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THE DURATION OF ADULT CRIMINAL CAREERS

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1.0 INTRODUCTION

1.1 CHARACTERIZING CRIMINAL CAREERS

When addressing the question of offending patterns, much of early criminological research focused on particular individuals, tracing the evolution of their patterns of criminality, or "criminal careers."[1] These studies provided interesting and often insightful reports on the individuals studied. There was, however, no indication that the experiences of these fascinating individuals could be generalized to the larger population of offenders – offenders who account for the bulk of crime and certainly represent the great majority of persons processed through the criminal justice system.

Another more recent body of research examines aggregate levels of offending in the general population. Largely motivated by a concern for identifying the social and economic correlates of crime, a primary focus of this research has been estimating the prevalence of offenders in different demographic (age, race and sex) or socio-economic groups (e.g., social class, occupation or income). Prevalence is typically measured from the number of persons indicating that they ever committed specified offenses in self-reports.[2] These estimates of prevalence have been criticized because they are typically dominated by relatively minor offenses (e.g., skipping school, smoking, engaging in sexual activities) by juveniles. Estimates of prevalence based on such a range of behavior are very different from those associated with more serious criminal offenses in the population (Hindelang, et al., 1979).

Other estimates of the prevalence of offending are available from officially recorded arrest and conviction histories.[3] These estimates use the number of first arrests (or first convictions) at each age to estimate the probability of ever being arrested (or convicted) during a lifetime. Blumstein and Graddy (1982), for example, estimate that 23% of males in large

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[1]Some of the classics among these studies are Booth (1929), Shaw (1930 and 1931), Sutherland (1937) and Martin (1952).

[2]The self-report literature is rather large, including at least one hundred separate studies. A partial bibliography is available in the review for the National Council on Crime and Delinquency (1970). Critical reviews of the validity of much of this research are found in Reiss (1973) and Hindelang et al. (1979). The following represent only a small sample of the available research in this area: Short and Nye (1957 and 1958), Reiss and Rhodes (1959), Gould (1969), Hirschi (1969), Gold (1970), Waldo and Chiricos (1972), Williams and Gold (1972), Elliot and Voss (1974), Elliot and Ageton (1980), and Hindelang et al (1981).

[3]See Little (1965), Christensen (1967), Farrington (1981) and Blumstein and Graddy (1982).

U.S. cities will have an arrest for an index offense by age 55.[4] Sharp differences in the prevalence of index arrests were found by race, with 51% of non-white males in large cities expected to be arrested for an index offense by age 55 compared to only 14% of white males. These large differences in prevalence by race suggest that observed differences in race-specific arrest rates may be due predominantly to differences in participation, and not to differences in the intensity of offending among active offenders.

In addition to estimates of prevalence, there are estimates of aggregate population arrest rates. Figure 1, for example, shows age-specific population arrest rates. While these population arrest rates have changed in absolute magnitude (almost doubling between 1965 and 1976), the pattern over age has persisted, with fifteen to seventeen year olds having the highest arrest rates per population of any age group followed by a sharp decline with age subsequently. This pattern has been taken as support for a belief that individual criminality declines with age, perhaps because of the aging process with its associated increased maturity and/or declining vigor.

Aggregate statistics of offending in the general population are insufficient to characterize the nature of individual offending for those who engage in criminal activities. Prevalence, for example, tells us nothing about the intensity or duration of that criminal involvement. Likewise, the sharp fall-off in arrests with age might be due to changes in the intensity of offending by active offenders or to reductions in the number of active offenders as individual offenders discontinue their criminal involvement.

It is only in the last decade that estimates have begun to be accumulated that characterize fundamental features of individual offending for large numbers of offenders. In separating the different aspects of individual offending, it is useful to conceptualize individual criminal activity in terms of a "criminal career," with entry into a career at or before the first crime committed and drop-out from the career at or after the last crime committed (Figure 2). During a criminal career, the offender has a continuing propensity to commit crimes, accumulates some arrests, is sometimes convicted and less frequently is incarcerated.

This characterization of an individual's criminal activity as a "career" is not meant to imply that offenders derive their livelihood exclusively or even predominantly from crime.

[4]The index offenses include homicide (murder and non-negligent manslaughter), rape, robbery, aggravated assault, burglary, larceny of more than $50, and auto theft. The index offenses were expanded in 1973 to include all larcenies regardless of value, and were augmented in 1981 to include arson.

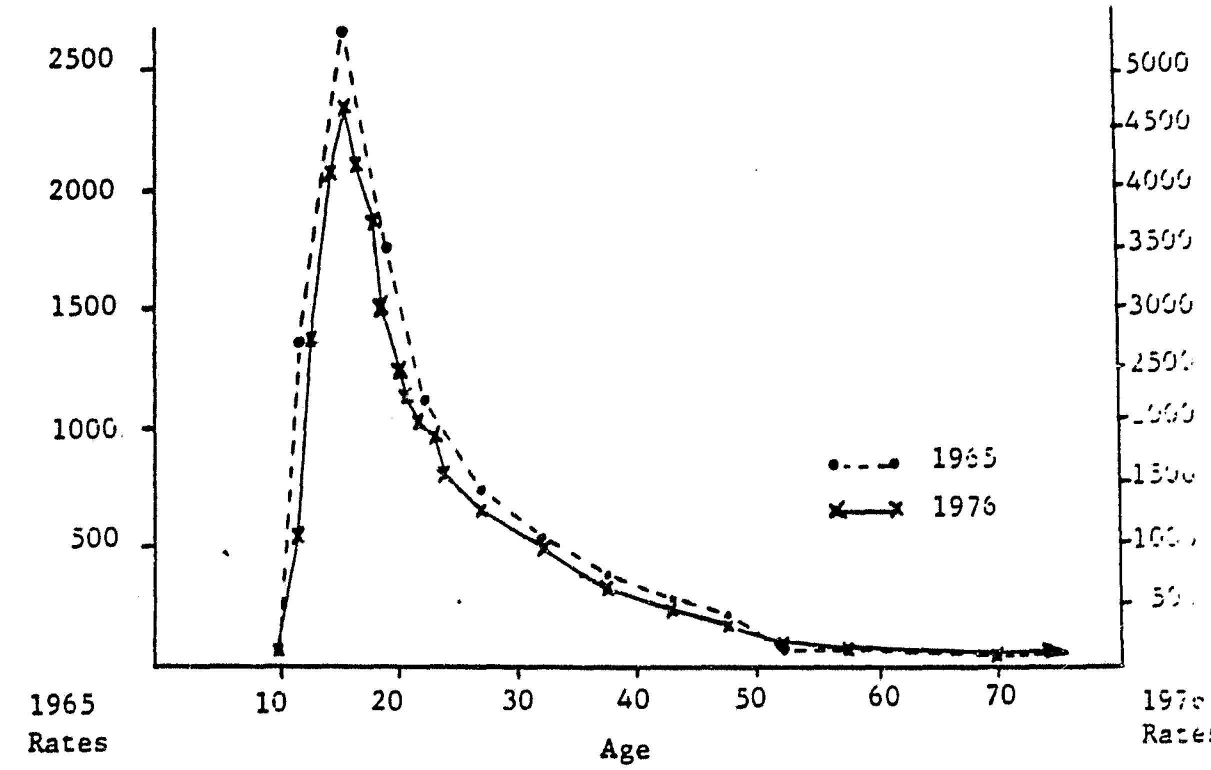

Figure 1

Arrests for Index Crimes Per* 100,000 Population by Age

* The 1965 arrest rates are taken from Table 1 of The Challenge of Crime in a Free Society (p. 56). For 1976, the number of reported arrests by age are from Table 32, Uniform Crime Report: 1976. Population estimates by age for 1976 are available in Bulletin 643 of the Current Population Reports.

Not all police agencies report arrests to the FBI; in 1976, arrests were reported for an estimated population of 175,499,000, or 82.6% of the estimated total population of 212,420,000 in 1976. To estimate arrest rates per population in 1976, the ratio of reported arrests to 82.6% of the total population in each age group is used. This ignores whatever differences there might be in the age distribution of the population in jurisdictions reporting to the FBI compared to that of the total population in 1976.

For multi-year age categories (e.g., 25 to 29), the arrest rate is noted at the midpoint of the category

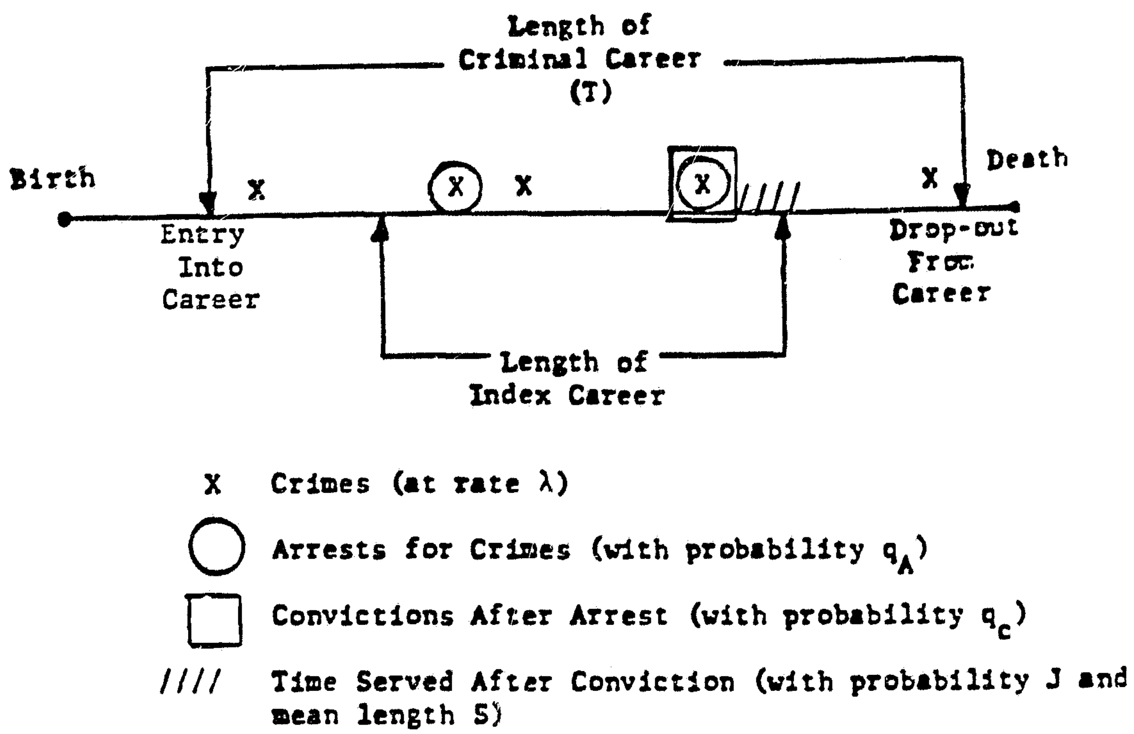

Figure 2

An Individual Criminal Career

The concept of a "criminal career" is intended only as a means of structuring the longitudinal sequence of criminal events associated with an individual in a systematic way. This notion of a criminal career can be applied to all crimes committed by an offender, or it can be restricted to subsequences of crimes which focus on selected crime types. For example, we may limit our attention to that portion of a criminal career involving only serious crimes by identifying the subsequence of events belonging to the FBI's category of index offenses.

As depicted in Figure 2, criminal careers can be characterized in terms of several parameters: (1) how long they last, T, (i.e., the number of years an offender remains criminally active), (2) the intensity of offending during a career, λ (i.e., the number of crimes committed per year per active offender), and (3) the crime type mix (e.g., the extent of specialization or escalation to more serious crimes during a career). Basic knowledge of these facets of individual criminality and the progress of adult criminal careers is fundamental to expanding our understanding of how various social factors may operate on the individual either to facilitate or to inhibit criminal activity.

For example, past empirical efforts investigating the impact of unemployment on crime have resulted in inconsistent conclusions, with some finding evidence in support of such a relationship while others find evidence to the contrary.[5] This inconsistency may be due in part to the exclusive focus in these studies on aggregate population crime rates as the dependent variable. It may well by that unemployment differentially impacts criminal participation rates and individual rates of offending. Or it may be that unemployment influences offending at certain ages, but not at others. Separating these impacts would permit a more precise determination of the nature of the influence of unemployment on crime and would thereby facilitate the development of more focused and more effective policies with respect to this contributing factor. Blumstein, et al. (1982) begins to pursue this more refined analysis.

Knowledge about patterns of individual criminality is also necessary for developing effective crime control policies. For example, incapacitation -- or physically preventing the crimes of an offender in the community (e.g., through incarceration) -- has emerged as a

[5]See, for example, Glaser and Rice (1959), Fleisher (1966), Singell (1967), Votey et al. (1969), Phillips et al. (1972), Ehrlich (1974), Votey and Phillips (1974) and Danser and Laub (1980).

popular crime control strategy.[6] Central to estimates of the crime-control effects of an incapacitation policy are empirical estimates of individual crime rates, λ, and of the average duration of criminal careers, T. If such a career is not interrupted by imprisonment, it can be expected to generate a total of λT crimes. Likewise, incarceration for a period of S years could potentially avert λS of those crimes in the community.[7] The benefits derived from incapacitation in terms of the number of crimes prevented will vary depending on the magnitude of the individual's crime rate and the length of his criminal career; the higher the individual's crime rate (λ) and the longer his career (T), the more crimes that can be averted through incapacitation.[8]

One incapacitative strategy calls for more certain and longer imprisonment for offenders with prior criminal records as reflected in "third-time-loser" or "habitual-offender" laws. But, if individual crime rates (λ) were to decrease as criminal careers progress, there are fewer crime-reduction benefits to be gained from incapacitating offenders already well into their criminal careers than from incapacitating those with only short prior criminal records.

The length of criminal careers (T) is also an important consideration. Any incapacitative policy is effective in averting crimes only if it is applied during a criminal career when an offender would be committing crimes if not incarcerated. Continuing to incarcerate an offender after the career ends – when no more crimes would be committed anyway – simply wastes limited prison capacity, at least from the perspective of incapacitation.

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[6]See, for example, Wilson (1975a, 1975b and 1977), Ford (1975a, 1975b, and 1975c), van den Haag (1975), and more recently, the calls for reform of bail release to permit pre-trial detention of "dangerous" defendants (Burger, 1981; Attorney General, 1981b) and the recommendations of the Attorney General's Task Force on Violent Crime to increase effectiveness in incarcerating career criminals through improved certification and prosecution programs (Attorney General, 1981a).

[7]Focusing on the problems of crime faced by the non-incarcerated community, the incapacitative effect refers only to those crimes averted in the community and ignores any crimes committed while incarcerated. A more general view of incapacitation would take some account of the crimes committed while incarcerated.

[8]The incapacitative effect is reduced below λS crimes if the criminal activity of the incarcerated offender persists in the community while the offender is incarcerated. This might happen if, for example, the offender is part of an organized economic activity such as drug sales or burglaries organized by a fence. In this event, a replacement might simply be recruited from an available "labor market." Also, if the offender is part of a crime-committing group, the remaining members of the group may well continue their criminal activity, with or without recruiting a replacement. See Reiss (1980) for a more detailed consideration of the potential impact of replacement and group offending patterns on incapacitation effects.

From the perspective of developing incarceration policies that maximize incapacitatitve effects, then, it is important to know how long criminal careers can be expected to last, and more importantly, to develop a capacity to estimate expected remaining career lengths from any point in a career. For example, if on the average career lengths are quite short, this suggests a general policy of incarceration only for short periods of time in order to avoid the possibility of wasting prison capacity on individuals whose careers have already ended. More precise determinations can be made with knowledge of the expected remaining career length as a function of time already in a career. To the extent that future career length is an increasing function of time already in the career, (i.e., the longer offenders have already been active, the longer still they can be expected to continue), this would suggest marginally greater use of prison for offenders with longer past careers because their future careers are also likely to be longer. The converse policy is appropriate when future career length is a decreasing function of time already in the career; in this event, offenders with long past careers are likely to terminate their careers very shortly.

1.2 PRIOR RESEARCH ON INDIVIDUAL CRIMINAL CAREERS

Both evaluating the crime control effectiveness of any incapacitation policy and improving our understanding of the extent and dynamics of individual criminality requires information on the patterns of individual criminality during a career. Since the daily criminal activities of individual offenders cannot be monitored directly, some secondary form of observation and inference is required to generate estimates of criminal-career parameters. Two primary approaches are available. One involves self-reports where individual offenders are identified and asked about their criminal activities, and the other relies on inferences from officially recorded arrest histories.

