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ABSTRACT

A maximum-likelihood method to estimate the average rate at which individuals terminate criminal activity is introduced. The method separates the influences of criminal career termination from frequency of offending in follow-up arrest information for a sample of offenders. The method also incorporates an accelerated failure time model to detect the influence of offender attributes on the termination rate.

A sample of 20,117 adult males arrested for a serious offense in the Detroit Michigan SMSA between January 1974 and December 1977 is analyzed. The estimated overall average termination rate from serious offending is 14% per year, which corresponds to an average career length of 7 years. Higher termination rates (and shorter offending careers) are exhibited by white than black offenders and by those arrested outside rather than inside the central city area of the SMSA. Additionally, among offenders arrested outside the city area, a higher termination rate is estimated for older than younger offenders, and by black offenders with prior arrests compared to first-time offenders.

I. INTRODUCTION

The National Research Council's Panel on Research on Criminal Careers characterizes criminal behavior along four key dimensions: 1) those who participate in criminal activity, 2) the frequency of offending while criminally active, 3) the seriousness of offenses committed, and 4) the length of time an offender is criminally active.[1] This characterization provides an analytical basis for planning crime related services: What will the demand for prison space be in 10 years? What is the incapacitative effect of incarceration? What types of offenders have the highest frequency of offending and are they also the most persistent?

The length of a criminal career is particularly difficult to measure since one cannot directly observe the date when an offender begins criminal activity, and one is never certain (short of death) if the career is ended. Observable arrests are usually the only evidence of an active career, and career termination is inferred from a lack of arrests over an extended period of time.

For a group of offenders, the average length of a criminal career corresponds to an average rate at which offenders terminate criminal activity. For instance, if 20% of all offenders terminate criminal activity each year, then the average criminal career

[1]Blumstein, Cohen, Roth and Visher, 1986, pp. 1-5.

length for these offenders is 5 years.[2]

Prior Research on Recidivism

Recidivism is a widely-used, traditional follow-up measure of individual offending. Criminal recidivism is defined as the future recurrence of criminal behavior by previously identified offenders. Maltz (1984) characterizes recidivism during some finite follow-up period as a two component process, the probability that an individual offender will eventually recidivate, γ, and the distribution of recidivism times for those who do recidivate, $\phi(t)$. Recidivism is alternatively defined in terms of the subsequent commission, arrest, conviction, or incarceration for a criminal act.[3]

The recidivism model parameters (γ,Φ) are directly observable from follow-up data of offender criminal records. However, these parameters are not direct indicators of the distinct offender behavioral characteristics that comprise the various aspects of individual criminal careers. For a group of arrestees, the proportion of offenders who do recidivate, γ, (whether defined as

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[2]This situation corresponds to a binomial distribution with a termination probability of p=.2 per year. The mean of a binomial distribution is 1/p or in this case 5 years.

[3]Of course, the rate of recidivism will vary with the definition that is used; the further the penetration into the criminal justice system that is required, the lower the recidivism rate.

criminal offense, arrest, conviction or incarceration) confounds the frequency rate at which recidivist events occur and the likelihood of remaining criminally active. Only those offenders who remain active long enough to incur a recidivist event will be counted among eventual recidivists. Thus γ is a function of the rate at which offenders terminate, and the rate at which recidivist events occurs. Likewise, the rate parameter for times to recidivism, Φ, also confounds these two dimensions of criminal behavior. Times to recidivism will be short for high frequency offenders who tend to recidivate soon after release but they will also be short for offenders who are highly prone to terminating criminal activity, since these offenders must either recidivate soon or not at all.

A number of studies have explored the covariates of recidivism. Schmidt and Witte (1989), using recidivism models similar to Maltz's, studied criminal offenders released from North Carolina prisons between July 1977 and June 1978, and between July 1979 and June 1980. The recidivism parameters were allowed to vary with offender attributes in order to detect covariates of recidivism. They found that the offenders more likely to return to prison and to return sooner were younger black males with many prior incarcerations, who had drug or alcohol addictions, and whose prior incarceration was lengthy and for a property offense.

Beck and Shipley (1989) analyzed recidivism of over 16,000 state prisoners released during 1983. They report that 62.5% of these offenders were re-arrested for a felony or serious misdemeanor within 3 years of release. Higher recidivism rates (proportion of offenders re-arrested) were exhibited by males, blacks, high school dropouts, those who were younger at release, had more prior adult arrests, were currently incarcerated for property offenses, and releasees who were younger when first arrested.

These results on the relationship of prior record, age at release, and offense type to recidivism mirror similar findings previously reported in studies of other inmates (e.g., Hoffman and Beck, 1980; Greenwood, 1982; Rhodes et. al. 1983). Because recidivism is related to termination, these covariates of recidivism represent natural candidates as offender attributes that are related to termination rates.

Prior Research on Termination Rates

While the research literature on participation, frequency, and seriousness of criminal activity is quite large[4], relatively few analyses have examined criminal career length or termination rates. This paucity of research reflects the difficulties inherent in trying to estimate with any precision the date when an individual actually terminates criminal activity.

One method of estimating the termination rate within a

[4]Appendices A and B of Blumstein, et. al., 1986, contain an extensive review of this literature.

population is the life-table approach which uses cross-sectional data on the age distribution of individuals arrested in a given year to infer the age-specific termination rate, much as actuarial estimates of death rates rely on the age distribution of a population.[5] Blumstein, Cohen, and Hsieh (1982) used life-table techniques to estimate the termination rates for adult arrestees in Washington, D.C., for the years 1970 through 1976 (each year was analyzed separately). Figure 1 shows the distribution of arrestees for criterion offenses[6] by age for 1973 reported by Blumstein et al. This raw count of arrestees by age was adjusted for the following:

- variations in the size of the base population at each age,
- offenders' age at the start of adult criminal activity,
- variations in participation and termination rates over time, and
- variations in the frequency of arrest across age.

