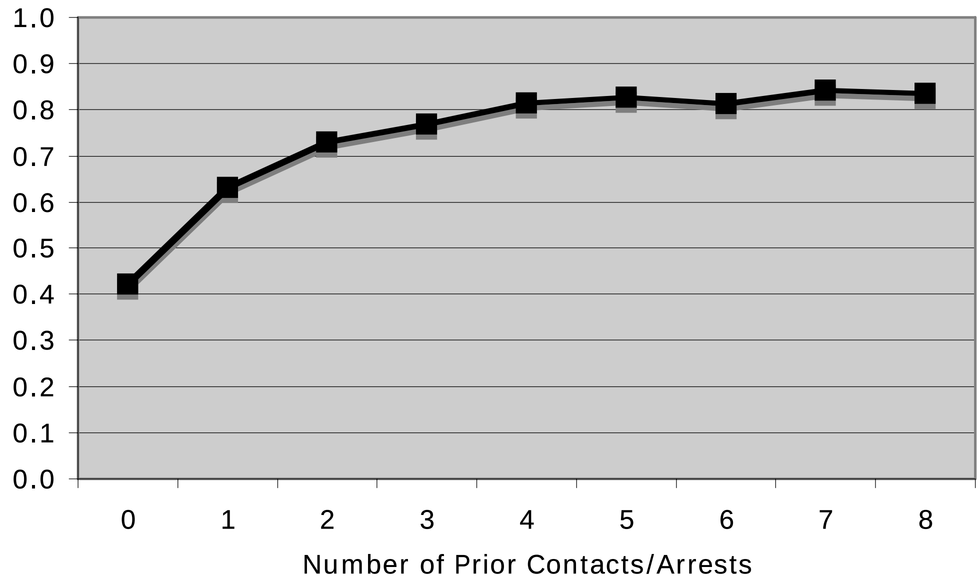

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Figure 2: 5-Year Arrest Recidivism Hazard Rate Among Offenders Arrested for the First Time at Ages 18-20 (N =805)

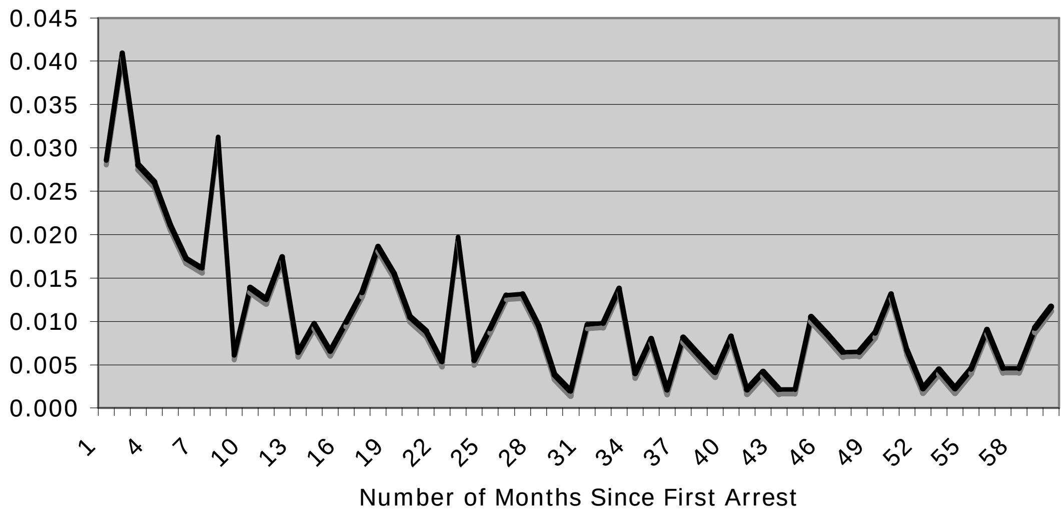

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Figure 3. Arrest Hazard Rate by Age (G_0, Age 18