The self-report approach provides direct information on criminal careers, but is subject to veracity errors resulting from deception by the respondent as well as to recall errors in reporting on events that may have occurred long ago. Recent studies of self-reported crime by prison inmates undertaken by the Rand Corporation (Peterson and Braiker, 1980; Chaiken and Chaiken, 1982), represent a major advance over earlier self-report studies (e.g., Williams and Gold, 1972) which provided only a limited view of criminal activity. Primarily motivated by a concern for levels of "hidden delinquency," or more precisely of "hidden delinquents," these early studies focused on the prevalence of offenders in a population. None tried to assess the intensity or duration of criminal activity for identified offenders. Furthermore, the sample populations were invariably school-age children or college students, and the "crimes" surveyed were usually dominated by minor legal infractions (e.g., skipping school). The Rand study is unique among self-report studies in its attention to developing estimates for adult offenders, a concern for their rate of offending, and a focus on more serious index offenses. The use of self-reports from prison and jail inmates, however, limits their ability to extrapolate directly to more general offending populations.

The other principal approach involves analysis of the arrest process which is more often recorded reliably at the time of the event. The information on arrests can then be used to yield inferences about the underlying crime process generating the observed arrests. This approach involves use of individual arrest histories linking a sequence of arrests to identified offenders. Analysis of these arrest histories provides direct characterization of the arrest process, which is certainly of interest, but which requires a variety of assumptions about the "sampling" process by which some crimes result in arrests in order to be able to infer the characteristics of the underlying criminal activity. This approach based on arrests is followed in this paper.

There are two principal parameters that characterize individual criminal careers – individual crime rates (λ) and the length of the career (T). Estimating the value of λ, the average annual rate at which individuals commit crimes, has been the subject of intensive exploration by the authors using arrest records (Blumstein and Cohen, 1979) and by others using self-reports by prisoners (Peterson and Braiker, 1980; Chaiken and Chaiken, 1982). Both approaches have yielded results that are reasonably consistent. In particular, those offenders who are active in the crime type (i.e., those who reported committing, or who were arrested at least once for the crime type) are found to commit an average of two armed robberies a year and six or seven burglaries a year. Furthermore, controlling for crime type, offenders who remain criminally active, commit crimes at a fairly constant rate over age.[9] Since the sources of error are quite different in the two approaches and independent data bases are used, the consistency of these results provides some degree of confidence in both approaches.

Estimating the duration of criminal careers is the principal focus of the present report. Despite the fundamental nature of this variable, prior research on the length of criminal

[9]Peterson and Braiker (1980) using self-reported crime note that total crime rates for individuals tend to decrease with age of the offender. This decrease with age, however, is apparently associated with a decline in the number of different crime types committed by older offenders. Controlling for crime type, older offenders report committing crimes at about the same rate as younger offenders. Blumstein and Cohen (1979) also note that when the histories of all arrestees in a year are examined, individual arrest rates, and inferentially their crime rates, decrease with age. Controlling for birth cohorts, however, the rates are found to be stable over age within a cohort, but more recent cohorts have higher stable crime rates than older cohorts.

careers is much more sparse than estimates of λ, and even when available it is generally inadequate.

A non-empirical approach to criminal career length is available in Avi-Itzhak and Shinnar (1973). Primarily for reasons of mathematical tractability and with no empirical support, their stochastic model of criminal careers assumes criminal career lengths to be exponentially distributed. Shinnar and Shinnar (1975) adds some empirical content to this basic model using data from the FBI's Computerized Criminal History files as reported in the Uniform Crime Reports: 1970. The career length is estimated from the average time between the first arrest in the record and the most recent arrest in the longitudinal arrest histories of offenders arrested on federal charges during 1970. For repeat offenders (persons with at least two arrests) the average time to the most recent arrest is about nine years, while for all offenders (repeaters and first-time arrestees), the average time is reduced to about five years.

Since the last arrest recorded in the data is not necessarily the final arrest in an offender's career, these data represent only a partial career length. If career lengths are exponentially distributed, however, this partial career length is an unbiased estimate of the total career length. Thus, by assuming career lengths to be exponentially distributed and adjusting for the time from first crime to first arrest, and from final arrest to final crime, Shinnar and Shinnar estimate that criminal careers average from ten to fifteen years in length. The accuracy of this estimate, however, rests on the representativeness of the population of federal offenders found in the criminal career profiles, and on the appropriateness of the assumption of an exponential distribution for their career lengths. These assumptions receive no empirical verification in the Shinnar and Shinnar paper.

Greenberg (1975) uses a different approach to estimate average career lengths. If μ is the average number of index arrests per year per offender, and T is the average career length for index offenses, $N = \mu T$ is the total expected number of index arrests in a completed criminal career. Using estimates of $\mu = .5$ and $N = \mu T = 2.5$, Greenberg calculates the average index career length to be five years. Aside from issues relating to the validity of the individual estimates of μ and N used, the accuracy of the Greenberg estimates rests on various steady-state assumptions of stationarity in the processes generating an active criminal population – assumptions that are not empirically validated.

The most methodologically sophisticated attempt to estimate career lengths is found in Greene (1977, Chapter 3) and Blumstein and Greene (1978). Following a method outlined in Shinnar and Shinnar (1975), Greene applies a life-table approach (derived from survival models in reliability testing) to the age distribution of adult arrestees in a year to estimate the total length of criminal careers. The results suggest that adult criminal careers for index offenses other than larceny follow an exponential distribution between ages 18 and 40 with a mean total length between 8 and 12 years.

While representing an advance over earlier estimates, the Greene results are still short of definitive. The validity of estimating the career length directly from the age distribution of arrestees in a single year rests strongly on the following assumptions:

1. All active offenders are equally likely to have at least one arrest in a year;
2. All offenders begin their adult criminal careers at age 18; and
3. The size of the offender population each age is constant over time.

The first assumption is intended to guarantee that the arrestees in a year are representative of the total active offender population, at least with respect to age. The second assumption justifies using age, a, as a direct measure of time already in a career, t (i.e., $t = a - 18$). The last assumption addresses the possible non-stationarities in the size of the offender population due to variations in the size of the base population, in recruitment into criminal careers, and in the dropout process.

The analysis in Greene (1977) and Blumstein and Greene (1978) indicates that the estimates of career length are quite sensitive to violations of these assumptions. Under conditions of a declining probability of arrest with age and/or of growth in the size of the offender population over time, just using the age distribution of arrestees in any year with its greater representation of young arrestees will underestimate the length of the career. Entry to criminal careers after age 18, on the other hand, will lead to overestimates of a career length as arrests of older offenders are mistakenly interpreted as long careers.

1.3 FOCUS OF THIS STUDY

We propose to extend the life-table approach introduced by Greene to develop estimates of criminal career length that explicitly address the underlying assumptions stated above. In particular, we will use several years of data in place of the single-year approach in order to consider explicitly variations in the rates of recruitment to and dropout from criminal careers. Adjustments for variations in the size of the base population over time as well as procedures that restrict the analysis to offenders who do begin their adult careers at a common age will also be used.

We will also develop techniques for using data on arrests rather than arrestees to estimate career lengths. In contrast to the existing method of Greene which requires data on arrestees – which are generally unavailable – the new method needs only data on arrests by age, which are well recorded. This generalization of the estimation technique to more widely available data will increase the potential for widespread use of the technique to generate career-length estimates in the variety of jurisdictions regularly recording annual arrest data.

Section 2 of this report details the basic method and its application to Washington, D.C. data. The method involves various adjustments to the original data, both to estimate unique arrestees from data on arrests and to increase the likelihood that the data satisfy the three underlying assumptions listed above. The section concludes with an analysis of the sensitivity of the career-length estimates to the various adjustments to the data.

The use of data from several different years provides an opportunity to examine explicitly the stability of career-length estimates over time. The results of this test of stationarity are discussed in Section 3, along with an analysis of the general level of variability in career-length estimates.

A key aspect of criminal career length is residual career length, or the expected time remaining in a career after having already been criminally active for x years. This variable, which is the subject of Section 4 of this report, is particularly relevant to developing incapacitation strategies based on past criminal record. The observation of declining population arrest rates with age (Figure 1) has led to the conventional wisdom that imprisonment after age 30 is not efficient because these older offenders are likely to be soon terminating their criminal careers.[10] It is clear from Figure 1 that the number of individuals who are still criminally active after age 30 is relatively small. It is not clear, however, whether the expected future career length of those few who are still criminally active at age 30 is also small. This kind of issue is central in the use of information on residual career lengths for policy purposes.

Age at first arrest, or at first conviction, has often been cited as a factor associated with greater individual commitment to sustained subsequent criminal activity (e.g., Sellin, 1958). To the extent that this is found to be empirically substantiated for career lengths, age at the start

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[10] This concern has been raised, for example, by administrators of career criminal prosecution units where the average age of targeted offenders has been observed to be in the late twenties or early thirties. (National Workshop on the Career Criminal Sponsored by the National Institute of Law Enforcement and Criminal Justice in Alexandria, Virginia, September 1979).

of criminal careers represents another potential discriminating variable in developing incapacitation strategies. This proposition is explicitly considered in the context of variations in criminal career length in Section 5. Arrestees are partitioned by entry age to their adult criminal careers and both length of total criminal careers and residual criminal careers are compared for different entry ages.

Population arrest rates exhibit very different patterns over age for different crime types. As illustrated in Figure 3, property offenses (burglary, larceny and auto theft) are characterized by very sharply peaked age-specific arrest rates per population, whereas the age-specific arrest rates for violent crimes (murder, rape and aggravated assault) decline much more slowly with age. This suggests that the duration of criminal careers may vary for different crime types, and be shorter for property crimes than for violent crimes. This issue is examined in Section 6.

Section 7 summarizes the results and discusses some policy implications of the findings on durations of criminal careers.

2.0 ESTIMATING THE DURATION OF CRIMINAL CAREERS

The most direct approach to estimating the length of criminal careers would be to follow individual offenders longitudinally, and note the time elapsed from start to end of a career. Such a longitudinal approach, however, is not very well suited to criminal-career research. To begin with, there is considerble ambiguity in identifying the exact start and end of a criminal career. Since the crimes of an offender are rarely observed directly, they cannot be used to mark the start and end of a criminal career. Using the time between the first and last arrest as a proxy is likely to understate career length because it ignores undetected criminal activity before and after these arrests. There is also uncertainty about identifying when the last arrest occurs. Offenders must be followed until their deaths to be sure of the time of the last arrest. Furthermore, full careers are likely to be relatively long (10 to 15 years) and if we wait until we have a sample of completed careers, the resulting career-length estimates may be obsolete with respect to the behavior patterns of currently active criminals. Thus, it is particularly desirable to develop procedures for estimating career lengths indirectly on the basis of patterns of currently active offenders.

Our basic approach to estimating duration of criminal careers derives from the observation that the numbers of arrestees in any year falls off dramatically with age. This fact is illustrated in Figure 4 showing the age distribution of arrestees for serious crimes in Washington, D.C. during 1973. This decrease in numbers with age is very similar to, but more

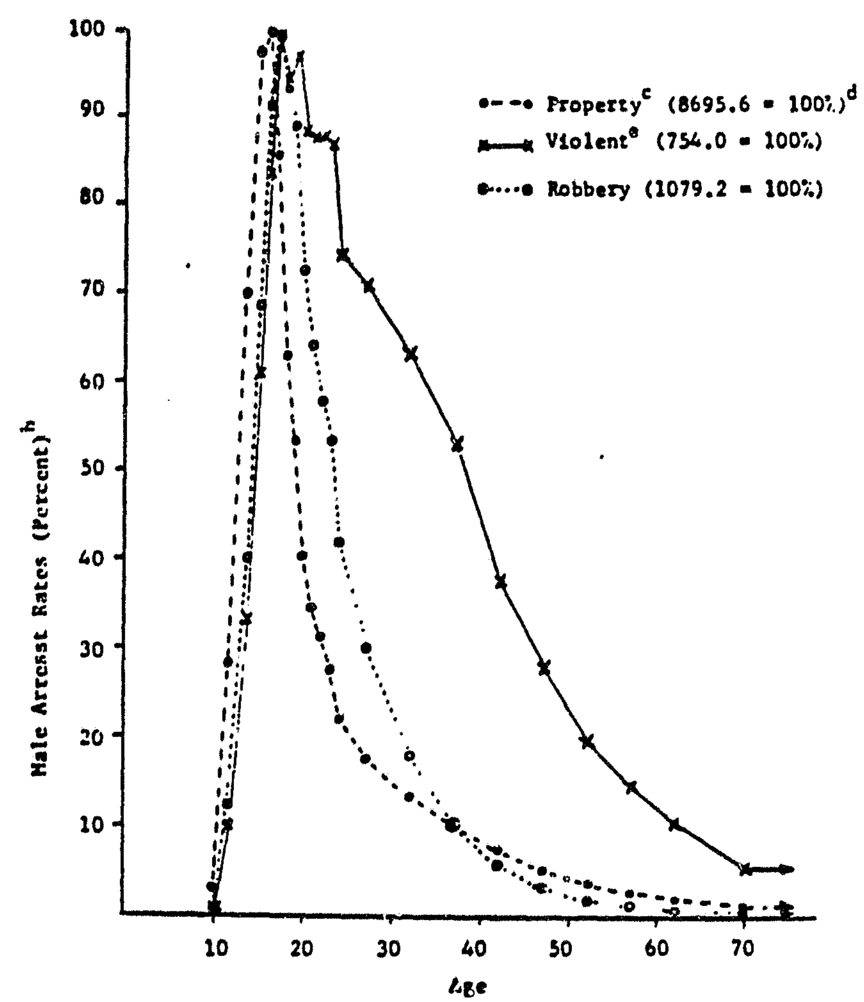

Figure 3

Male Arrest Rates by Age and Crime Type in 55 Large U.S. Cities in 1970[a]

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[a] The data include those U.S. cities with populations in excess of 250,000 in 1970. For multi-year age categories (e.g., 25 to 29), the arrest rate is noted at the midpoint of the category.

[b] The arrest rates are expressed as percentages of the peak rate for each crime type. The actual rates are available in Appendix K.

[c] Property offenses include burglary, larceny and auto theft.

[d] The peak rate is expressed as arrests per 100,000 male population.

[e] Violent offenses include homicide, rape, and aggravated assault.