Once these various other factors that might influence the age distribution of arrestees independently of career termination were accounted for, the remaining changes in the size of the adjusted

[5]This approach for estimating the criminal career termination rate was first suggested by Shinnar and Shinnar (1975).

[6]The criterion offenses include homicide, forcible rape, aggravated assault, robbery, burglary and auto theft. The FBI index offenses of larceny and arson (which was not added to the index offenses until 1979) are excluded from the criterion offenses.

population by age, and particularly the decline in the number of arrestees with age, imply age-specific termination rates.

Blumstein et. al. reported that the variation with age of the termination rate is characterized by three distinct periods: 1) the 18-29 year-old "break-in" period when offenders terminate criminal activity at high rates early in their careers, 2) the 30-39 year-old "more enduring" period in which few offenders terminate, and 3) the over 40 "burn-out" period during which offenders terminate criminal activity at an increasing rate. In the break-in and burn-out periods, expected residual adult careers in criterion offenses are 6 to 7 years, while offenders in their thirties average 10 years of remaining criminal activity.

In further analyses, Blumstein et. al. also found that termination rates vary by crime type. Adult criminal offending in serious violent crimes (murder, rape, or aggravated assault) tends to last longer and have lower termination rate, while adult careers in property offenses (burglary, auto-theft or robbery[7]) are on average shorter.

In contrast to the life-table approach, several more recent studies have used maximum likelihood techniques to estimate the termination rate. Barnett, Blumstein, and Farrington (1987)

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[7]Robbery can be viewed as both a violent and a property offense. To the victim robbery is violent since the offender threatens physical harm. However, from the offender's perspective, robbery is also a property crime since it is committed in order to obtain money. Blumstein et. al. found that the termination rate for robbery resembled that of property offenses more than violent offenses.

modelled the criminal activity of a sample of London males from the age of 10 to 24.[8] Their model consisted of two groups of offenders: "Frequents" who had a higher arrest rate μ_1 and a probability P_1 of terminating their criminal career following each conviction, and "Occasionals" with a lower arrest rate μ_2 and a probability P_2 of terminating. They found that the average career length for each group of offenders is between 7 and 9 years.

Barnett, Blumstein and Farrington (1988) tested the predictive value of this model on additional follow-up data for the same offenders between the ages of 25 to 30. Based on the conviction data for ages 10 to 24, they were able to accurately predict the number of offenders who would be re-convicted during ages 25 to 30, the total number of reconvictions during this follow-up, and the average time interval between reconvictions during this follow-up.

Ahn (1986) modelled the criminal careers of adult arrestees in Detroit and Southern Michigan. The primary focus of his analysis is using hierarchical models to estimate the heterogeneity in the rate at which active offenders are re-arrested. However, as part of that analysis, he also estimated the overall termination rate during a limited 18 month follow-up period. Under the assumption that career lengths are exponentially distributed, the termination rate was estimated as .09 per year, which corresponds

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[8]A total of 82 out of the 411 youths studied were convicted of one or more criminal offenses.

to an average career length of 11 years.[9]

Focus of this Study

The previous analyses of termination rates have generally ignored variations across types of offenders and focused on estimating overall average termination rates. The present study introduces a maximum-likelihood technique for estimating the termination rate and explores its variation across selected offender attributes.

The data analyzed in this study include official adult arrest records from the Detroit SMSA.[10] Each offender record is partitioned between an initial and follow-up period. The initial or prior record period is used to establish offender attributes. In this study, only those attributes identifiable from an official criminal record (or rap sheet) are explored. Maximum likelihood techniques are then applied to the follow-up information to estimate the termination rate as a function of offender attributes.

This work expands upon the maximum likelihood analyses of Ahn (1986) and Barnett, Blumstein and Farrington (1988) by focusing on

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[9]The mean of an exponential distributions is 1/rate and in this cases 1/.09 = 11 years.

[10]The data for both this study and Ahn (1986) were drawn from computerized criminal history files maintained by the Federal Bureau of Investigation. The data in the present study, however, is augmented by a more extensive 4½ to 8½ year follow-up of the sampled arrestees.

the variation in termination rates across offender attributes. Blumstein, Cohen, and Hsieh (1982) provides the only previous estimates that considered variations in termination rates for offenders. Relying on life-table techniques, however, these estimates required strong assumptions to extrapolate about the expected progress of future offending from current cross sectional data. The present analysis avoids these assumptions by relying on observed arrests during a follow-up period in order to estimate the termination rate.

II. THE DATA

The data used in this study consist of the adult[11] arrest histories of 20,117 males arrested for a criterion offense in the Detroit SMSA between January 1974 and December 1977. The limited number of female offenders and offenders whose race is identified as other than white or black are excluded from the analysis.

An individual's arrest history includes for each adult arrest the date of arrest, a list of the offenses charged at the arrest, the final disposition of the arrest (whether convicted or not) and sentence length for terms of incarceration. Each offender's history includes arrests from age 17 through the end of the observation period in June 1982.

[11]The age of adult jurisdiction in Michigan is 17.

Arrestee Attributes

An offender's target arrest is defined as his first criterion arrest in the 1974 through 1977 window period. Figure 2 displays the division of an offender's criminal record into a pre-target history -- used to establish an offender's attributes at the time of the target arrest -- and a post-target, follow-up period.

The offender attributes that are studied derive from those found in previous studies of termination or recidivism rates. Each attribute tests the extent to which the data support theoretically hypothesized influences on the termination of criminal offending.[12] First, it is hypothesized that offenders who have been criminally active longer are more committed to criminal behavior.[13] Therefore, offenders with more prior arrests, those who have been previously incarcerated, or who started offending at an earlier age are expected to have lower termination rates (and longer offending careers).

In a previous study using life-table techniques, Blumstein et al. (1982) found that offenders who were active in adult careers

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[12]A summary of offender attributes and their associated values is provided in Table 1.