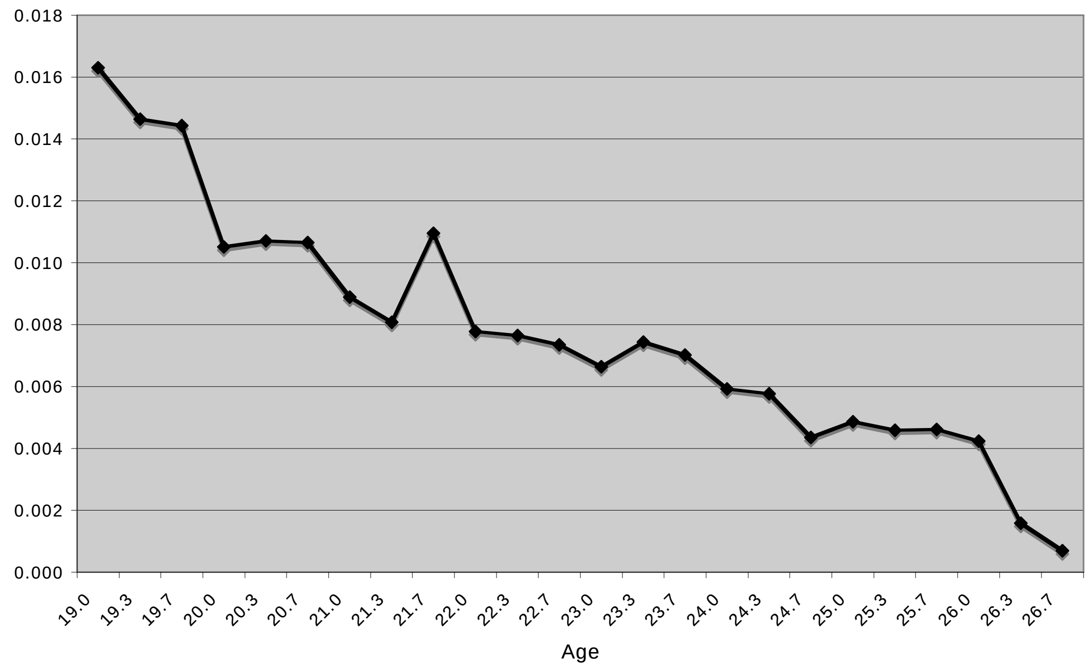

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Figure 4. Arrest Hazard Rate by Age