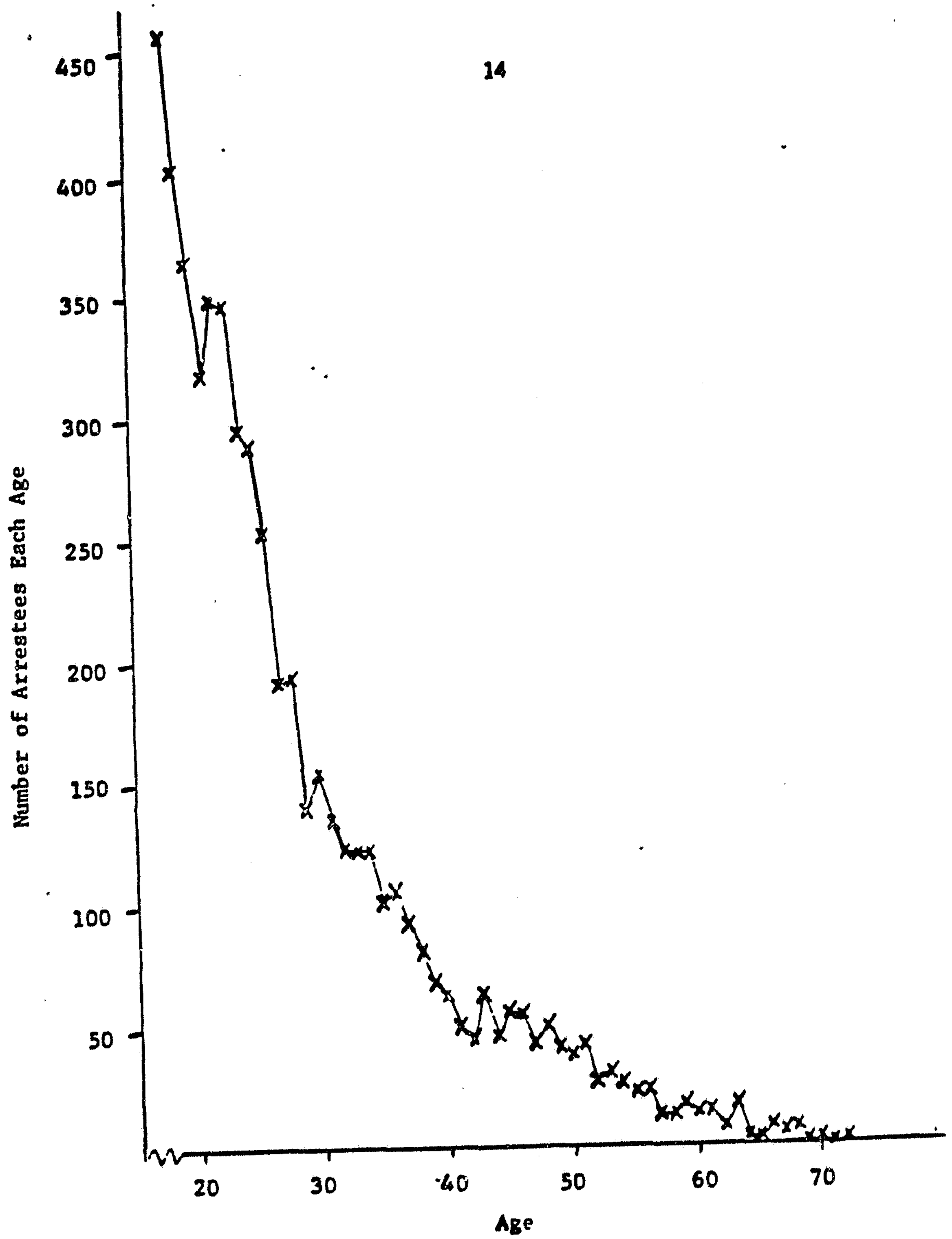

Figure 4

Age Distribution of "Criterion"
Adult Arrestees in Washington, D.C.
During 1973 [a]

[a] "Criterion" arrestees include those adults arrested during 1973 for the index offenses of homicide, rape, robbery, aggravted assault, burglary, and auto theft (i.e., arrestees for all index offenses other than larceny).

rapid than, the decline in the age distribution observed in the general population. After controlling for the size of different birth cohorts,[11] the drop-off in the general population with age reflects mortality rates at different ages. These age-specific mortality rates, as well as the consequent life expectancies for the population, can be estimated directly from observing the age distribution of the population in any year.

The same basic principle underlies our approach to estimating criminal career lengths. At least in part, the reduced numbers of older arrestees reflects a career equivalent of mortality, namely the dropout from criminal careers as active offenders terminate their criminal activity. This manifestation of the dropout process can be used to develop empirical estimates of dropout rates from criminal careers, and of the associated expected length of criminal careers.

There are, however, factors other than dropout that affect the number of arrestees of each age that must be controlled in the estimates. Arrestees, like the rest of the population, are vulnerable to changing birth, death and migration processes that affect the size of different age cohorts. Some of the fall-off in arrestees with age is simply a reflection of an increase in the size of more recent birth cohorts and of increased mortality with age. These more general population dynamics must be separated out before estimating career lengths.

In estimating expected lifetimes for a population, age is a direct indicator of how long a person has lived so far. For criminal careers, age is only a proxy for time already elapsed in a career that depends on the age at which the career began. For a career that begins at age a_o, for example, arrestees at age a will have been criminally active for x years where $x = a-a_o$. Age at which a criminal career starts is thus a critical variable in estimating career length from the age distribution of arrestees.

Just as general populations are vulnerable to variations in birth and death processes over time, the different age cohorts of arrestees observed in a single year are the product of potentially varying recruitment and dropout processes over time. Changes in the proportion of birth cohorts that enter criminal careers, or changes in dropout rates from criminal activity over time will differentially affect the numbers of arrestees at each age. Increases in recruitment in recent years, for example, would result in disproportionately larger numbers of young arrestees relative to old arrestees found in a year. Such variations must also be considered when estimating career length.

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[11] For populations that are defined narrowly geographically, additional adjustments for migration into and out of the area are also required.

One final consideration is the degree to which the age distribution of arrestees is an adequate reflection of the age distribution of all active offenders. If the age distribution of arrestees is representative of that of all offenders, the career-length estimates obtained here will represent the total length of criminal careers. Otherwise, the career length estimates accurately reflect the length of arrest careers (i.e., the expected time from first to last arrest). Arrestees are representative of active offenders in general with respect to age if the probability of at least one arrest in a year for offenders is stable over age. On the other hand, a decrease with age in arrest vulnerability would underestimate criminal career length as older offenders are underrepresented among arrestees, and vice-versa.

Building on the life-table approach to estimating mortality rates and expected lifetimes for a population, the age distribution of arrestees is used to estimate dropout rates from criminal careers (analogous to mortality rate), the expected total length of criminal careers (analogous to the expected total lifetime at birth) and expected residual career lengths (analogous to life expectancy at any age). The technical details involved in making these estimates are provided in Appendix A. Applying the estimates developed in Appendix A to the age distribution of arrestees, requires adjustments for:

1. variations in the size of the base population each age;
2. age at the start of a criminal career;
3. variations in rates of recruitment to and dropout from criminal careers over time; and
4. age variations in the probability of an offender being arrested at least once in a year.

Application of these adjustments to data on age-specific arrests and arrestees are considered individually below.

2.1 EXTENSIONS TO ARREST DATA

Estimating career-length parameters ideally requires data on the number of distinct arrestees, or different persons arrested at each age in a year. While data on arrestees are rare, data on arrests by age are widely available. Because some people are arrested several times in a year, and thus are counted more than once in their age group, however, arrests by themselves are not a satisfactory proxy for arrestees. In this section, we examine the potential for adjusting arrest data to generate estimates of the number of individual arrestees.

2.1.1 Converting Arrests to Arrestees

Converting age-specific numbers of arrests to numbers of arrestees requires data on both arrests and persons arrested in order to compute the ratio of individual arrestees to total arrests in a year. The necessary data on arrestees and their arrests were available to us for all adults arrested for an index offense other than larceny in Washington, D.C. during 1973.[12] These data included all arrests for each arrestee during the sample year.

The arrestee-to-arrest ratio by age observed for each index offense type in Washington, D.C. during 1973 is presented in Figure 5, along with the best straight-line fit through the observed ratio values. The arrestee-to-arrest ratios vary by crime type, with robbery, aggravated assault and larceny[13] exhibiting increases in the ratio of arrestees to arrests with age. This reflects a greater incidence of multiple arrests per person in a year for younger offenders in these crime types. The greater prevalence of multiple arrests is especially evident for robbery and larceny which average from 1.3 to 1.4 arrests/arrestee for young adults. In contrast, the remaining crime types have generally stable ratios over age.

A principle focus of this research will be on estimating the duration of index criminal careers - that is, the portion of a criminal career during which the more serious, index offenses are committed. This will require aggregating arrestees for the individual index offense types to yield the total number of index arrestees. Because the same offender may be arrested for more than one index crime type in a year, a simple sum across the crime types will involve potential multiple counting of the same arrestee. This can be adjusted for by using the ratio of unique index arrestees found in the sum across index crime types. Figure 6 presents the observed ratio by age for the Washington, D.C. arrestees, along with the best straight line fit through the observed values. The proportion of unique arrestees increases steadily with age indicating that younger offenders are more likely to have arrests for more than one index crime type in a year.

2.1.2 General Utility of Conversion Factors

The kind of data linking arrestees with their arrests used in Figures 5 and 6 are usually

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[12] These data were provided by the FBI from their computerized criminal history file.

[13] The 1973 arrestee data are complete for all index offenses other than larceny. In the case of larceny, only those larceny arrestees who are also arrested for some other index offense during 1973 are included. Thus, the pattern of multiple arrests per arrestee for larceny is characteristic of larceny offenders who get arrested for other index offenses as well, and so it may not be representative of all larceny arrestees.

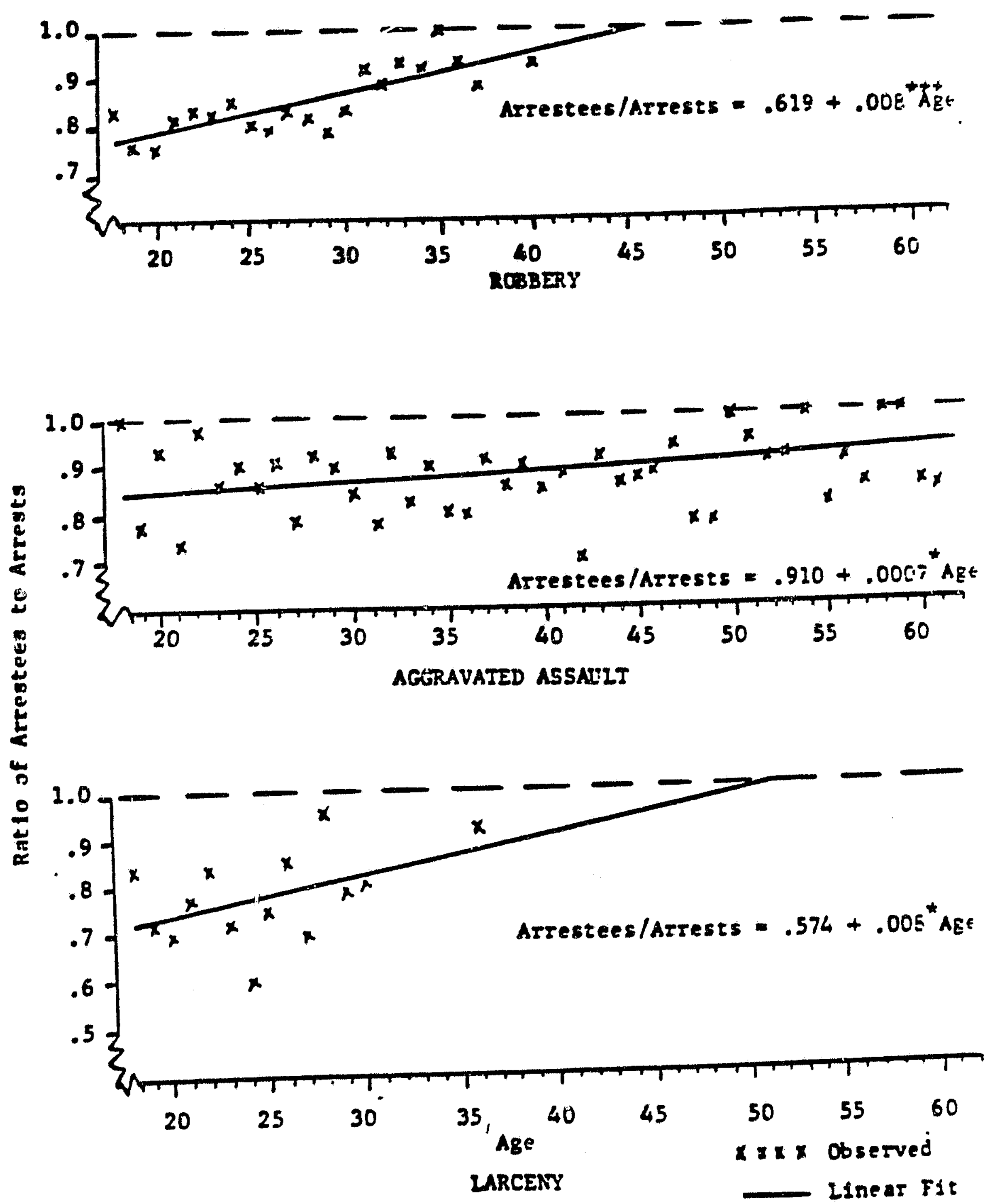

Figure 5

Ratio of Arrestees to Arrests by Crime Type and Age in Washington, D.C. During 1973

* Significant at .10 level using a 2-tailed t-test.

*** Significant at .001 level using a 2-tailed t-test.

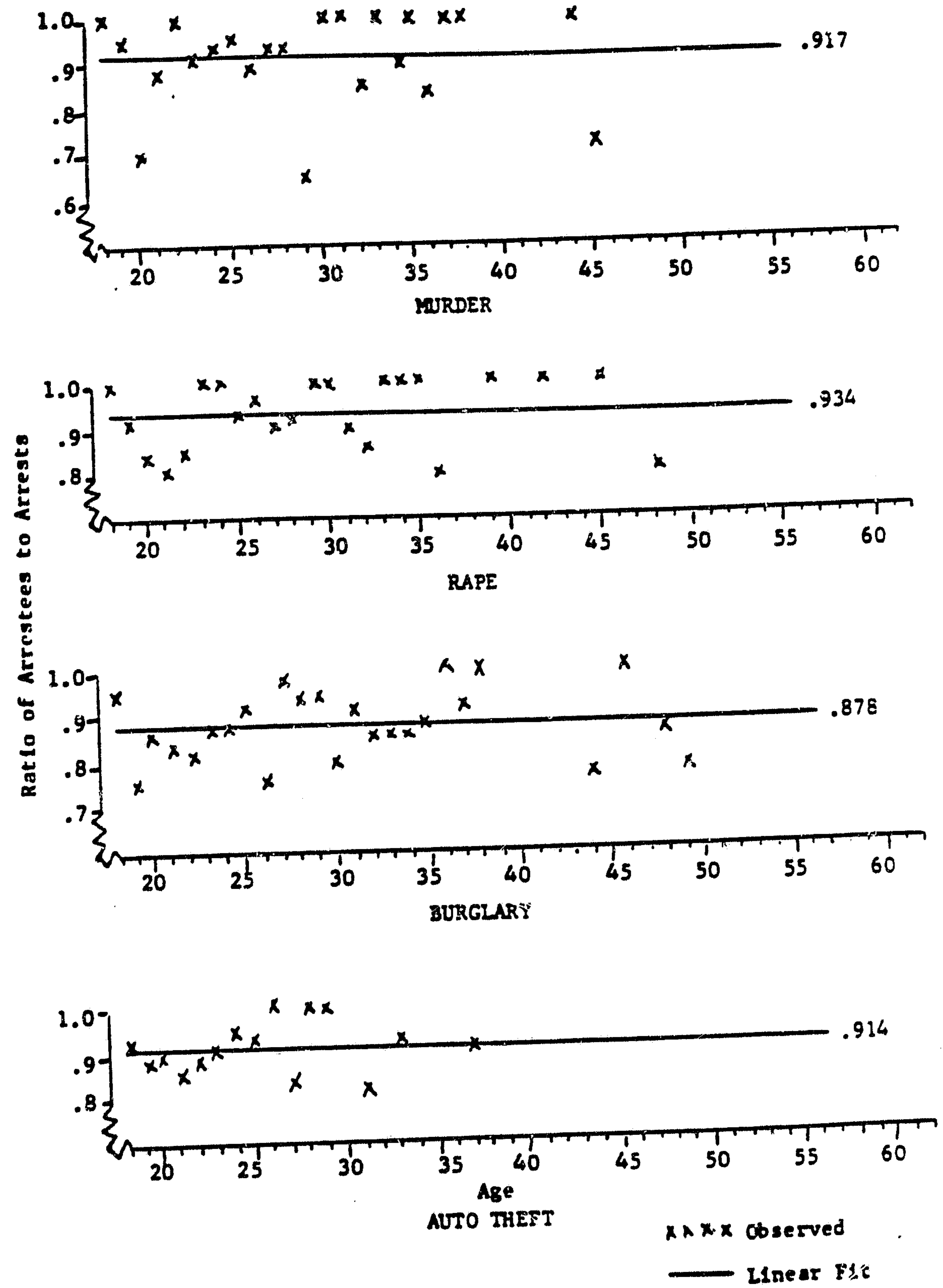

Figure 5 (continued)

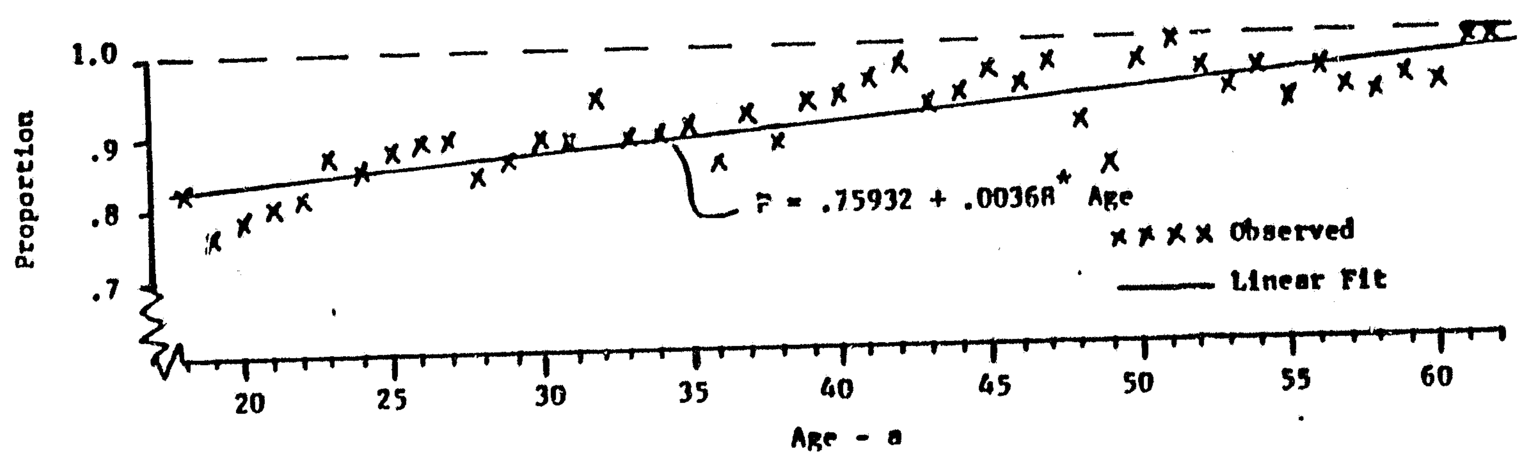

Figure 6

Proportion of Unique Index Arrestees
Among All Index Arrestees in Washington, D.C.
During 1973

* Significant at .001 level using a 2-tailed t-test.

not available. In terms of the general utility of the methods for estimating career length proposed here, it is important to assess how useful the estimates derived in one place and time may be in other settings.