[13]"Commitment" does not necessarily imply a value choice by offender; it may also reflect increasing limitations on the opportunities for non-criminal activities that are available to offenders with extensive criminal records.

at the age of majority (18 in Washington DC and 17 in Michigan) and who were still active into their thirties had the lowest termination rates (and correspondingly, the longest remaining careers). Presumably, early in their adult careers such as during their teens and twenties offenders have greater access to alternatives to crime and many of them stop offending. Those who continue offending into their thirties are a more serious group of offenders. However after age forty, the tolls of a life of crime as well as of aging more generally, are felt and older offenders increasingly end criminal activity. Based on this characterization, offenders in their thirties who have long past criminal careers are expected to exhibit the lowest termination rates.

It is further hypothesized that the personal traits which lead to violent offending are more enduring and less opportunistic. Therefore, offenders with a prior or target arrest for a violent offense -- either murder, rape or aggravated assault -- are expected to remain criminally active longer and thus exhibit a lower termination rate. Arrest for robbery is analyzed as a separate category due to its ambiguous status as a violent or property crime.

Offenders with a prior or target arrest for a drug-related offense are hypothesized to be highly committed to crime, possibly to support a personal drug habit. It is further hypothesized that they have ample opportunity to commit crime due to association with others involved in crime. Therefore, offenders with a drug-related arrest are expected to have longer offending careers and a lower termination rate.

Race is also considered as an attribute potentially correlated with the termination rate. Previous studies have established that a higher proportion of urban black males than urban white males participate in serious criminal activity.[14] However, of those individuals who do become criminally active, black and white offenders exhibit similar rates of offending. Generalizing these prior results, black and white offenders are expected to exhibit similar termination rates once other factors are accounted for.

III. THE MODEL

The explanatory model of offender follow-up data includes two sub-models. The first is a probabilistic model which accounts for an individual offender's follow-up record in terms of two behavioral parameters, the termination rate (δ) and the frequency of arrest (μ). This individual behavioral model is augmented by an accelerated failure time model which accounts for the variation in δ and μ across offender attributes. The maximum likelihood estimates of the full model are determined by searching for the parameter values most likely to have produced the observed follow-up arrests.

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[14]Blumstein et al. (1986) pp. 252-253 & 352.

Probabilistic View of Criminal Careers

The behavioral model describing an individual offender's follow-up arrests poses two parallel competing risks for arrest and termination. The basis of the probability model is two simplifying assumptions about these competing processes.

1. An individual's propensity to be arrested while active (μ) remains constant for the time from the target arrest until the offender's next criterion arrest, until the offender terminates criminal activity, or until the end of the follow-up period (June 1982), whichever occurs first. It is assumed that an offender can not be arrested while incarcerated.

2. An individual's propensity to terminate offending (δ) remains constant for the time from the target arrest until the offender's next criterion arrest, until the offender terminates criminal activity, or until the end of the follow-up period (June 1982), whichever occurs first. It is further assumed that an offender can terminate a criminal career while incarcerated.

Under the assumption of a time-invariant termination rate, the distribution of career length is exponentially distributed with an expected career length $1/\delta$.[15] Under the assumption of a time-invariant arrest rate, the distribution of inter-arrest intervals without consideration of career termination is exponentially

[15]For a more complete discussion of the calculus of duration data see Lawless, pp. 8-10.

distributed with an expected inter-arrest time $1/\mu$.

The arrest and termination processes can be viewed as a combined process of competing events where an event is defined as either an arrest or career termination.[16] This combined process results in a series of arrests that end with an unobserved career termination event as illustrated in Figure 3.

The combined process is characterized by the distribution of inter-event times and the probability that an event is an arrest. The inter-event times for a combination of processes with exponentially distributed inter-event times and expected inter-event times of $1/\mu$ and $1/\delta$ is also exponentially distributed and has an expected inter-event time of $1/(\mu+\delta)$. The probability that an event is an arrest is equal to the competing rates ratio $\mu/(\mu+\delta)$, and the probability an event is career termination is $\delta/(\mu+\delta)$.[17]

In this study, the basic observations are each offender's interval to a next event -- defined as the time from the target arrest until the offender's next criterion arrest, or until the end of the observation period in June 1982, when no criterion arrest is recorded during the follow-up. These two cases are illustrated in Figure 4.

For offenders who spend no time in jail subsequent to their

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[16]For the moment the model ignores the role of time spent incarcerated.

[17]For a more complete discussion of results associated with parallel processes and competing rates see Lawless (1982), pp. 484-491.

target arrest the probability that a criterion re-arrest is observed X years after the target arrest is as follows:

$$L(X|\text{Case}=1,J=0,\delta,\mu) = \Pr\begin{bmatrix}\text{RE-ARREST}\\ \text{X MONTHS}\\ \text{LATER}\end{bmatrix}$$

$$= \Pr\begin{bmatrix}\text{A:NO}\\ \text{EVENT}\\ \text{BEFORE X}\end{bmatrix} \times \Pr\left[\begin{matrix}\text{B:ARREST}\\ \text{AT TIME}\\ \text{X}\end{matrix}\middle| \text{A}\right]$$

$$= e^{-(\delta+\mu)X} \times \mu \, dt \qquad \text{<1>}$$

Likewise, the probability of no criterion arrest in the follow-up for offenders who spend no time in jail following the target arrest is:

$$L(X|\text{Case}=2,J=0,\delta,\mu) = 1 - \Pr\begin{bmatrix}\text{RE-ARREST}\\ \text{BEFORE X}\end{bmatrix}$$

$$= 1 - \Pr\begin{bmatrix}\text{A:NEXT}\\ \text{EVENT OCCURS}\\ \text{BEFORE X}\end{bmatrix} \times \Pr\left[\begin{matrix}\text{B:NEXT}\\ \text{EVENT IS}\\ \text{AN ARREST}\end{matrix}\middle| \text{A}\right]$$

$$= 1 - \left[1 - e^{-(\mu+\delta)X}\right] \times \left[\frac{\mu}{\mu + \delta}\right] \qquad \text{<2>}$$

The Detroit data include information about sentence lengths imposed at conviction, but do not include a record of the actual time spent incarcerated. The distribution of time an offender actually spends incarcerated is assumed to be exponentially distributed.[18] The expected time served in prison or jail is estimated from the minimum sentence length imposed using a formula provided by the Michigan Department of Corrections. Taking time served into account for offenders incarcerated subsequent to their target arrest, the likelihood of a rearrest is:[19]

[18]The reasonableness of this assumption was confirmed in an analysis of the distribution of time actually served conditioned on minimum sentence length for the subset of 1983 releasees from Michigan State Prisons in the Bureau of Justice Statistics national sample.