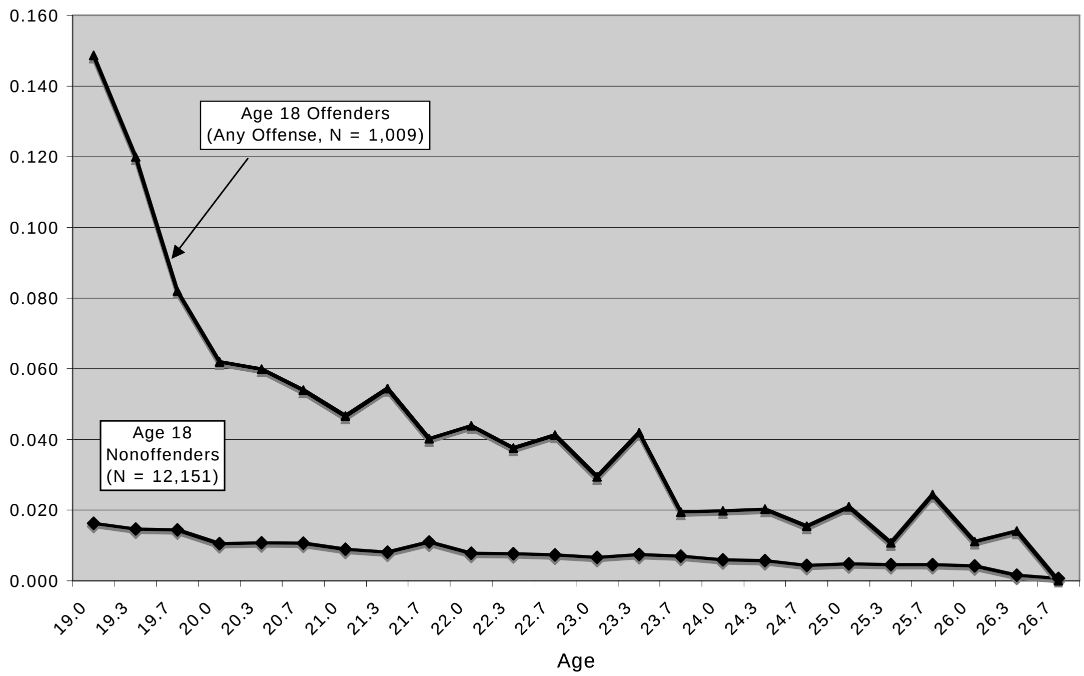

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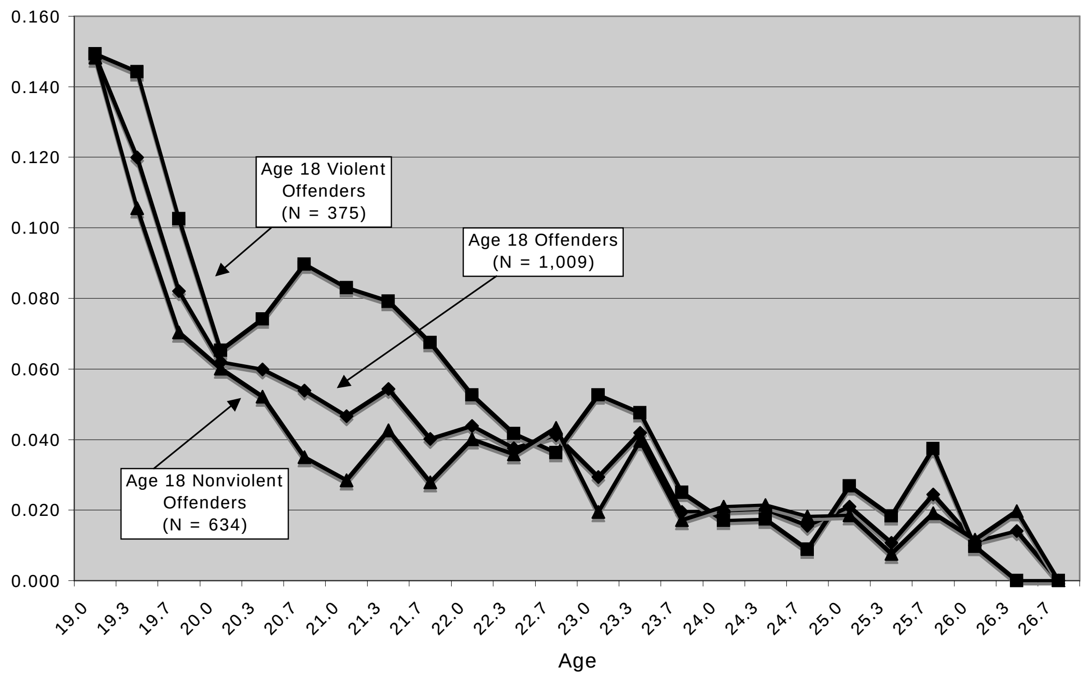
Figure 5. Arrest Hazard Rate by Age Among Age-18 Offenders (N = 1,009)