To explore the generalizability of the arrest-to-arrestee conversion factors, data were obtained for adult arrestees in the state of Michigan during the years 1974 through 1977.[14] The arrestee-to-arrest and unique-index-arrestee ratios were estimated separately for four years in eleven large counties in Michigan.[15] These ratios were regressed against age (as in Figures 5 and 6) and the resulting regression coefficients were examined for stability over time and across jurisdictions.[16] (See Appendix B.)

Comparing across the four years 1974 to 1977 in each county revealed considerable stability over time in the arrestee-to-arrest ratios for individual crime types and in the proportion of unique index arrestees. In comparisons for 88 separate ratios across time, only eight were found to have statistically significant time trends. These eight cases, however, did not exhibit any distinctive pattern and a single combined test failed to reject the null hypothesis that all eighty-eight ratios are time stationary ($p = .08$).[17]

While generally stable over time (at least for the four years studied), the values of the ratios did vary significantly across different counties in Michigan (Appendix B). As in Washington, D.C., the arrestee-to-arrest ratios were generally stable over age for murder, rape and auto theft. The mean value, however, varies from county to county. Also as in

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[14]The data were again obtained from the FBI's computerized criminal history file and included all adults arrested in Michigan for an index offense other than larceny at some time from 1974 to 1977. This provided a complete inventory of arrestees for the selected crime types. Data on all arrests for the selected arrestees were included.

[15]Those counties with about 900 or more index arrests annually were selected.

[16]A standard F-test suggested by Chow was used to compare the results from an unconstrained regression (in which the parameters are estimated separately for different years, or different counties) with those of a constrained regression (in which the parameters are assumed to be equal in all years, or in all counties). See Fisher (1970) or Rao (1973:281-4) for details of this test.

[17]The test combines the individual p_i-levels of the separate F-tests to form the statistic:

$$P_\lambda = \Sigma_{i=1}^{k} -2\ell n p_i$$

which is distributed as X^2 with 2k degrees of freedom. The individual F-values and P_λ are reported in Appendix B.

Washington, D.C., the remaining crime types have positive trends over age in at least some of the counties, although the trends were not present in all counties. The proportion of unique index arrestees always has a distinct upward trend with age, but the intercept varies across the counties from .858 to .954. Washington, D.C. and Michigan are also distinguished by different levels of multiple arrests, with Michigan arrestees having fewer multiple arrests for individual crime types and fewer arrests for multiple crime types in a year than were found in Washington, D.C. (See Appendix B).

Thus, there is strong stability in the ratios over time, but with some small variations across jurisdictions. As indicated in Appendix B, within the range of jurisdictional differences in the ratios observed in Michigan and Washington, D.C., the impact of different ratios on the career length estimates is small. The estimates derived from the eleven Michigan counties and from Washington, D.C. thus appear to offer reasonably generalizable factors for converting arrests to arrestees in order to develop career-length estimates for other jurisdictions.

2.1.3 Washington, D.C. Arrests

To assess the variability in career-length estimates derived from arrests in a single year, data on index arrests in Washington, D.C. were obtained for seven separate years (1970 to 1976).[18] Unfortunately, the arrest data for each year were only reported for aggregated age groups (e.g., 25 to 29 year olds), while the career length analysis focuses on each of the individual ages contained in these groups. Again, the detailed data for 1973 arrestees were used to disaggregate the number of arrests to each individual age. (See Appendix C).

Since the age-specific data are only available for adults arrested in 1973, the career length analysis is restricted to adult careers (i.e., the portion of the criminal career occurring after age 18). Also, we only consider the age distribution for index crimes, and the resulting length of index-crime careers (i.e., the period during which adult offenders commit index offenses). A total adult criminal career, including non-index offenses, will in general be longer than the index-crime career.

2.1.4 Final Estimates of Arrestees

The age-specific numbers of arrests for each index offense available in section 2.1.3 were first multiplied by the arrestee-to-arrest ratios estimated in section 2.1.1 to yield arrestees for each index offense type. Summing over all index offense types provides a first estimate of

[18]These data were obtained from the Annual Report of the Metropolitan Police Department of Washington, D.C. issued for the years 1970 to 1976.

total index arrestees of age a in year t. Because the same individual may be counted more than once if he is arrested for more than one index offense type in a year, however, this simple sum overestimates index arrestees. To correct for this multiple counting, we multiply by the proportion of unique index arrestees estimated in section 2.1.1. This yields the final estimate of the number of index arrestees of each age a in year t.[19]

To generate estimates of the career length variables, the resulting data on the age distribution of arrestees must be adjusted to bring the data into conformity with the analytical assumptions identified in section 2.0 and Appendix A. In particular, we must assure that the arrestees at each age are representative of the larger group of offenders of that age, that the effects associated with different sizes of birth cohorts are removed, and that age becomes a reliable measure of time already spent in a criminal career. We will explore each of these issues in turn, testing the validity of the assumptions in some cases and adjusting the arrestee estimates in others.

2.2 REPRESENTATIVENESS OF ARRESTEES

The first assumption requires that the probability of at least one arrest in a year does not vary with age. In other words, the individual arrest rate (the number of arrests per year per active offender) must be constant over age. A higher arrest rate for certain age groups would increase the representation of these age groups among arrestees and bias the career length estimates. Previous analysis of arrest-history data for Washington, D.C. offers some preliminary empirical evidence to support the assumption of stationarity over age within a cohort of offenders (Blumstein and Cohen, 1979). There was, however, evidence of variations in arrest rates across different cohorts for some crime types (robbery, burglary and larceny). Thus, the effect on the career-length estimates of any age dependencies in the likelihood of arrest are examined explicitly in section 4.2 and Appendix G.

2.3 CORRECTION FOR VARIATIONS IN THE SIZE OF THE BASE POPULATION

In measuring criminal career length and dropout from careers using the age distribution of arrestees, we must control for the changes in the number of arrestees each age that are due to changing birth, death and migration patterns in the base population. To control for the influence of these base-population variations, we take the ratio of arrestees to the base

[19]For $A_i(a,t)$ – the number of arrests for each index crime type i at age a in year t, $k_i(a)$ – the ratio of arrestees-to-arrests by age for index type i, and m(a) – the proportion of unique index arrestees by age among the sum of arrestees for individual index types, the final estimate of the total number of index arrestees at age a in year t is given by:

$$N(a,t) = m(a) \Sigma_i k_i(a) A_i(a,t).$$

population at each age. The resulting arrestees per capita at each age normalizes the age-specific numbers of arrestees with respect to the size of the base population at each age. This adjustment accounts for any variability in the offender population due to birth, death and migration to the extent that the birth, death and migration patterns of offenders are like those of the general population.

As indicated in Table 1, index arrestees in Washington, D.C. are predominantly non-white males. The most appropriate base population for normalizing is then the number of non-white males by age in Washington, D.C. each year. With the exception of 1970 when the detailed results from the decennial population census are available, the annual population figures are available only for aggregate age groups. The required population estimates for single ages in each year after 1970 were generated using the procedure for distributing population age groups over the individual ages described in Appendix D.

2.4 CORRECTION FOR LATE ENTRY INTO CRIMINAL CAREERS

The career-length analysis requires some means of estimating the time already elapsed in a criminal career from the observed age, a, of arrestees. If all offenders begin their adult index careers at the same age, a_o, then time in the career for an offender age a is just $x = a-a_o$. To identify a_o, we need data on the age at first index arrest for arrestees. The 1973 arrestee data provides a basis for determining the age of the first adult index arrest for the 1973 arrestees. The analysis is restricted to adult criminal careers, in part because these data do not contain information on juvenile arrests. The earliest age at which adult index careers can begin is 18, so we begin by setting $a_o = 18$.

Two different approaches could be used to assure that the index arrestees included in the analysis were indeed active as index offenders at age 18:

1. All adult index careers could be assumed to begin at age 18, regardless of the age at first index arrest; or
2. The analysis could focus on only those offenders who do have an index arrest on or before some threshold age b.

The first approach includes all arrestees in the analysis. While the bulk of adult index

Table 1

Distribution of Arrests and Arrestees in Washington, D.C. by Race and Sex

Criterion Arrests:*

Year	% Male	% Nonwhite	% Nonwhite Males
1970	93.4	93.0	86.8
1971	93.3	94.6	87.9
1972	91.3	93.6	85.4
1973	91.1	94.8	86.3
1974	90.8	93.8	83.9
1975	93.2	95.3	N.A.
1976	92.0	96.2	N.A.
Average	92.2	94.5	86.1
Criterion Arrestees:**			
1973	89.7	91.8	83.8

N.A. - Not Available.

*Derived from tables reported in the Annual Reports of the Metropolitan Police Department, Washington, D.C. Criterion arrests include arrests for homicide, rape, robbery, aggravated assault, burglary and auto theft.

The percentages presented are based on arrests for all ages. When adults could be identified separately, the percent nonwhite was an average of 1.5 percentage points less for a seven-year average of 93.0% and the percent male was an average of 1.3 percentage points less for a seven-year average of 90.9%.

**Derived from the F.B.I. computerized criminal history file of individual adult arrestees for criterion offenses in Washington, D.C. during 1973.

careers do start at age 18,[20], there are nevertheless some adult offenders who do not begin their adult index careers until well after age 18. Failure to exclude these late starters from an analysis that assumes a_o = 18 for all arrestees will overestimate the career length by mistakenly attributing long careers to individuals whose first adult arrests occur at older ages. Approach (2) reduces the overestimation bias due to these late starters by restricting the analysis only to arrestees who are more likely to have started their adult index careers at 18.

The 1973 arrestee data provide estimates of the proportion, $P_b(a)$, of 1973 arrestees at each age a who had their first adult index arrest between age 18 and some cut-off threshold age, b. By assuming stationarity in $P_b(a)$ over time, these proportions can be applied to the annual arrestees per capita each age available from section 2.3 to eliminate those arrestees who do not have an index arrest until after age b.

The use of a threshold age, b, to identify 18-year-old starters involves two types of error:

1. Errors of Omission: missing a true 18-year-old starter who fails to have an index arrest between ages 18 and b, and
2. Errors of Commission: mistakenly identifying someone who has a first index arrest as late as age b as having started at age 18.

As b increases, errors of omission decrease while errors of commission increase. For any given value of b, when these two error rates are uniform at every age, with either the same proportion of missing true starters at each age a, or the same proportion of mistakenly identified late starters at each age a, the age distribution of arrestees and the resulting career-

[20]Follow-ups beyond age 18 of the Philadelphia birth cohort (Wolfgang et al, 1972) indicate that of adults with arrest records between the ages of 18 and 22, 75% also had juvenile arrest records (Wolfgang, 1977). When followed to age 30, 60% of adults with arrest records also had juvenile arrest records (Collins, 1976). This continuity of offending between juvenile and adult criminal careers also appears to be more prevalent among non-whites. In the follow-up to age 22 (Wolfgang, 1977) 65% of white adult offenders also had juvenile arrest records compared to 83% of non-white adult offenders.

length estimates are not biased.[21]

When the error rates vary with age, however, the age distribution of arrestees is affected by shifts in b. This will result in underestimates or overestimates of career length as either type (1) or type (2) errors become more likely. If older offenders are more vulnerable to type (1) errors in year t (perhaps because older arrestees have had lower arrest rates throughout their careers), we are more likely to miss true 18-year-old starters among older arrestees when b is small. This will decrease the representation of older arrestees in the age distribution and lead to underestimates of career length. These type (1) errors can be reduced by increasing the age threshold b. As we increase b, however, we increase the likelihood of type (2) errors where late starters among older arrestees are mistakenly identified as active at age 18. This increases the representation of older arrestees in the age distribution resulting in overestimates of career length.

The choice of the threshold age, b, for a first index arrest thus represents a balancing between potential underestimates and overestimates of career length. To assess the sensitivity of the resulting career-length estimates to particular values of b, three different values of b were used in this analysis, b = 20, 23, and 25.

The values of $P_b(a)$ observed for the 1973 arrestees are presented in Figure 7. This figure shows that the lower the threshhold age b, the smaller the fraction of arrestees at any age a who satisfy the "early-starter" criterion. The observed values of $P_b(a)$ were smoothed by fitting an exponential function through the points beyond the respective b thresholds, with

$$P_b(x) = \alpha e^{\beta x}, \text{ where } x = a-b.$$

The smoothed $P_b(a)$ functions resulting from these least-square estimates are also presented in Figure 7.

[21]For the same error rate e at every age a, and n_a the observed number of 18-year-old starters at each age a, the true number of 18-year-old starters, n_a^*, is $n_a/(1+e)$. This leaves the age distribution unchanged at,

$$g(a) = \frac{n_a}{\sum_a n_a} = \frac{n_a^*}{\sum_a n_a^*} = \frac{n_a/(1+e)}{\sum_a n_a/(1+e)}$$

and the career-length estimates are not affected when the error rates are uniform at every age.