[19]The data include all times served on sentences during the interval for both the target criterion arrest and any intervening non-criterion offenses. For convenience, it is assumed that all time spent incarcerated occurs at the beginning of the follow-up interval even though time served for non-criterion offenses can occur any time during the interval.

This simplification has no impact on the likelihood in the case of re-arrest observed. However, this simplification does have an impact when a re-arrest is not observed and the offender has a non-criterion arrests that lead to incarceration. In this event, the probability of not observing a criterion re-arrest is higher if the non-criterion incarceration period occurs at the start of the follow-up interval rather than at the end. This simplification should have a small impact on the estimates of μ and δ because it affects only a small proportion of all cases in the sample. (17% of cases rearrested; 16% of cases not rearrested).

$L(X|\text{Case}=1, J, \delta, \mu)$

Where,

J = expected time spent incarcerated as estimated from sentence length

s = 1/J = release rate from jail

$$= \int_{J=0}^{X} \Pr\begin{bmatrix}\text{A:RELEASE}\\ \text{FROM JAIL}\\ \text{AT TIME J}\end{bmatrix} \times \Pr\left[\begin{array}{l|l}\text{B:DID NOT} & \\ \text{TERMINATE} & \text{A}\\ \text{IN JAIL} & \end{array}\right] \times \Pr\left[\begin{array}{l|l}\text{C:ARREST} & \\ \text{AT} & \text{A,B}\\ \text{TIME X} & \end{array}\right]$$

$$= \int_{J=0}^{X} s\, e^{-sJ} \times e^{-\delta J} \times \mu\, e^{-(\mu+\delta)(X-J)}\, dt\, dJ$$

$$= s\, \mu\, e^{-(\mu+\delta)X}\, dt \int_{J=0}^{X} e^{-(s-\mu)J}\, dJ$$

$$= \frac{s\, \mu\, e^{-(\mu+\delta)X}\, dt}{(s-\mu)} \left(1 - e^{-(s-\mu)X}\right) \qquad \text{<3>}$$

The probability of no rearrest for a criterion offense when the target arrest is followed by incarceration is given by:

$$L(X|\text{Case}=2,J,\delta,\mu) = 1 - \int_{t=0}^{X} \Pr\begin{bmatrix}\text{ARREST}\\ \text{BY TIME}\\ t\end{bmatrix}$$

$$= 1 - \int_{t=0}^{X} \frac{s\ \mu\ e^{-(\mu+\delta)t}}{(s-\mu)} \left[1 - e^{-(s-\mu)t}\right] dt$$

$$= 1 - \frac{s\mu}{(s-\mu)} \left[\frac{1 - e^{-(\mu+\delta)X}}{(\mu+\delta)} - \frac{1 - e^{-(\delta+s)X}}{(\delta+s)}\right] \qquad \text{<4>}$$

ACCELERATED FAILURE TIME MODEL

The maximum likelihood estimates of offender parameters (δ,μ) for a sample of n offenders are the parameter values $(\hat{\delta},\hat{\mu})$ which best account for the observed next-event intervals:

$$\max_{\delta,\mu} \prod_{i=1}^{n} L(X_i|J_i,\delta,\mu) \qquad \text{<5>}$$

where,

i = index of offenders in the sample

This estimation model assumes that offenders are homogeneous, each with the same parameters, δ and μ. When heterogeneity in δ or μ exists, the maximum likelihood estimate provides a summary value for (δ,μ) which reflects the variety of parameter values and the proportion of offenders associated with each.

The variation in (δ,μ) associated with offender attributes is estimated by augmenting the basic likelihood model using an accelerated failure time model. Offender attributes are assumed to have the following multiplicative effect on δ and μ:

$$\delta = e^{\beta_{10} + X_{11}\beta_{11} + \ldots + X_{1p}\beta_{1p}} \quad \text{<6>}$$

$$\mu = e^{\beta_{20} + X_{21}\beta_{21} + \ldots + X_{2q}\beta_{2q}} \quad \text{<7>}$$

where,

x_{1i} = ith attribute associated with δ

x_{2j} = jth attribute associated with μ

β_{1i} = coefficient of ith δ attribute

β_{2j} = coefficient of jth μ attribute

To estimate these coefficients, the accelerated failure time equations <6> and <7> are substituted into the likelihood equations, <1> though <4>. Then, the values for the β coefficients which maximize the product of likelihoods for observed next-event intervals, <5>, are obtained using the Fletcher-Powell numerical search procedure.

IV. RESULTS

Model Selection

The initial model includes a binary variable for each level of the explanatory variables. The results of estimating this model (refer to Table 2) reveal a particularly large and statistically significant variation in $\hat{\delta}$ associated with race. Only two other coefficients, for the oldest offenders (AGENOW = 4) and those with more than two prior arrests (CPRIOR = 3), are statistically significant (α=.01 level). One factor in the lack of other significant effects may be that variations across race mask the effect associated with other attributes. To control for possible confounding effects of race, coefficients for δ can be estimated separately for black and white offenders.