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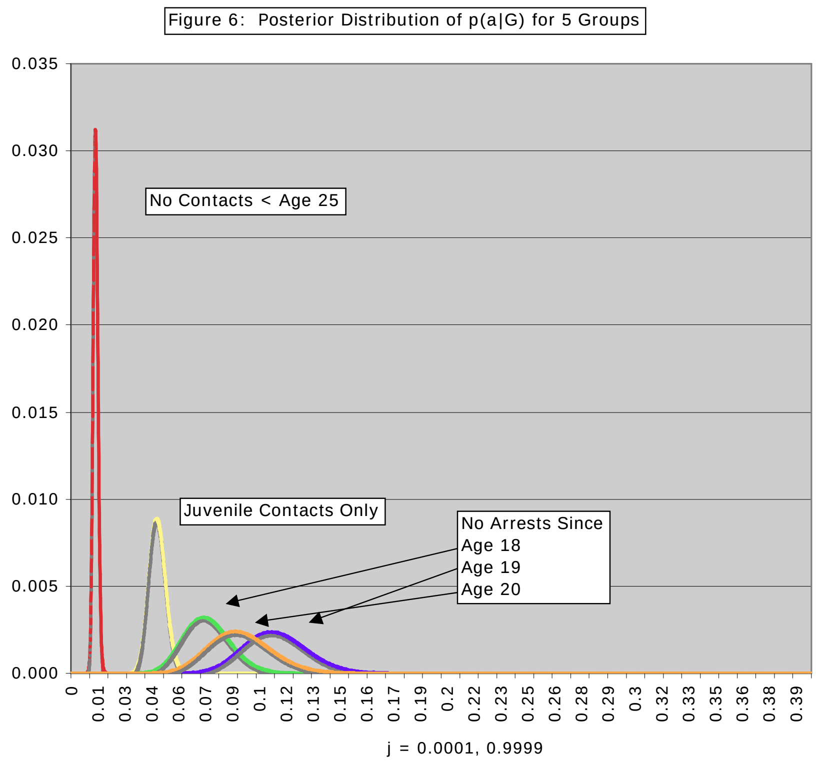
Figure 6: Posterior Distribution of p(a|G) for 5 Groups
No Contacts < Age 25
Juvenile Contacts Only
No Arrests Since
Age 18
Age 19
Age 20
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
j = 0.0001, 0.9999

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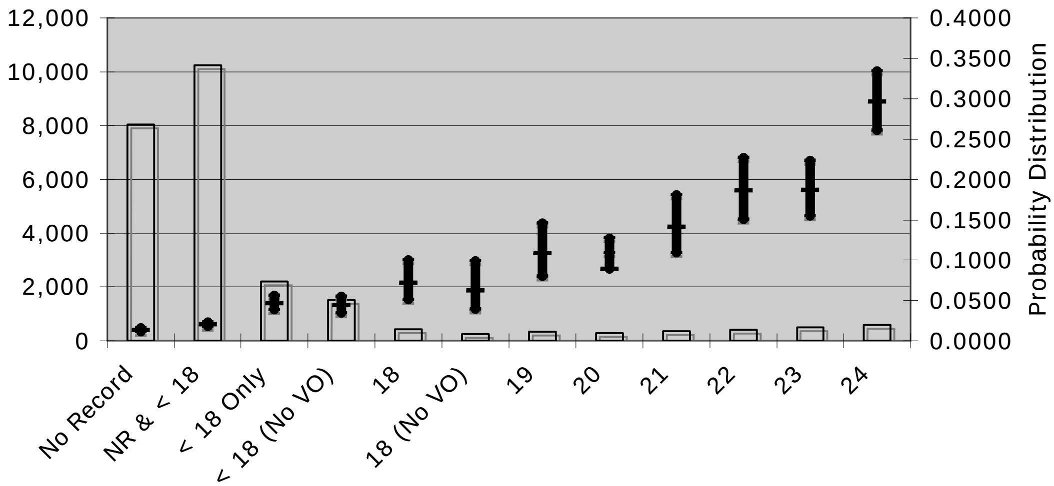
Figure 7. Probability of Arrest at Age 25-26



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