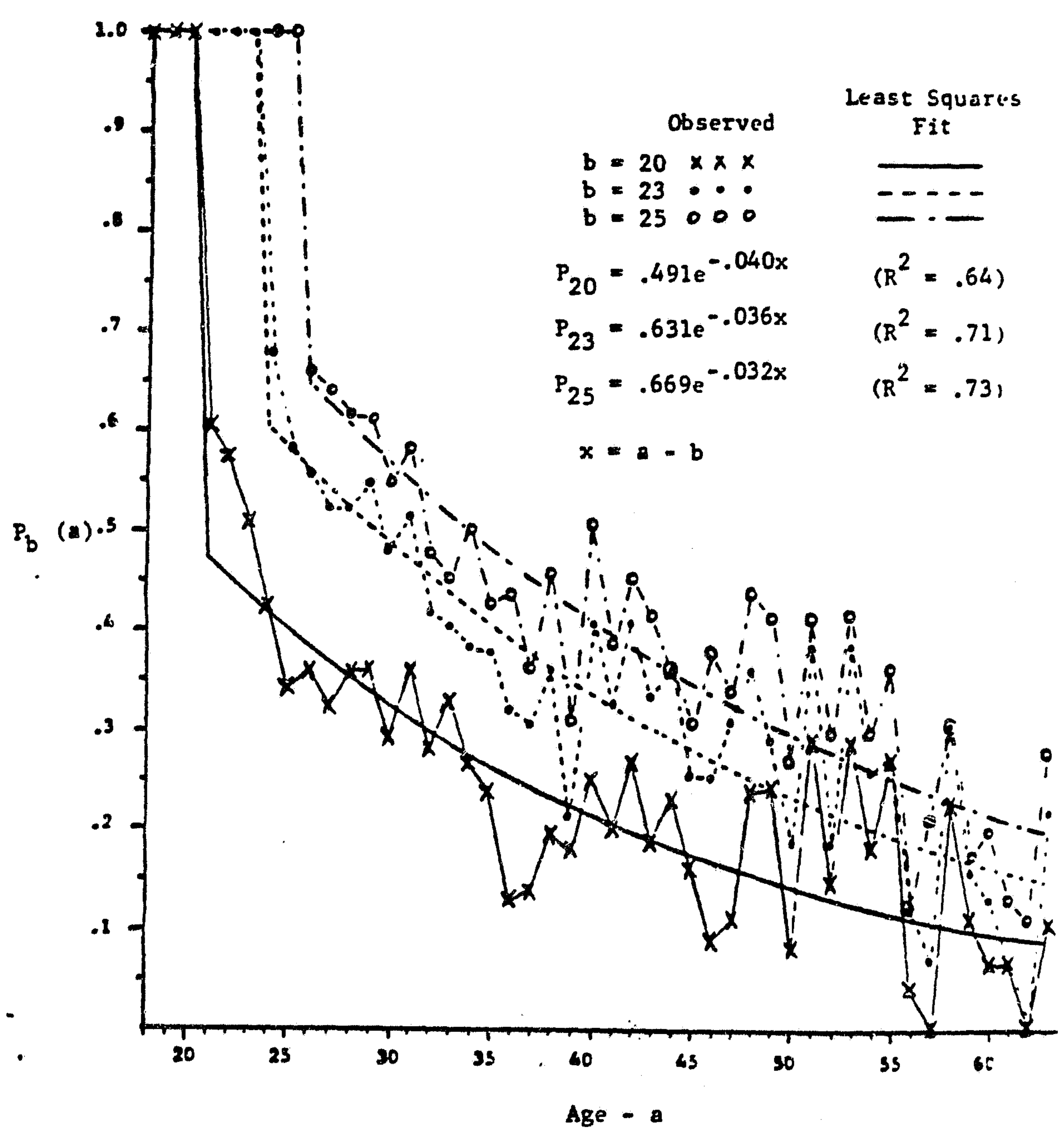

Figure 7

Proportion of 1973 Index Arrestees at Each Age a With an Index Arrest Before Threshold Age b (b = 20, 23, 25)

2.5 ADJUSTMENT FOR STABLE RECRUITMENT AND DROPOUT OVER TIME

In the last adjustment to the arrestee variable, the number of arrestees per capita (generated in section 2.3) was multiplied by $P_b(a)$ (derived in section 2.4) to eliminate late entrants to criminal careers. Using this adjusted variable to reflect the age distribution of arrestees in a year, dropout rates (r(a)), mean residual career lengths (τ(a)), and mean total career length (T) can be estimated from equations (A4), (A8), and (A9) in Appendix A.

In accord with the life-table procedures, we would like to be able to use the age distribution of arrestees in a single year t to estimate the career-length variables. This requires stable recruitment and dropout processes over the different cohorts. When estimating career-length parameters using data from a single year t, the adjusted numbers of arrestees per capita each age, N(a,t), actually come from different cohorts; those who are age a in year t began their careers at age 18 in year t-(a-18). Thus the final adjustment to the number of arrestees must account for any changes in recruitment among these different cohorts. Failure to adjust N(a,t) for growth (or decline) in recruitment across different cohorts will result in biased estimates of the career-length parameters. When there is growth in recruitment, for example, the dropout rate will be overestimated and career length will be underestimated because of the greater representation in year t of younger people from more recent cohorts.

If all offenders begin their adult careers at age 18, then the ratio N(18,t+1)/N(18,t) = $k_t(18)$ for $k_t(18)>1$ is a measure of growth (or decline if $k_t(18)<1$) in recruitment between t and t+1. A value of unity for this ratio indicates stable recruitment rates from year to year. In Appendix E, the recruitment ratio $k_t(a)$ is examined separately for each age 18, 19 and 20 over the period 1970 to 1976. This analysis provided no evidence of any systematic time trend in the $k_t(a)$ ratio, and the mean of $k_t(a)$ is never significantly different from the stable value of unity. The recruitment rate appears to have been reasonably stable, at least over the seven years, 1970 to 1976. Thus, the analysis of criminal-career length using the annual age distribution of arrestees will not be adjusted for changes in recruitment. Since recruitment patterns for the earlier cohorts (those who began their careers before 1970) could not be explicitly examined with the available data, however, they may possibly have had different recruitment rates; any potential bias this might introduce in the career-length estimates will be considered in section 4.2.

Aside from stable recruitment, the use of a single year's data to estimate career-length variables also requires stable dropout over time. If the dropout rate is increasing for more recent cohorts, then the number of arrestees age a in year t is likely to overestimate the expected number of arrestees who would reach age a under the higher dropout rate prevailing in year t. The dropout rates estimated from a single year's data, then would underestimate the true dropout rate prevailing in year t. The extent of this bias will be explicitly considered in section 3 by examining the stability of the career-length estimates derived for each year 1970 to 1976.

2.6 SMOOTHING THE DATA

All the career-length variables depend heavily on point estimates of the proportion of arrestees at different ages, g(a), and also on differences between g(a) at adjacent ages ($g'(a) = g(a)-g(a+1)$). Sampling error generates variance in the $\hat{g}(a)$ estimates distributed around the true g(a) distribution. While this error may be small and acceptable with respect to the g(a) values, the error in the estimates of $\hat{g}'(a)$ is much more sensitive to those sampling errors, and so is more severe. Since the estimates of dropout rates are highly sensitive to the differences between g(a), even reasonable errors in $\hat{g}(a)$ can lead to sizeable errors in the estimates of g'(a), and hence in the estimated dropout rates, $\hat{r}(a) = -\hat{g}'(a)/\hat{g}(a)$ (as derived in Appendix A).

This problem can be reduced by first smoothing the observed $\hat{g}(a)$ distribution to reduce the size of the errors around the true g(a). Figure 8 presents the observed $\hat{g}(a)$ for index arrestees per population for one year in Washington, D.C., and the smoothed $\hat{\hat{g}}(a)$ obtained by taking the average value of $\hat{g}(a)$ for the three-point neighborhood around $\hat{g}(a)$.[22] To further reduce the impact of the errors remaining in the smoothed $\hat{\hat{g}}(a)$, $\hat{g}'(a)$ is estimated by the slope of the regression line fit through the smoothed $\hat{\hat{g}}(a)$ in the k-point neighborhood around $\hat{\hat{g}}(a)$ (for k = 3, 5, 7, 9, 11).

2.7 SENSITIVITY OF THE CAREER-LENGTH ESTIMATES TO THE VARIOUS ADJUSTMENTS TO THE DATA.

The primary data for this career-length analysis were the annual police reports of the number of index arrests by age in Washington, D.C. This arrest data underwent a number of transformations to yield an arrestee distribution that satisfies the assumptions underlying the basic life-table approach. The sensitivity of the estimates of the career-length variables to each of the various adjustments discussed above was explored by estimating career length from the age distribution obtained after each adjustment to the data. Table 2 compares the resulting

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[22] $\hat{\hat{g}}(a) = \sum_{x=a-1}^{a+2} \hat{g}(x)/3$. Using a larger neighborhood around $\hat{g}(a)$ will result in a still smoother g(a) distribution. A three-point neighborhood was chosen to get some smoothing, while maintaining a substantial influence of the observed $\hat{g}(a)$ value on the smoothed $\hat{\hat{g}}(a)$ value. Other possible transformations of the data might include:

$$\sum_{x=a-2}^{a+2} \hat{g}(x)/6 + \hat{g}(a)/6,$$ a five-point smoothing with a double weight for $\hat{g}(a)$ itself.

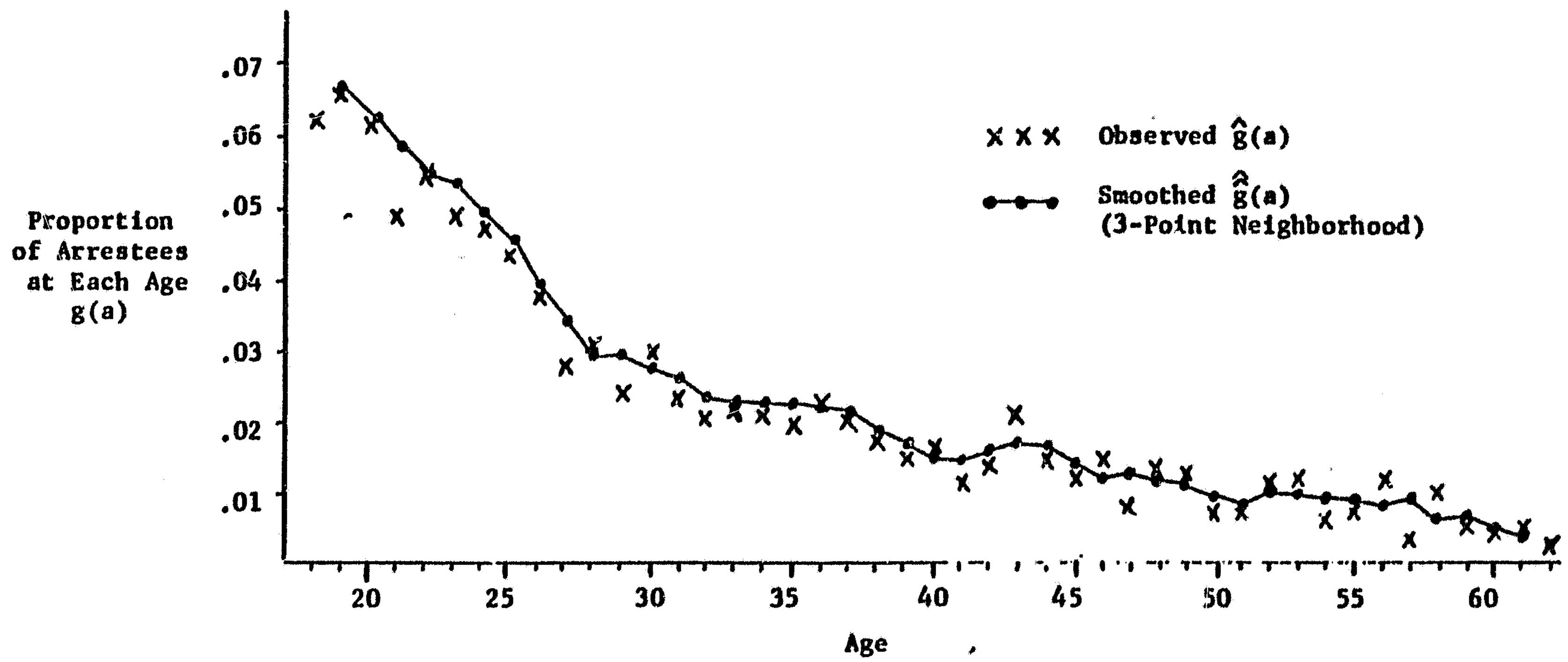

Figure 8

Smoothing the Age Distribution of Index Arrestees/Population

mean total career-length estimates (T) and Figure 9 presents the different estimates of the mean residual career length at each age, $\tau(a)$.[23]

After all the corrections are made, the mean total index career of those with a first index arrest between ages 18 and 20 is estimated to be 5.6 years long (Table 2). This is considerably shorter than the 10 to 15 year career length estimated by Shinnar and Shinnar (1975) and Blumstein and Greene (1978), but close the crude estimate in Greenberg (1975).

As is evident in Figure 9, the residual career-length estimates at younger ages are most sensitive to the corrections. Beyond age 50, on the other hand, there is very little difference between the alternative estimates. The major changes in the career-length estimates result from the population correction and the elimination of late-starters. The transformation of arrests to arrestees has relatively less impact on the career-length estimates. Indeed, using the original arrest data (with no adjustments) instead of the transformed arrestee data would underestimate the career length by about 15% (Table 2).

In going from arrests to arrestees, there are more multiple arrests per arrestee, as well as more multiple index crime types per arrestee at younger ages. These adjustments thus remove disproportionatley more offenders at younger ages in the age distribution, thus driving the career-length estimates up somewhat. The population correction adjusts for the greater number of younger people in the general population and drives the career-length estimates even higher. Also after the population correction, the peak of the mean residual career length in Figure 9 appears to be at age 28 (or after ten years into the career) instead of age 40 (or twenty-two years into the career).

The late-starter correction eliminates people who do not start adult index careers until after age 18. This removes many older arrestees, especially older first-time arrestees, who would otherwise have been treated as if their careers started at age 18. This drives the career-length estimates down, especially for the youngest ages. The more restrictive the definition of the population treated as 18-year-old starters, the greater the decrease in the career-length estimates. Excluding people with a first index arrest after age 20 (b = 20) results in a shorter career-length estimate (T = 5.6 years) than excluding only those with a first index arrest after age 25, b = 25 (T = 9.4 years).

Failure to adjust for the disproportionate numbers of young people in the population

[23] The age distributions, g(a), underlying all estimates in Table 2 and Figure 9 are smoothed by averaging over the three-point neighborhood around each $\hat{g}(a)$.

Table 2

Impact of Various Adjustments on Estimates of the Mean Total Career Length - T

Adjustment	Estimating Population	Estimated Mean Total Career Length T (Years)	Percentage Change Between Estimates
1. None	Distribution of Index Arrests	9.6	
2. Conversion of Arrests to Arrestees (Arrestee to Arrest Ratio)	Age Distribution of Index Arrestees (with multiple counting)	10.3	+6.2% (1 to 2); +15.5% (1 to Multiple Crime Type Ratio); +8.7% (2 to Multiple Crime Type Ratio)
(Multiple Crime Type Ratio)	Age Distribution of Unique Index Arrestees	11.2	+25.9% (Multiple Crime Type Ratio to 3)
3. Changes in Base Population	Age Distribution of Arrestees/Population	14.1	
4. Eliminating Late Starters			-33.3% (3 to b = 25)
b = 25	Age Distribution of Arrestees/Population, 18-25 year old starters only	9.4	-41.8% (3 to b = 23)
b = 23	Age Distribution of Arrestees/Population, 18-23 year old starters only	8.2	-60.3% (3 to b = 20)
b = 20	Age Distribution of Arrestees/Population, 18-20 year old starters only	5.6	

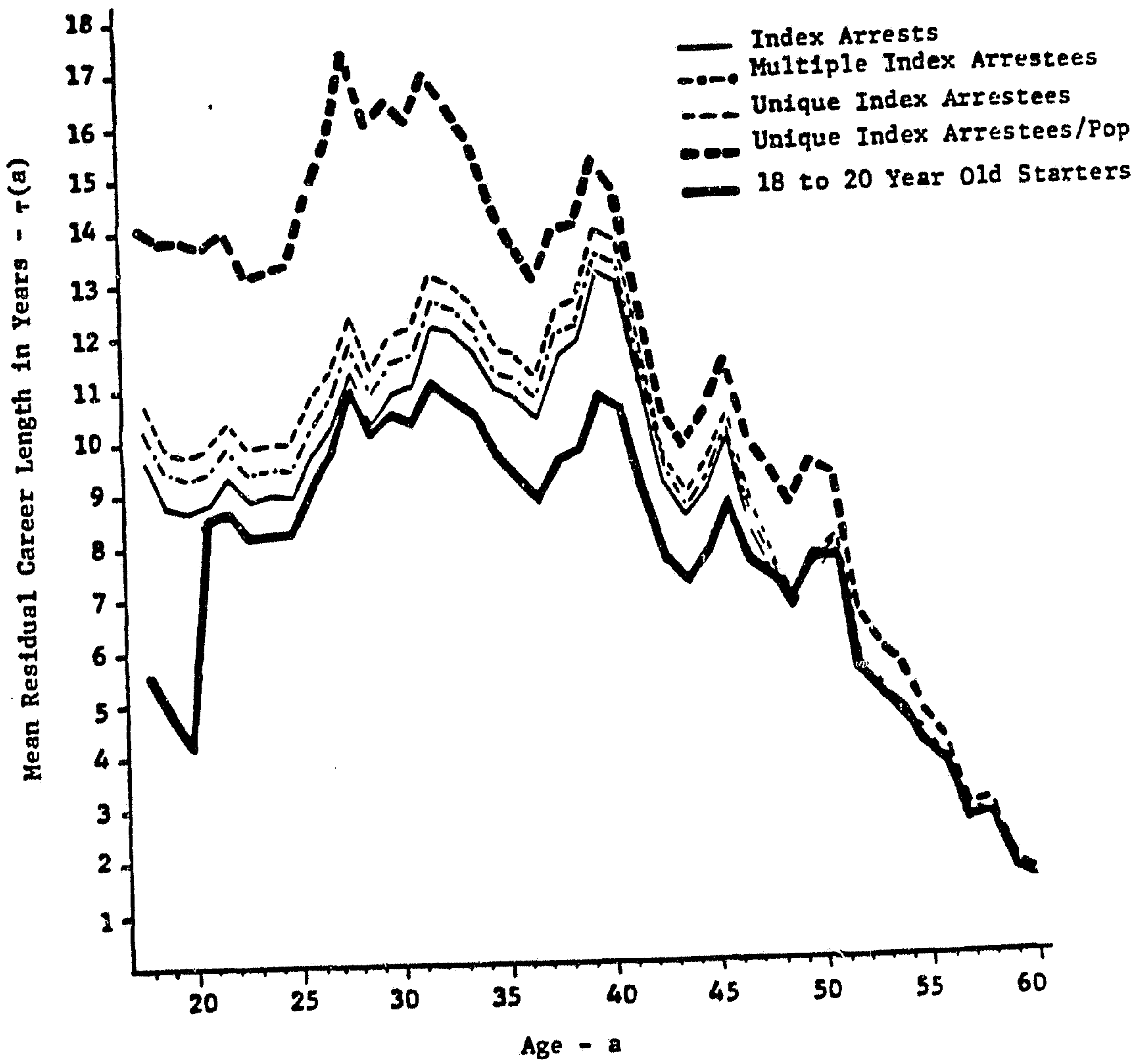

Figure 9

Impact of Various Adjustments on the Mean Residual Career Length at Each Age

seriously underestimates the career length, while failure to adjust for late-starters seriously overestimates the career length, especially at younger ages.