It is also possible that the variation in $\hat{\delta}$ with race reflects variation in (δ,μ) across jurisdictions. The Detroit SMSA includes the central city of Detroit located within Wayne County, and suburban areas, in five counties outside of Wayne County. About 40% of arrests which occur in Wayne County are reported to the

State Police Central Criminal history data repository compared to over 55% in other counties within the Detroit SMSA.[20] The differences in reporting combined with the much higher proportion of black offenders arrested in Wayne County than in the other SMSA counties (79% versus 45%) might contribute to the difference in $\hat{\delta}$ estimates for black and white offenders. Furthermore, variations in δ and μ between Wayne County and Non-Wayne County offenders may reflect differences between urban and suburban offender behavior. These additional considerations suggest that the coefficients of δ may vary by race and by whether an offender's target arrest occurred within Wayne County or not.

Three models of the offender follow-up data are compared to determine whether race and Wayne County arrest interaction terms are necessary. The first is the initial model which includes a binary variable for each attribute level including race. In the second model, the sample is split into subsamples of black and

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[20]The complete census of arrests for adults ($\geq$ 18 years old) available in the computerized arrest history data for counties in the Detroit SMSA is compared to local police reports of arrests in the same counties and years (Michigan Department of State Police (1975) and (1977)). Adult arrests in the police reports are estimated by applying the statewide fraction of arrests of persons age 18 or older to the total number of arrests in police reports for each county. The ratio of arrests in arrest histories to arrests in police reports over the period 1974 to 1977 for the counties in the Detroit SMSA is as follows:

Offense Type	Wayne County	Outside Wayne County
Robbery	.37	.64
Aggravated Assault	.34	.58
Burglary	.43	.55
Auto Theft	.38	.56

white offenders and coefficients of each attribute level (excluding race) are estimated. In the third model, the sample is split into four subsamples on the basis of race and Wayne County target arrest prior to estimating the coefficients.

The likelihood ratio test is used to determine whether each successive model provides significant improvement over its predecessor (Kalbfleisch and Prentice (1980), p. 46).[21] The results of these tests are presented in Table 3. The p-values in the final column indicate the probability of a difference in likelihoods as large as that observed under the null hypothesis of no improvement associated with the unconstrained model. This analysis suggests that each successive model does provide significant improvement. Therefore $(\hat{\delta},\hat{\mu})$ are analyzed separately for each of the four subsamples of offenders distinguished by race and Wayne County target arrest.

Aggregate Results

For the entire Detroit SMSA sample, offenders terminate criminal activity at a rate of 14% per year with a standard error

[21]The test analyzes the difference between the logarithm of the likelihood for the unconstrained model which permits interactions with race or jurisdiction and a constrained model with no interactions. Under the null hypothesis that the constrained model is correct, twice the difference has an underlying chi-square distribution with degrees of freedom equal to the difference in the number of coefficients estimated in the two models.

of .3%. This corresponds to criminal careers that average 7 years. The overall estimate of the arrest rate is .23 arrests per year with a standard error of .002. These overall rates are estimated using the basic maximum likelihood model without covariates. The estimates are thus an average of the range of parameter values occurring within the sample population.

The aggregate termination and arrest rates for each of the four subsamples by race and Wayne County target arrest are presented in Table 4. The estimated termination rate $\hat{\delta}$ is higher (and careers shorter) for both white offenders and for non-Wayne County offenders. The most persistent offenders are found among black, Wayne County offenders. The estimated arrest rate $\hat{\mu}$ is lower for Wayne County offenders, which is consistent with the lower proportion of arrests from that county recorded in that data. The arrest rate is also higher for black offenders.

Coefficient Estimates

Table 5 reports the effects on δ and μ of covariates other than race and jurisdiction. Very few coefficients of δ are statistically significant, in spite of their often large magnitude. This result indicates that the data do not provide very much information about some of these coefficients, a failing that can be partially attributed to the limited variety of offenders included in the sample. Overall, 66% of all offenders included in the sample have no prior record of a criterion arrest, 83% are under the age of 30, and 59% are first-time criterion offenders under age 30. This preponderance of young, first-time offenders limits the amount of information available to estimate the effects of attributes of a prior record on subsequent termination of offending.

Contrary to the finding for the coefficients of δ, however, many coefficients of μ are statistically significant. This result suggests that a sample of follow-up arrest information tends to provide more information about the arrest rate (μ) than about the termination rate (δ).

Across the four subsamples of offenders, and excluding the intercept terms, 4 out of 44 coefficients of δ are significant at the α=.01 level. Three of these coefficients are for AGENOW among non-Wayne County, white and black offenders. These coefficients indicate that older, non-Wayne County offenders have a higher termination rate than their 17-19 year-old counterparts. The termination rate for white offenders in their thirties is 2.3 times larger than their 17-19 year-old counterparts.[22] Black offenders in their thirties have termination rates that are 3.6 times larger than 17 to 19 year old offenders, while those over forty terminate criminal activity at rates 6.6 times higher than 17 - 19 year-olds.

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[22]The multiplicative factor on δ for offenders with AGENOW = 3 is e^{β}, or in this case $e^{.82} = 2.3$.

The fourth significant coefficient of δ is for non-Wayne County black offenders who have many prior criterion arrests, CPRIOR=3. This coefficient indicates that offenders with extensive prior records of arrests for criterion offenses have a much lower termination rate -- only .36 times that of their counterparts with no prior arrests.

With respect to μ, 25 out of 44 non-intercept coefficients are significant at the α=.01 level, which indicates considerable variation in the rate of arrest with the covariates examined. Eleven out of twelve AGENOW coefficients are significant and indicate that older offenders are arrested for criterion offenses less frequently than are younger adult offenders during active criminal careers.[23] In contrast to the results for AGENOW, no coefficients associated with age at first adult criterion arrest, AGE1, are significant.

The coefficients of μ associated with number of prior arrests for criterion offenses, CPRIOR, indicate that μ is higher for offenders who have already accumulated more prior arrests record increases (7 out of 8 of these coefficients are significant and positive). One out of four coefficients associated with IPRIOR is significant, indicating that non-Wayne County black offenders who

[23]This pattern of variation in arrest rates with age is consistent with other results (Blumstein and Cohen, 1979; Cohen 1986.) which find decreases in arrest rates in aggregate crime categories. Similar declines with age have not been observed among active offenders in individual crime types, and the decline in aggregate rates with age appears to reflect a decline in the number of active crime types for older offenders.

have a prior incarceration for a criterion offense also have a higher arrest rate.