3.0 VARIABILITY IN CAREER-LENGTH ESTIMATES FROM ANNUAL DATA

Seven years of data (1970 to 1976) were used to generate separate career-length estimates. These multiple estimates provide an opportunity to explore the general level of variability in the estimates, as well as any time trends in career length. Figure 10 illustrates the variability in the residual career-length estimates for 18 to 20 year old starters (b = 20). In the figure, the mean estimate from the seven years is surrounded by a band representing ±1 standard deviation in the separate estimates. The estimates are spread fairly tightly about the mean with an average coefficient of variation (s.d./mean) in the estimated residual career length of 8.1%. The largest coefficient of variation in residual career length is found at ages 46 to 49 where it ranges from 13.1 to 17.5%. The mean total index career length of 5.6 years has a standard deviation of .58 years for a coefficient of variation of 9.5%. In view of the narrow range of variability over time, only the seven-year average of the estimates will be reported in the remaining career-length analysis.[24]

The estimates for individual years were also used to explore any time trends in career length over time. With the general increase in crime rates experienced over the 1960's and 1970's, one might expect to find that offenders who started careers more recently (i.e., those from later cohorts) have more enduring criminal careers. This would be reflected by a positive time trend in the career-length estimates. To test for the presence of such trends, the mean residual career-length estimates for each year t, $\tau_t(a)$, were analyzed for time trends for each age separately.[25] As indicated in Appendix J, the $\tau_t(a)$ are generally stable over time with no detectable monotonic increases or decreases in career length between 1970 and 1976. The one clear exception to this pattern is a decline in mean residual career length with time for ages 25 to 29.

Arrestees of ages 25 to 29 in 1970 to 1976 come from cohorts of offenders who began their adult criminal careers in the decade of the 1960's (reaching age 18 between 1959 and

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[24]In all cases, separate analyses for each of the seven years mirrored the results obtained based on the seven-year average of the number of arrestees per population at each age. Only the results based on the seven-year average of the age distribution are presented.

[25]Simple regressions with $\tau_t(a) = \alpha_a + \beta_a t + \epsilon_a$ for each age a were used to assess the presence of any linear time trends (reflected in the magnitude of B_a) in the mean residual career length over the period 1970 to 1976.

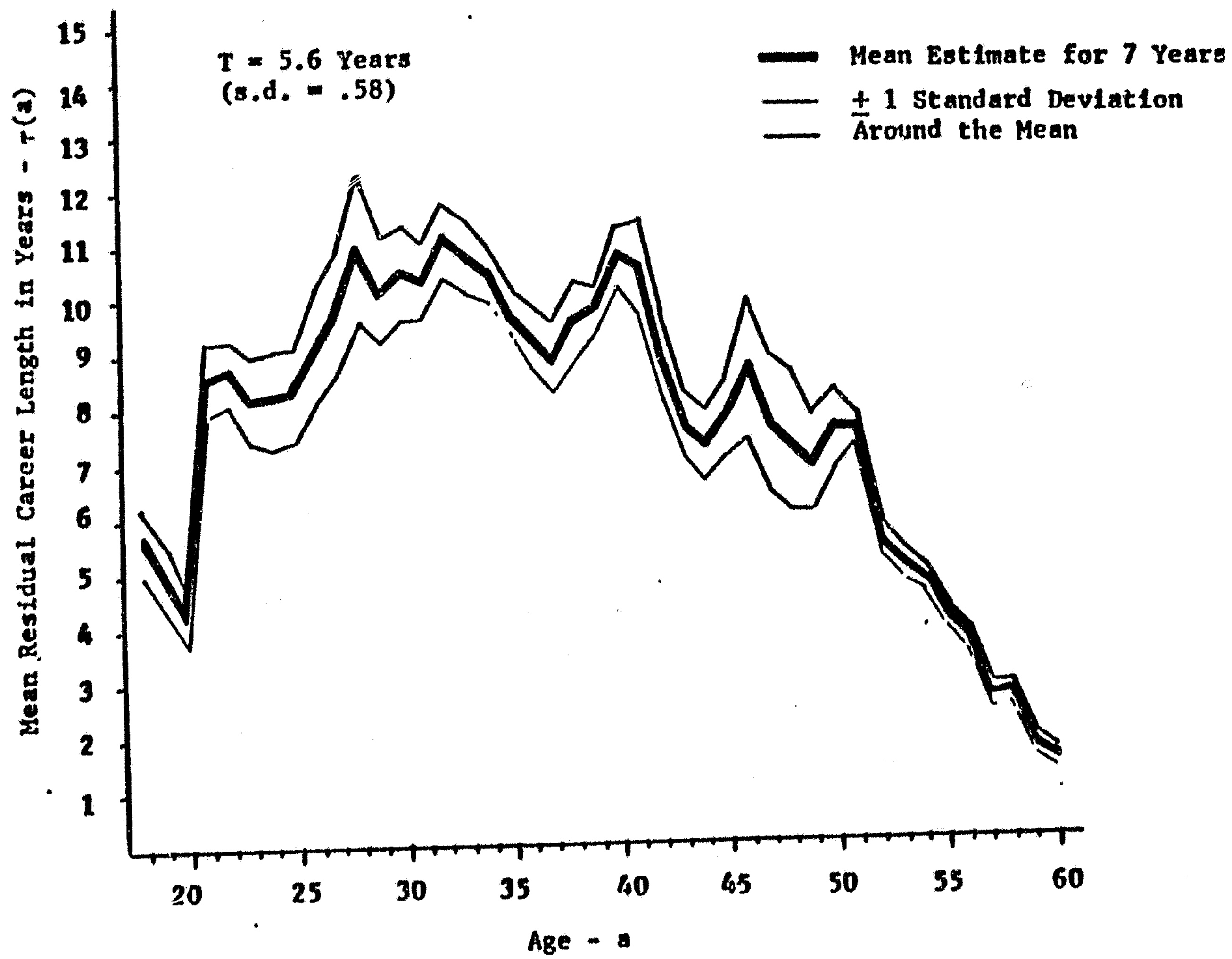

Figure 10

Variability in Career Length Estimates from Annual Data for 1970 to 1976
(18-20 Year Old Starters Only - b = 20)

1969), a period of substantial increases in the index crime rate (crimes/population).[26] The decline in career length for these offenders is thus somewhat surprising. This period of decline in career length, however, also corresponds precisely to ages with a significant increase in the number of arrestees per population between 1970 and 1976 (Appendix J). The increases in the number of arrestees at ages 25 to 29 without corresponding increases over time at older ages as well, increases the portion of the age distribution found at ages 25 to 29 relative to the portion found at older ages in each subsequent year. This increasing differential in the age distribution between arrestees ages 25 to 29 and those of older ages results in increases in the dropout rate over time and decreases in the associated residual career length estimated for ages 25 to 29. The changes over time in career length observed for ages 25 to 29 are consistent with the observed increases in the number of arrestees for these ages.

There is thus evidence that the decade of the 1960's was a period of change in criminal involvement. The number of arrestees ages 25 to 29 in our data, representing cohorts of offenders beginning their adult careers in the 1960's increases significantly between 1970 and 1976. The increase in arrestees of these ages could be due to inceases in recruitment to criminal careers during this decade, or to decreases in dropout from criminal careers for those offenders entering careers in the sixties. The implications of this brief period of possible non-stationarity for the estimates of the career-length variables over age will be discussed in section 4.2.

4.0 VARIATIONS IN CAREER-LENGTH VARIABLES WITH TIME ALREADY ELAPSED IN A CAREER

Both from a substantive and a policy perspective, a key question about criminal careers is the degree to which residual career length, $\tau(x)$, depends on time already elapsed in a career (x). If all offenders had the same total career length, T, then $\tau(x)$ would be $T-x$, and so would decrease with x. If, however, career length varies among offenders and the short-career offenders drop out at early ages, leaving behind the more seriously committed offenders, then $\tau(x)$ could well increase with x.

The variation in $\tau(x)$ with x permits the identification of those ages (or durations in a career) when the expected remaining career is increasing and other ages when it is decreasing. Any intermediate ages when $\tau(x)$ is at a maximum would be prime occasions for intervention for reasons of incapacitation.

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[26]The index crime rate increased an average of 7.8% per year between 1960 and 1969, compared to an average annual increase of 4.3% between 1970 and 1975 (FBI, 1976).

For those offenders whose adult index careers start at age 18 ($a_o = 18$), time already in a career (x) is obtained directly from age (a) with $x = a - a_o$. Figure 11 presents the estimated dropout rate from index careers at each age (duration) for those with a first adult index arrest between ages 18 and 20. The dropout rate exhibits a pattern common to life expectancies of human populations and many mechanical systems, namely a period of "break-in" with high failure rates at early ages, followed by a period of relative stability, leading finally to a period of more rapid "wear-out."

Figure 12 displays the mean residual career length associated with these dropout rates. As dropout rates decrease in the early years of a career, the mean residual career, or the expected time remaining in a career, increases in length. This is followed by a period of relatively stable residual career lengths. Finally, during the period of increasing dropout rates, the expected time remaining in careers gets shorter.

During the first period, the dropout rate r(a) decreases and the mean residual career-length τ(a) increases with increasing time in a career. As those with short careers and high dropout rates drop out early in index careers, the remaining offender population is increasingly left with more hard-core, committed offenders – those with longer average index careers. The weeding out process continues until about age 30, or 12 years after the start of adult index careers.

During period II (approximately ages 30 to 42), the dropout rate and mean residual career length are more stable. During that period, the dropout rate is at a minimum, and the expected time remaining in the career is longest at about ten additional years, regardless of the prior duration of careers. Whether one has 12 years already in a career or 24 years, the expected time remaining in index criminal careers is about the same.

After age 42, the "wear-out" process begins: the dropout rate increases and the mean residual career-length decreases with increasing time in the career. This increasing rate of dropout from index careers during this period may be associated with aging and particularly decreases in the vigor and stamina necessary for sustaining index crimes. To some extent, mortality may account for a portion of this growing dropout rate, especially if index offenders are found to have much higher mortality rates compared to the general population.

From the perspective of crime control policy, those adult index offenders who started index careers at age 18 and who continue to be criminally active between the ages of 30 and 42 are seen to be the most persistent offenders, and so represent a prime target group for

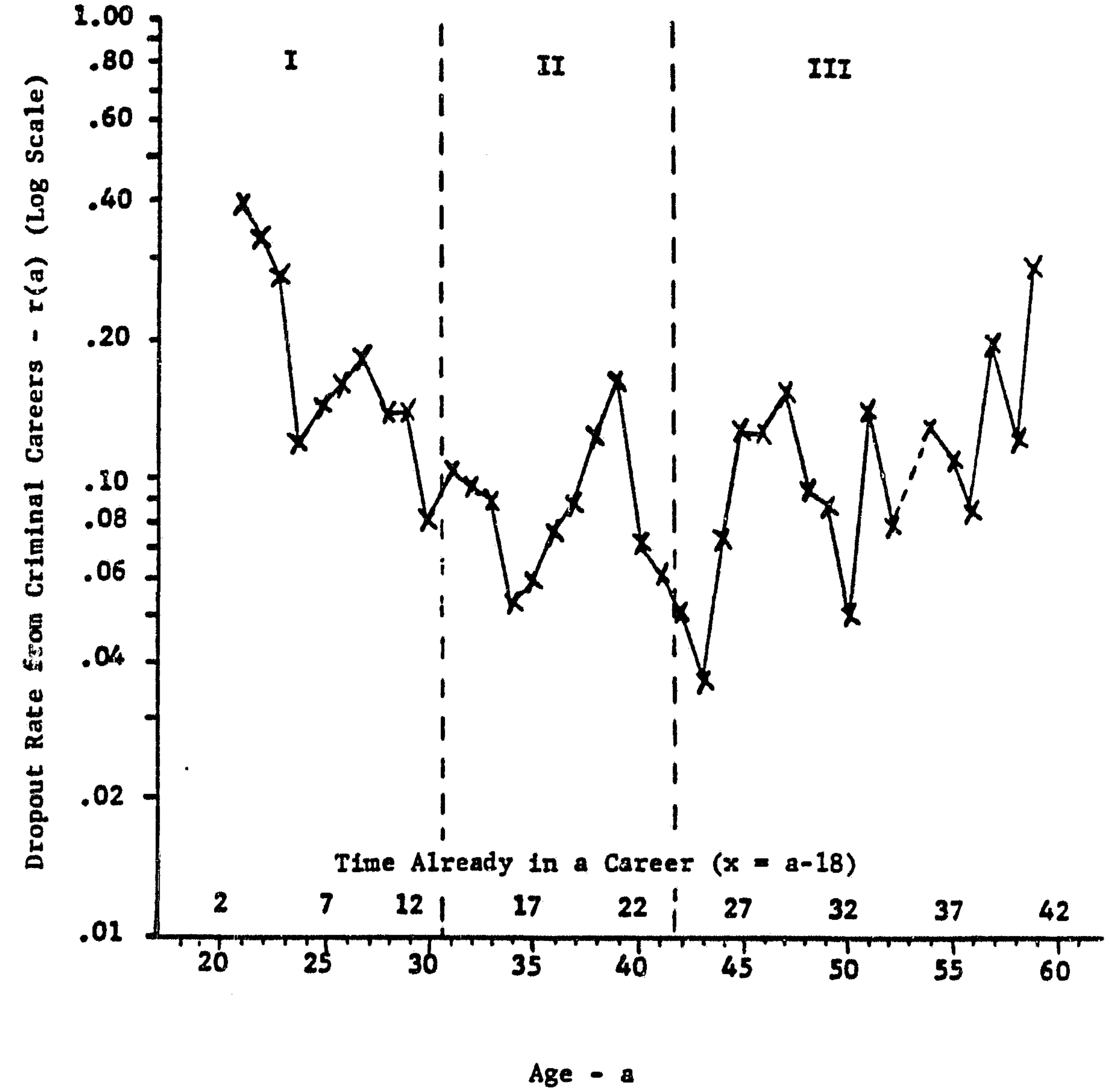

Figure 11

Variation in Dropout Rate from Criminal Careers - r(a)
With Time Already in a Career
(18-20 Year Old Starters Only - b = 20)