The coefficient of μ associated with violent offending, VEVER, is significant in each subsample indicating that criterion arrest rates for violent offenders are lower than the same rate for non-violent offenders. The effects associated with robbery and drug-related offending, REVER and DEVER, are less clear. Only one out of four coefficients associated with each of these crime type variables is significant. The significant robbery coefficient indicates that non-Wayne County black robbers have a marginally lower μ for criterion offenses (14% lower) than do non-robbers. The significant drug-related coefficient indicates that non-Wayne County, white offenders who have been charged with drug-related offenses have a higher arrest rate for criterion offenses than do offenders who have no drug-related charges.

V. CONCLUSION

This study introduces a maximum-likelihood technique for estimating the rate at which offenders terminate criminal activity from longitudinal data. For serious offenders in the Detroit SMSA, the average termination rate is 14% per year, which corresponds to an average adult career in criterion offenses of 7 years. This estimate using prospective follow-up data is similar in magnitude to the previous life table estimates of Blumstein and Cohen (1985) based on cross-sectional data.

The termination rate exhibits significant variation across several offender attributes, most notably across race and jurisdiction of arrest. Termination rates from offending in criterion offenses vary from most persistent for black, urban offenders with an annual termination rate of 9% (residual career of 11 years) to least persistent for white suburban offenders with an annual termination rate of 20% (residual career of 5 years).

Variations in δ associated with the other seven prior record attributes included in this study appear to be limited. Only two factors are statistically significant -- current age, and number of prior arrests for criterion offenses -- and these occur only in the suburban counties outside Wayne County. Older, suburban black and white offenders exhibit significantly higher termination rates than their 17-19 year-old counterparts. Suburban black, offenders with 3 or more prior criterion arrests exhibit a lower termination rate than similar offenders with no prior arrests.

The estimated coefficients associated with many of the other parameters are large, but so are their standard errors. Such high variance results are often indicative of insufficient information about the attributes' effects within the data. Thus, the lack of significant coefficients associated with age at first arrest, prior incarceration, and types of crimes engaged in by offenders may result from the limited range of offender types included in the sample, and the limited information about the termination process that is provided by a sample of prospective arrest events during a follow-up period that is time-censored relative to the expected remaining lifetimes of offenders. The data support better estimates of the covariates of the frequency of arrest, μ, for active offenders.

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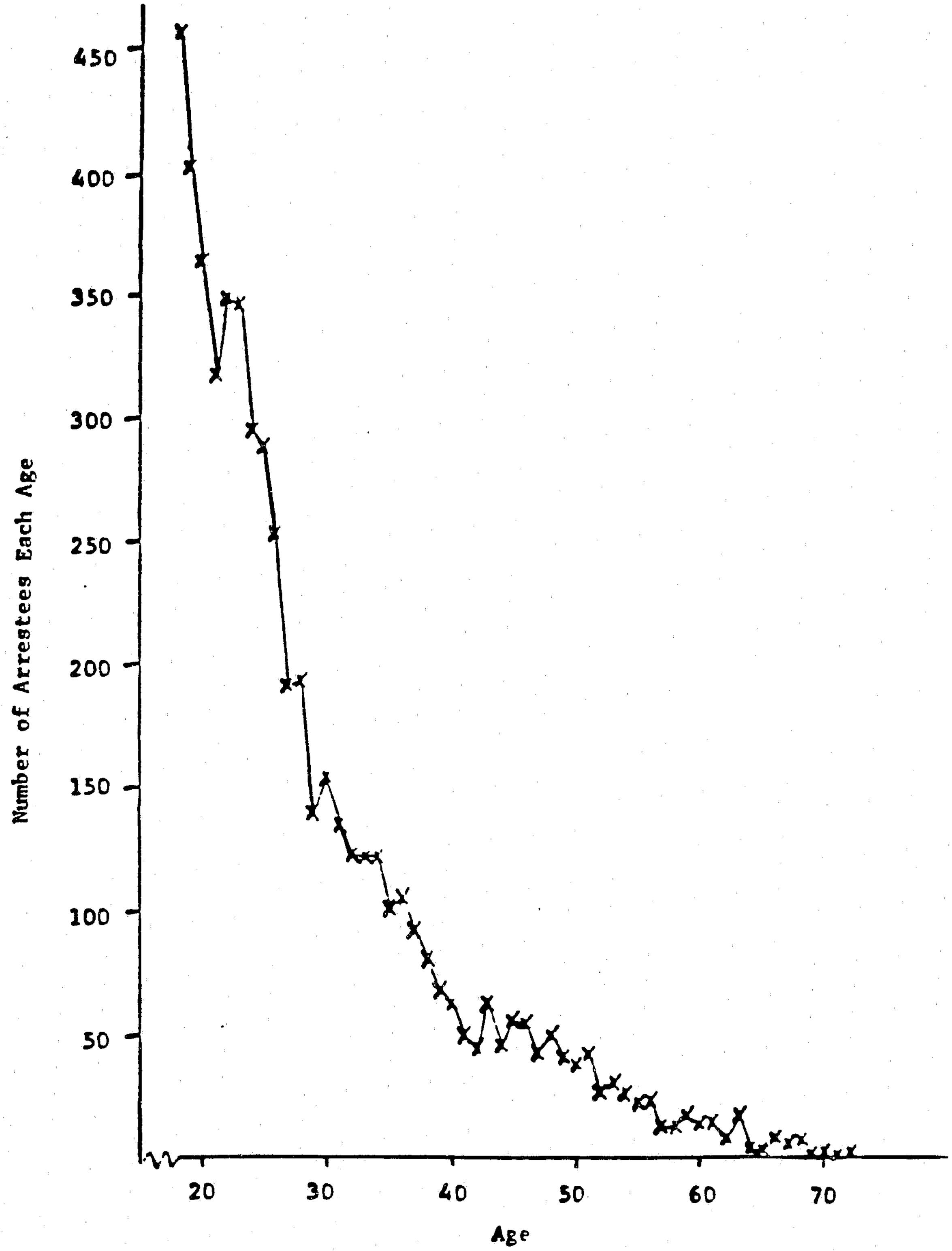
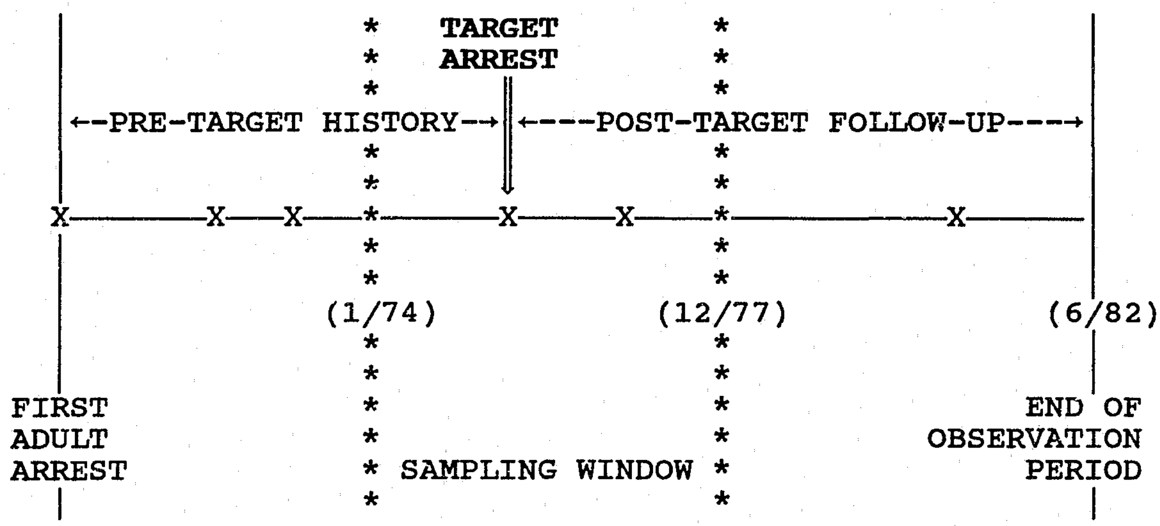