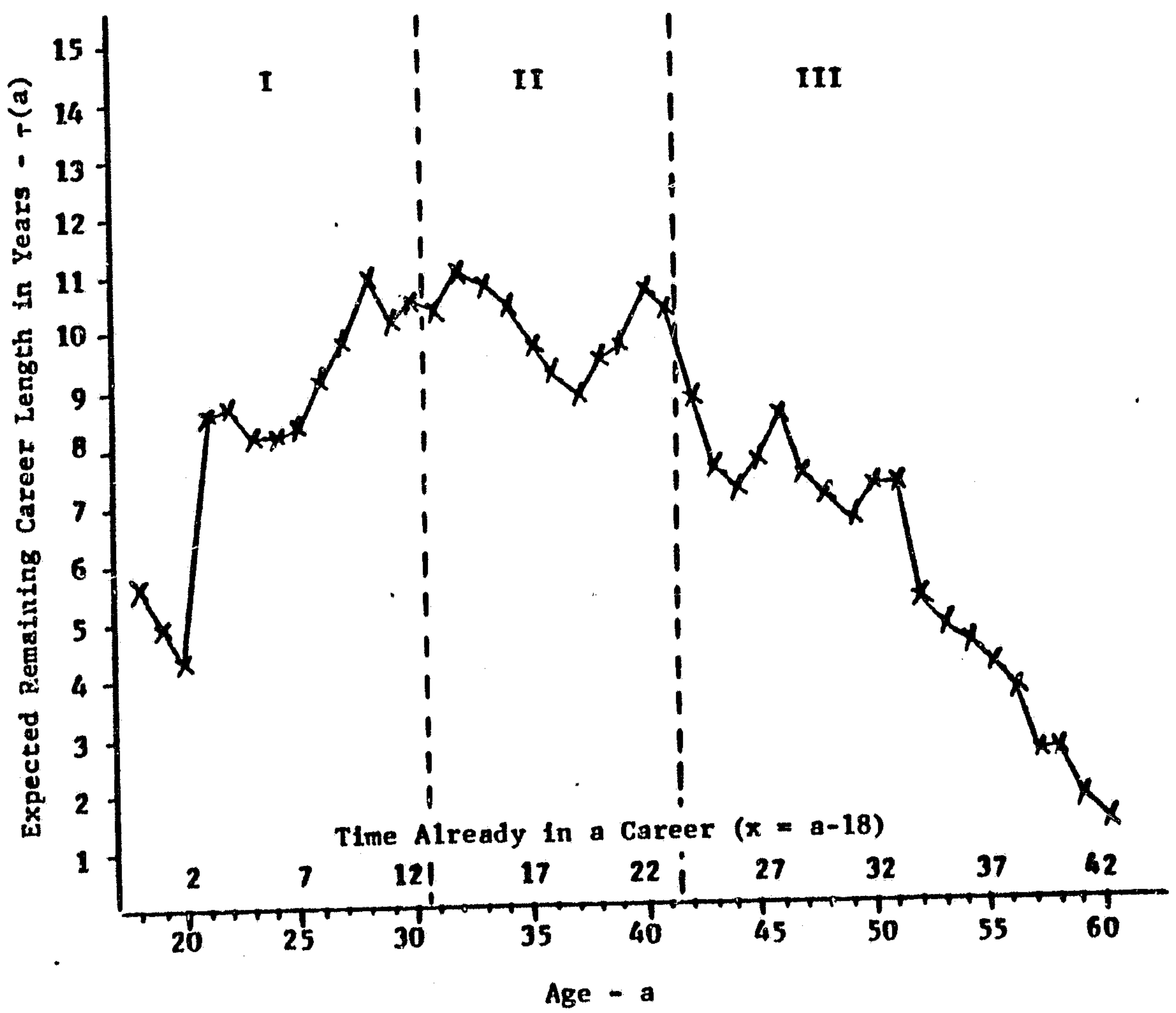

Figure 12

Variation in Mean Residual Career Length - $\tau(a)$
With Time Already in a Career
(18-20 Year Old Starters Only - b = 20)

incapacitation. Sanctions imposed earlier or later in index careers are more likely to be applied to offenders who will discontinue criminal activity shortly anyway.

4.1 MODELING CRIMINAL CAREER LENGTH

The form of the dropout rate in Figure 11 suggests that career length can be modeled as a three piece function with exponentially decreasing dropout rates in the first period, constant dropout rates in the second, and exponentially increasing dropout rates in the last period.

$$r(x) = \begin{cases} b_1 e^{a_1 x}, & 0 \leq x \leq x_1 \\ b_2, & x_1 \leq x \leq x_2 \\ b_3 e^{a_3 x}, & x_2 \leq x \leq MAX \end{cases} \quad \text{for } x = a - a_o \tag{1}$$

Using the relation between r(x) and g(x) in eq. (A4), the age distribution g(x) associated with this three-piece dropout rate is derived in Appendix F. The resulting distribution is:

$$g(x) = \begin{cases} \exp(-b_1/a_1 e^{a_1 x} + b_1/a_1 e^{a_1 x_1} - b_2 x_1), & 0 \leq x \leq x_1 \\ \exp(-b_2 x), & x_1 \leq x \leq x_2 \\ \exp(-b_3/a_3 e^{a_3 x} + b_3/a_3 e^{a_3 x_2} - b_3 x_2), & x_2 \leq x \leq MAX \end{cases} \tag{2}$$

The values of coefficients a_i and $b_i (i = 1, 2, 3)$ in eq. (1) are estimated by regression through the observed r(x) data points.[27] The normalization factor,[28] K, is then estimated by numerical integration with:

$$K = 1 \Big/ \Big[\int_0^{x_1} \exp(-b_1/a_1 e^{a_1 x} + b_1/a_1 e^{a_1 x_1} - b_2 x_1)dx + \int_{x_1}^{x_2} \exp(-b_2 x)dx + \int_{x_2}^{MAX} \exp(-b_3/a_3 e^{a_3 x} + b_3/a_3 e^{a_3 x_2} - b_2 x_2)dx \Big]$$

Having estimates of the parameters, a_i, $b_i (i = 1, 2, 3)$, and K, the predicted values of g(x) and 1–G(x) can be numerically evaluated for all values of x using eq (2). These quantities can then be used in eqs. (A6) and (A8) to yield the predicted mean residual career length $r(x)$, associated with the r(x) function in eq. (1). Figure 13 presents the estimated regression lines

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[27]In estimating a_i and b_i from the observed r(x), we do not require continuity of the r(x) function. For the exponentially changing r(x) in periods 1 and 3, the estimating equation is $\ln(r(x)) = \ln b_i + a_i x$ (i = 1,3), while for constant r(x), $a_2 = 0$ and b_2 is the mean value of r(x) over the interval x_1 to x_2. The associated g(x) function is, however, constrained to be continuous through the addition of the appropriate constants in each segment of the g(x) function.

[28]The factor K normalizes the predicted values of g(x) to sum to 1, thus assuring that g(x) is a proper probability density function.

through r(x),[29] and the resulting parameter estimates for those arrestees most likely to have started their index careers at age 18 (i.e., those with an index arrest between ages 18 and 20, b = 20). As indicated in Figure 14, the resulting predicted mean residual career length is a good fit to the estimate from the arrest observations.

Similar three-period models of the dropout rate were estimated for those arrestees with a first adult index arrest between ages 21 and 23 (a_o = 21) and those first arrested between ages 24 and 25 (a_o = 24). The fits between the mean residual career lengths estimated from the observed age distribution and those from the model of dropout rates for these different starting ages are presented in Figures 15 and 16. Regardless of the starting age, adult index careers appear to be modeled reasonably well by a "break-in" period with exponentially decreasing dropout rates, followed by a period of relatively stable dropout rate, followed finally by a "wear-out" period with exponentially increasing dropout rates.

4.2 FACTORS POTENTIALLY AFFECTING RESIDUAL CAREER LENGTH ESTIMATES.

All of the analysis so far has assumed that the probability of at least one arrest in a year is stable for offenders of different ages. It is important that arrest probabilities be stable with age to assure that the arrestees are a representative sample of all active offenders, at least with respect to age. There are, however, several factors that might introduce age variations into this arrest probability. These include:

1. A cohort effect where, for example, more recent cohorts of offenders might have higher arrest rates resulting in the younger arrestees in a single year's cross-section having higher arrest probabilities;

2. Age bias in apprehension where younger, less skillful offenders might be more likely to be arrested, or where older offenders might be better known to the police, and so more vulnerable to arrest; and

3. Differences in time served by age – the greater the time served, the less time the offender is available to generate an arrest in a year.

Such age variations in the likelihood of an arrest for offenders could distort the career-length estimates; higher arrest probabilities for some ages increase the representation of these ages among arrestees beyond their representation among active offenders. A higher arrest probability for younger offenders, for example, overstates the relative portion of young ages found among arrestees, and yields overestimates of the dropout rate and underestimates of the residual career length.

[29] In both Figures 11 and 13, the dropout rate r(x) is presented on a semi-log scale on which exponential functions appear as straight lines.

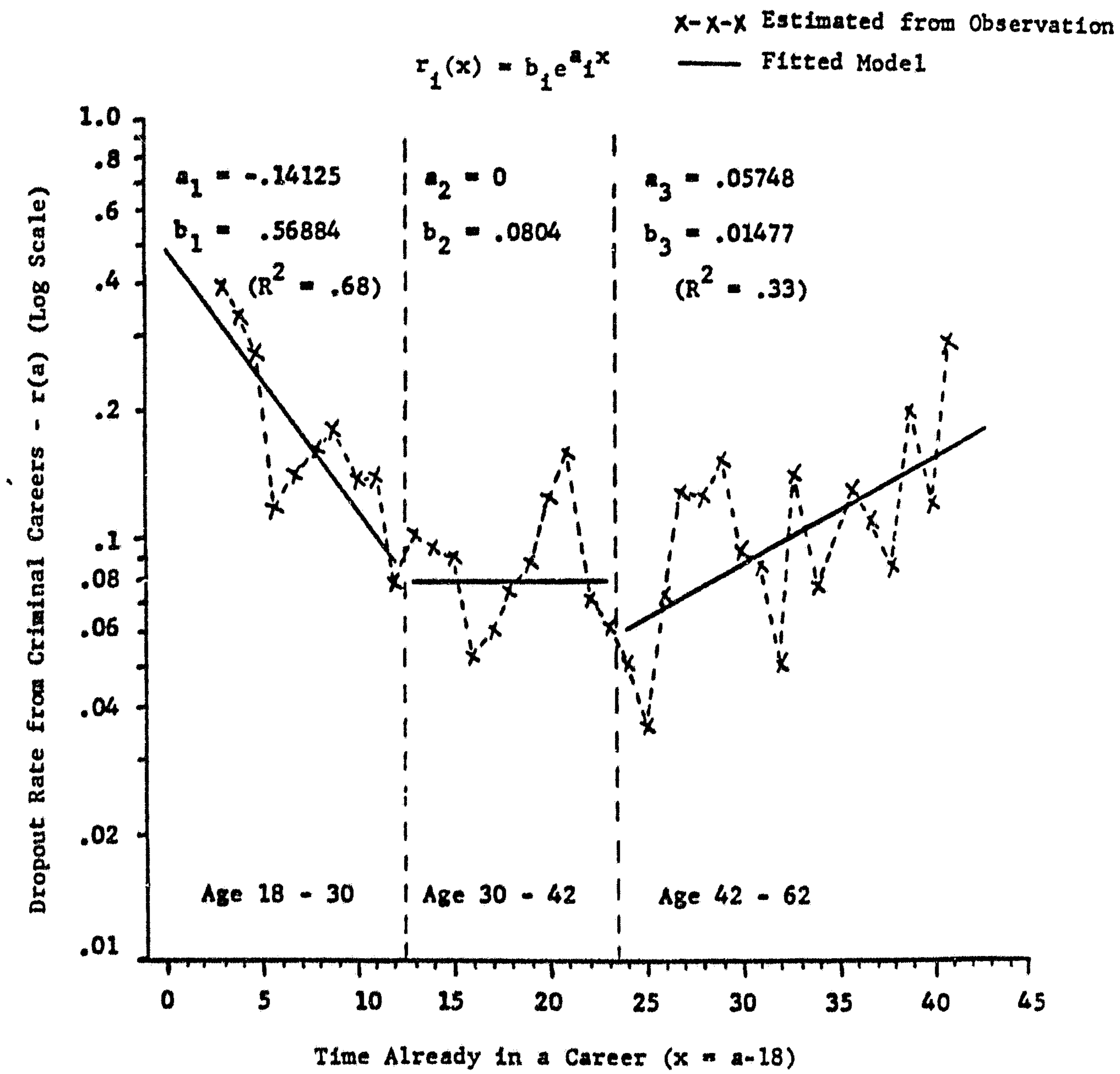

Figure 13

Regression Lines Through the Observed Dropout Rate for 18-Year-Old Starters (b = 20) and Associated Parameter Estimates: a_i and b_i (i = 1,2,3)

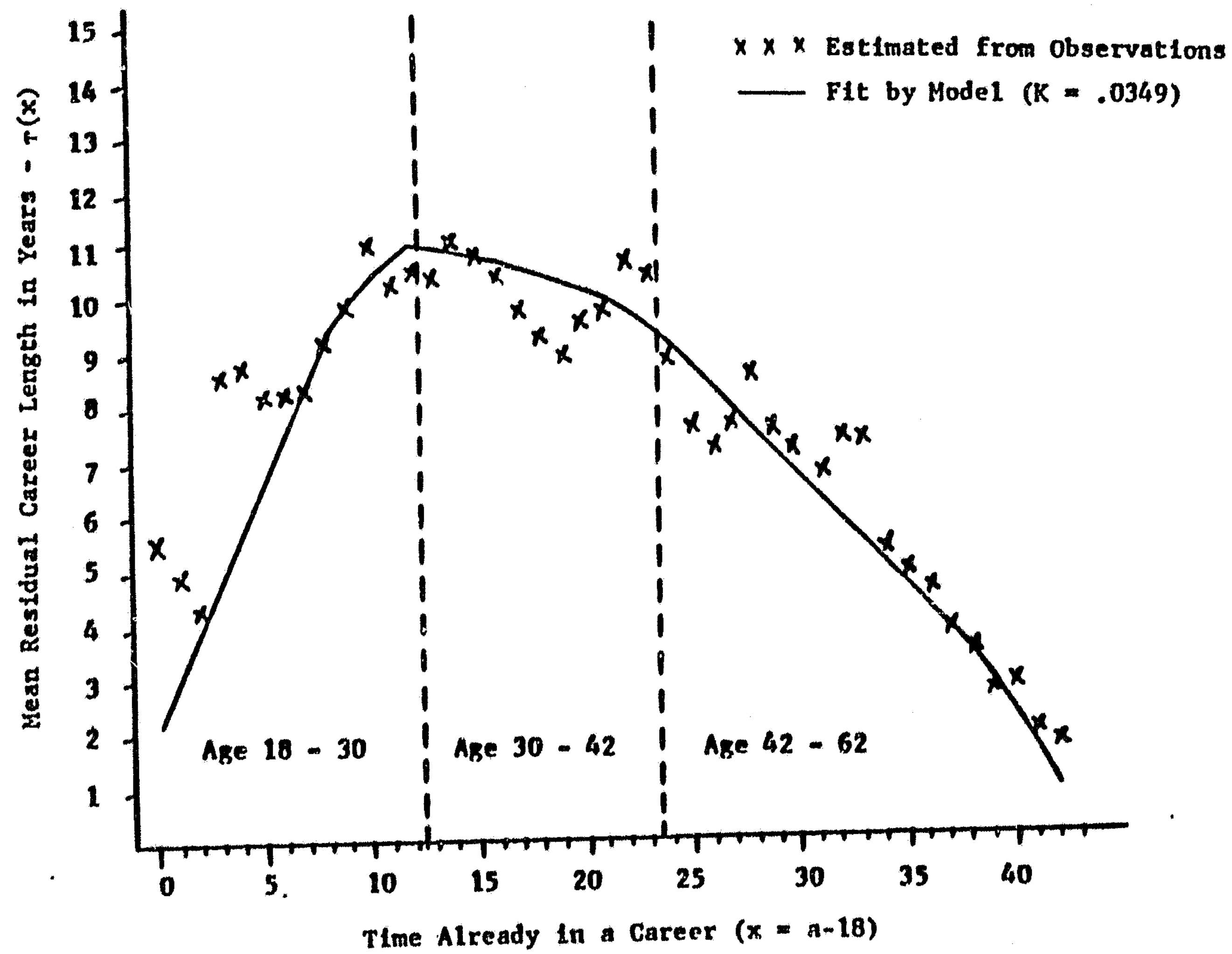

Figure 14

Mean Residual Career Length
Estimated from Observations and Fit by Model
for 18-Year-Old Starters