Figure 1: Distribution of 1973 Washington DC Arrestees by Age (Source: Blumstein, Cohen and Hsieh (1985).



X indicates an arrest

Figure 2: Pre-Target, Post-Target Partition of an Arrest Record

```
Arrest Process      : X————————X————————————————X————X————
Termination Process: ————————————————————————♦
Combined Process    : X————————X——————————————♦
                                                   time →
```

X indicates an arrest

♦ indicates career termination

Figure 3: Example of a Criminal Career

1) Criterion Re-Arrest Observed

```
X<---J---><-----------F----------->X

Target                                Next
Arrest                                Criterion
                                      Arrest
```

2) No Criterion Arrest Through June, 1982

```
X<---J---><---------------F--------------->|

Target                                    6/82
Arrest
```

J = time spent incarcerated
F = time spent free from prison

Figure 4: Examples of Observations Used in Maximum Likelihood Estimates

Table 1: Arrestee Attributes

Attribute	Levels	Description
RACE	W. White B. Black	Arrestee's race. Only white and black arrestees are included in the database.
AGE1	1. 17-19 2. 20-29 3. 30+	Arrestee's age at his first adult criterion arrest ever.
AGENOW	1. 17-19 2. 20-29 3. 30-39 4. 40+	Arrestee's age at his target arrest (first criterion arrest between 1/74 and 12/77).
CPRIOR	0. No Arrests 1. 1 or 2(few) 3. 3+ (many)	The number of adult criterion arrests recorded prior to the target arrest.
IPRIOR	0. No Prior Incar. I. 1+ Incar.	Indicator of whether the arrestee was ever incarcerated for a criterion arrest prior to his target arrest.
VEVER	0. No Violent V. Violent	Indicator of whether the arrestee was ever charged with a violent offense either prior to or on his target arrest.
REVER	0. No Robbery R. Robbery	Indicator of whether the arrestee was ever charged with robbery either prior to or on his target arrest.
DEVER	0. No Drugs D. Drugs	Indicator of whether the arrestee was ever charged with a drug-related offense either prior to or on his target arrest.

Table 2: Coefficient Estimates for a Single Sample

Log-Likelihood -30,737.74
Number of Offenders 20,117

Variable	δ Parameters Coeff.	(S.E.)	P-Value	μ Parameters Coeff.	(S.E.)	P-Value
INTERCEPT	-1.706*	(.044)	.0001	-1.212*	(.027)	.0001
BLACK	-0.665*	(.059)	.0001	0.293*	(.031)	.0001
AGE1=2	0.195	(.108)	.0710	0.048	(.055)	.3828
AGE1=3	-0.182	(.241)	.4501	-0.116	(.133)	.3831
AGENOW=2	-0.056	(.109)	.6074	-0.525*	(.057)	.0001
AGENOW=3	0.431	(.198)	.0295	-1.037*	(.102)	.0001
AGENOW=4	0.859*	(.266)	.0012	-1.625*	(.155)	.0001
CPRIOR=1	-0.178	(.094)	.0583	0.393*	(.053)	.0001
CPRIOR=3	-0.617*	(.207)	.0029	0.665*	(.091)	.0001
IPRIOR	-0.275	(.108)	.0109	0.096	(.055)	.0809
VEVER	-0.124	(.064)	.0527	-0.439*	(.034)	.0001
REVER	-0.044	(.064)	.4918	-0.101*	(.035)	.0039
DEVER	-0.015	(.066)	.8202	0.172*	(.039)	.0001

* Significant at the α=.01 level

Table 3: Comparison of Alternative Models Using the Likelihood Ratio Test

Model	# of Coefficients	Log Likelihood	Test Statistic	Degrees of Freedom	P-Value
1) All Offenders	26	-30737.74	-	-	-
2) By Race	48	-30682.41	110.66	22	.0001
3) By Race & Wayne County	96	-30623.15	118.52	48	.0001

Table 4: Aggregate Estimates of Offending Parameters by Race and County of Target Arrest for Arrestees in Detroit SMSA

$\hat{\delta}$ (S.E.) $\hat{\mu}$ (S.E.)	White	Black
Wayne County	.16 (.008) .19 (.006)	.09 (.005) .26 (.006)
Outside Wayne County	.20 (.007) .22 (.006)	.12 (.009) .35 (.014)

Total Detroit SMSA	.14 (.003) .23 (.002)

Table 5: Coefficient Estimates for Four Subsamples

Wayne County - White Offenders

Log-Likelihood	-7,161.52
Number of Offenders	5,042

Variable	δ Parameters Coeff.	(S.E.)	P-Val	μ Parameters Coeff.	(S.E.)	P-Val
INTERCEPT	-1.768*	(.076)	.0001	-1.284*	(.050)	.0001
AGE1=2	0.549	(.284)	.0532	0.129	(.129)	.3173
AGE1=3	0.608	(.551)	.2698	0.213	(.267)	.4250
AGENOW=2	-0.422	(.278)	.1290	-0.606*	(.129)	.0001
AGENOW=3	-0.656	(.580)	.2580	-1.418*	(.217)	.0001
AGENOW=4	0.776	(.540)	.1507	-1.142*	(.303)	.0002
CPRIOR=1	-0.188	(.187)	.3147	0.424*	(.112)	.0002
CPRIOR=3	-0.298	(.544)	.5838	0.745*	(.215)	.0005
IPRIOR	-0.759	(.349)	.0296	0.026	(.134)	.8462
VEVER	-0.376	(.167)	.0244	-0.611*	(.079)	.0001
REVER	0.300	(.118)	.0110	0.142	(.081)	.0796
DEVER	-0.036	(.132)	.7851	0.160	(.077)	.0377

Wayne County - Black Offenders

Log-Likelihood	-11,502.40
Number of Offenders	7,001

Variable	δ Parameters Coeff.	(S.E.)	P-Val	μ Parameters Coeff.	(S.E.)	P-Val
INTERCEPT	-2.557*	(.101)	.0001	-0.845*	(.043)	.0001
AGE1=2	0.479	(.255)	.0603	0.122	(.090)	.1752
AGE1=3	0.823	(.542)	.1289	0.107	(.232)	.6447
AGENOW=2	-0.281	(.255)	.2705	-0.641*	(.095)	.0001
AGENOW=3	0.174	(.446)	.6964	-1.122*	(.163)	.0001
AGENOW=4	0.483	(.670)	.4710	-1.980*	(.272)	.0001
CPRIOR=1	0.184	(.176)	.2958	0.275*	(.089)	.0020
CPRIOR=3	-1.197	(.840)	.1542	0.317	(.157)	.0435
IPRIOR	-0.283	(.213)	.1840	0.125	(.091)	.1696
VEVER	0.208	(.126)	.0988	-0.326*	(.055)	.0001
REVER	-0.147	(.132)	.2654	-0.146*	(.054)	.0069
DEVER	-0.559	(.262)	.0329	-0.093	(.077)	.2271

Table 5 Continued

Non-Wayne County - White Offenders

Log-Likelihood	-8,759.20
Number of Offenders	6,180

Variable	δ Parameters Coeff.	(S.E.)	P-Value	μ Parameters Coeff.	(S.E.)	P-Value
INTERCEPT	-1.614*	(.060)	.0001	-1.260*	(.043)	.0001
AGE1=2	0.068	(.166)	.6821	-0.063	(.107)	.5560
AGE1=3	-0.405	(.321)	.2071	-0.096	(.237)	.6854
AGENOW=2	0.085	(.174)	.6252	-0.439*	(.114)	.0001
AGENOW=3	0.817*	(.271)	.0026	-0.731*	(.187)	.0001
AGENOW=4	0.961	(.387)	.0130	-1.381*	(.295)	.0001
CPRIOR=1	-0.225	(.146)	.1233	0.436*	(.103)	.0001
CPRIOR=3	-0.492	(.291)	.0909	0.866*	(.172)	.0001
IPRIOR	-0.433	(.173)	.0123	0.144	(.108)	.1824
VEVER	-0.193	(.096)	.0444	-0.403*	(.064)	.0001
REVER	-0.129	(.113)	.2536	-0.132	(.078)	.0906
DEVER	-0.020	(.092)	.8279	0.354*	(.065)	.0001

Non-Wayne County - Black Offenders

Log-Likelihood	-3,178.72
Number of Offenders	1,894

Variable	δ Parameters Coeff.	(S.E.)	P-Value	μ Parameters Coeff.	(S.E.)	P-Value
INTERCEPT	-2.764*	(.188)	.0001	-1.025*	(.073)	.0001
AGE1=2	0.140	(.231)	.5445	0.183	(.129)	.1560
AGE1=3	-0.219	(.583)	.7072	-0.365	(.413)	.3768
AGENOW=2	0.567	(.300)	.0588	-0.293	(.146)	.0448
AGENOW=3	1.267*	(.432)	.0034	-0.705*	(.253)	.0053
AGENOW=4	1.888*	(.484)	.0001	-1.129*	(.383)	.0032
CPRIOR=1	-0.751	(.298)	.0117	0.525*	(.135)	.0001
CPRIOR=3	-1.030*	(.380)	.0067	0.682*	(.196)	.0005
IPRIOR	0.328	(.271)	.2262	0.324*	(.127)	.0107
VEVER	0.218	(.175)	.2129	-0.350*	(.097)	.0003
REVER	0.253	(.163)	.1206	-0.095	(.087)	.2749
DEVER	0.166	(.202)	.4112	0.074	(.131)	.5722

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