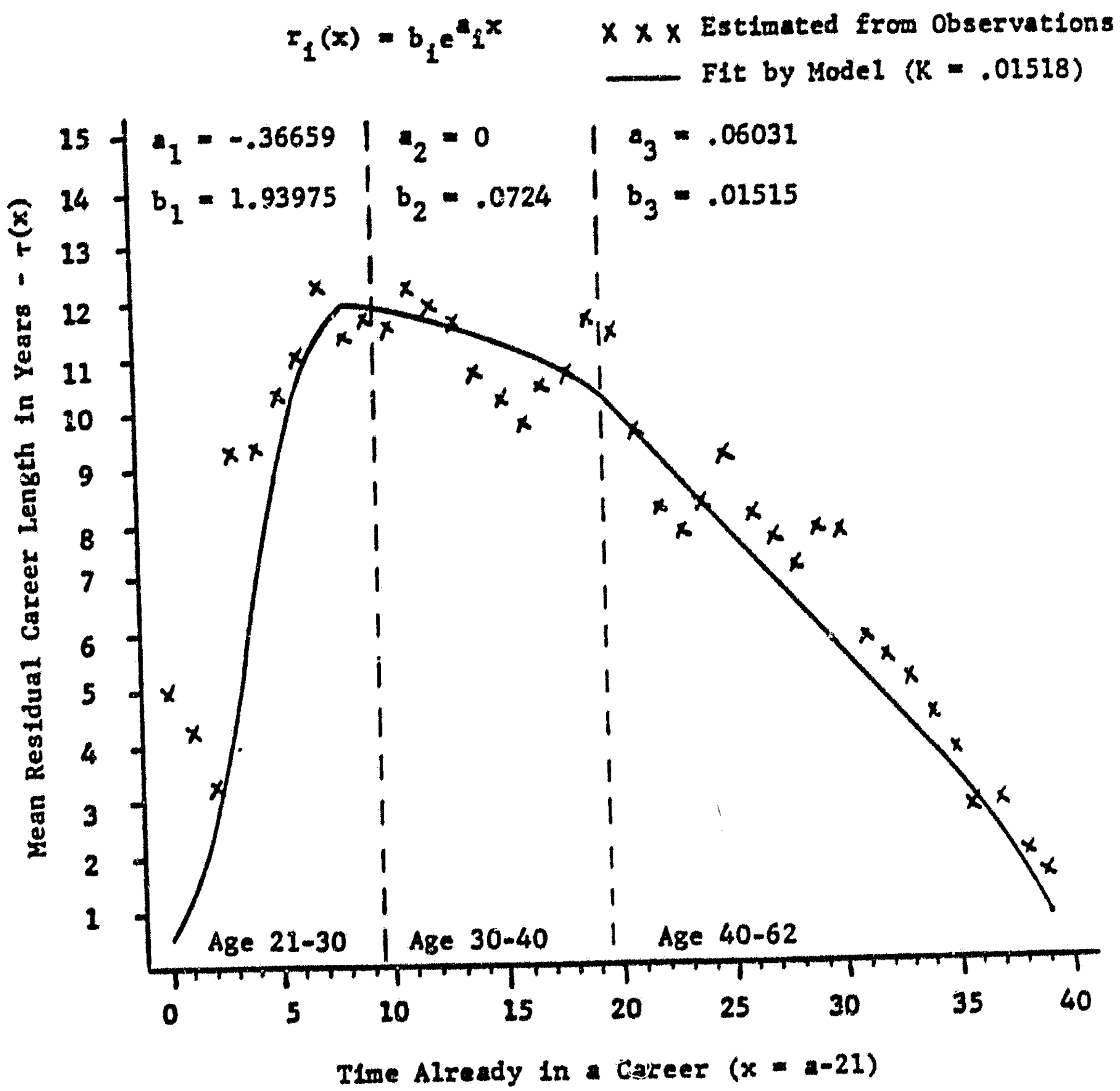

Figure 15

Mean Residual Career Length
Estimated from Observations and Fit by Model
for 21-Year-Old Starters

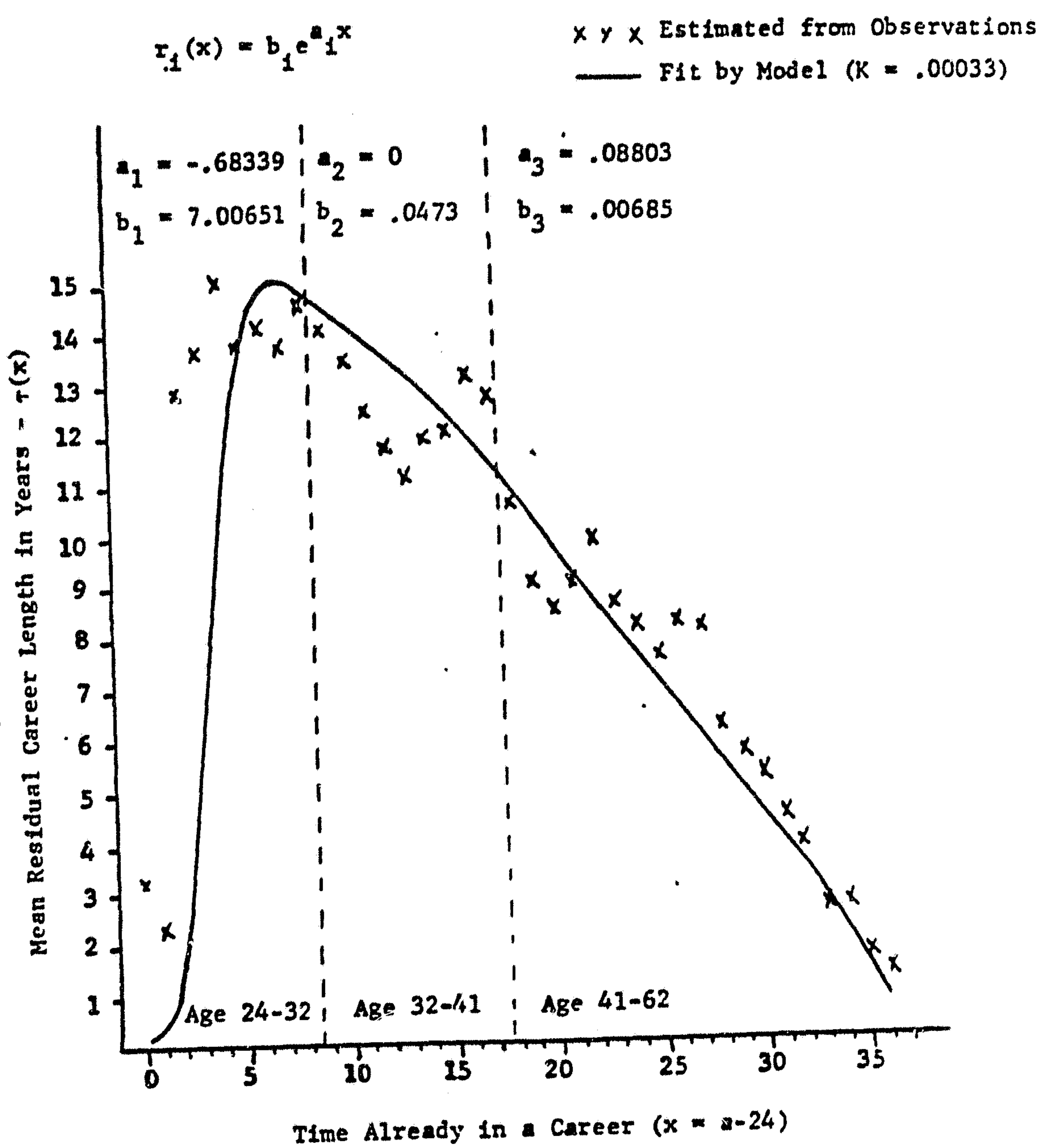

Figure 16

Mean Residual Career Length
Estimated from Observations and Fit by Model
for 24-Year-Old Starters

Figure 17 presents one possible pattern of age variations in the probability of at least one arrest in a year for offenders. It reflects a general decline in the arrest probability with age. Between ages 18 and 30, the arrest probability decreases at an increasing rate with age. This period of rapid decline results from two factors.[30] First, time served decreases from age 18 and then increases again reaching another peak at age 30. Additionally, it reflects a cohort effect of increasing arrest probabilities for younger ages that is more pronounced for those children of the post-World War II baby boom who reached adulthood in the late 1960's and were in their twenties in 1973. The increasing time served for offenders in their late twenties and the more dramatic post-war cohort effect for these same offenders combine to yield the especially rapid decline in arrest probability from about age 23 to age 30 proposed in Figure 17.

The impact on career-length estimates of age variation in the arrest probability like that proposed in Figure 17 is considered in detail in Appendix G. Failure to adjust the age distribution of arrestees for age variations like those found in Figure 17 would result in underestimates of the mean residual career length, with the actual residual career length having even sharper increases and decreases with age in periods I and III than are currently estimated.

5.0 VARIATIONS IN CAREER LENGTH WITH AGE AT THE START OF ADULT CRIMINAL CAREERS

Previous research has explored the degree to which age at the start of criminal careers affects the level of future criminal activity.[31] Using the proportion of offenders who recidivate by some time t, it has been observed generally that the younger an offender at the the "start" of a career (typically indicated by age at first arrest, first conviction, or first commitment to an institution as a juvenile), the more likely the offender is to recidivate. This might be an indication of a greater propensity to commit crime among those who start young, or the possibility that starting crime when young generates continued criminality by some form of labeling effect that reduces the availability of legitimate options to the offender.

The time to recidivism underlying the outcome measure in these studies is affected by both career length (time to dropout) and the rate at which active offenders commit crimes. Thus, younger starters might have higher recidivism probabilities by time t because: (1) they have longer careers and so are less likely to have dropped out of criminal activity by time t; and/or (2) they commit crimes at a higher rate than older starters and so are more likely to

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[30]The factors influencing Figure 17 are elaborated in greater detail in Appendix G.

[31]See, for example, Glueck and Glueck (1937 and 1940), Sellin (1958), Presidents's Commission (1967), Mulvihill, et al. (1969) and Hoffman and Beck (1974).

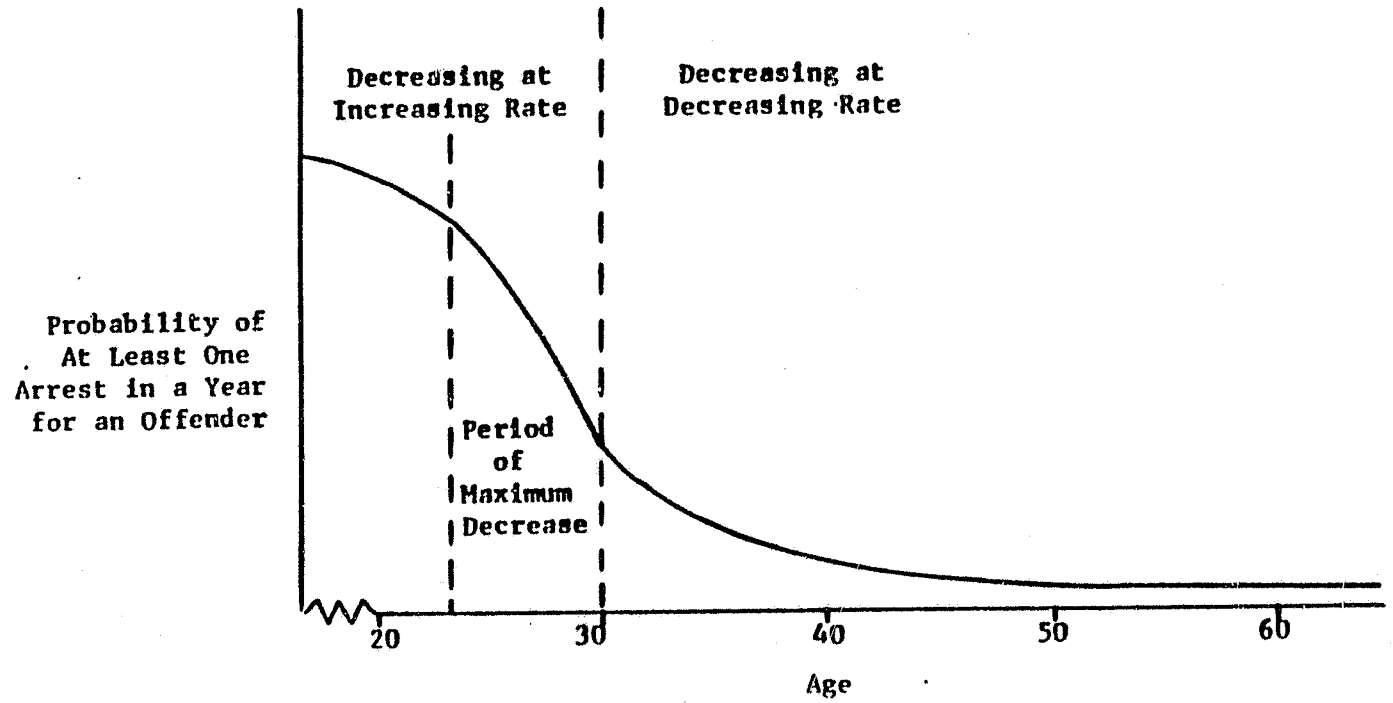

Figure 17

Possible Age Variation in Arrest Probability for Offenders have a recidivist event by time t. The analysis of career length reported here provides an opportunity to isolate the relative impact of career length on the higher recidivism rates of younger starters.

The previous findings of the impact of age at the start of a career on future criminal activity have also typically cited the role of first criminal involvement as a juvenile. The current analysis of adult careers provides an opportunity to assess the degree to which the finding of greater involvement for younger juvenile starters also applies to younger adult starters.

Using estimates of the age at a first adult index arrest as an indicator of the start of adult index careers, the arrestees in Washington, D.C. were separated into those starting at age 18 (i.e., having their first adult index arrest between ages 18 and 20), those starting at age 21 (i.e., having their first adult index arrest between ages 21 and 23), and those starting at age 24 (i.e., having their first adult index arrest at ages 24 or 25).[32] Table 3 reports the distribution of arrestees over these starting-age groups. Almost half of the adult arrestees have a first adult index arrest between ages 18 and 20, but almost one-third do not begin their adult index careers until after age 25.

The mean total career length for different starting ages is also reported in Table 3. Total career length does vary with starting age and is consistent with the previous results on recidivism probability; younger starters tend to have longer careers (Table 3). Mean total index careers range from about three years for 24-year-old starters to over five years for 18-year-old starters.

The predicted mean residual career lengths for each starting age are presented in Figure 18. During the first few years of the career, younger starters are found to have longer remaining careers (Figure 18). While the results in the early years of careers are consistent with the general finding in recidivism research (i.e., early starters have longer careers), the pattern is reversed for those offenders who attain longer careers. For offenders with more than seven years already elapsed in index careers, <u>older</u> starters have <u>longer</u> remaining careers.

This reversal in the direction of the relationship is unexpected and without any immediate behavioral interpretation. One possible explanation is differences in the crime-type mix of

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[32]To get the number of 18-year-old starters among arrestees at each age, the product $n(a)P_{20}(a)$ was used; 21-year-old starters were obtained from $n(a)(P_{23}(a) - P_{20}(a))$ and 24-year-old starters from $n(a)(P_{25}(a) - P_{23}(a))$.

Table 3

Variation in Mean Total Career Length
With Age at Start of Adult Index Careers

Starting Age	Proportion of All Index Arrestees in Each Starting-Age Group	Mean Total Career Length (years)
18*	41.6%	5.6
21**	17.4%	5.0
24***	7.7%	3.3
>25+	31.2%	---

*First adult index arrest between ages 18 and 20

**First adult index arrest between ages 21 and 23

***First adult index arrest between ages 24 and 25

+First adult index arrest after age 25

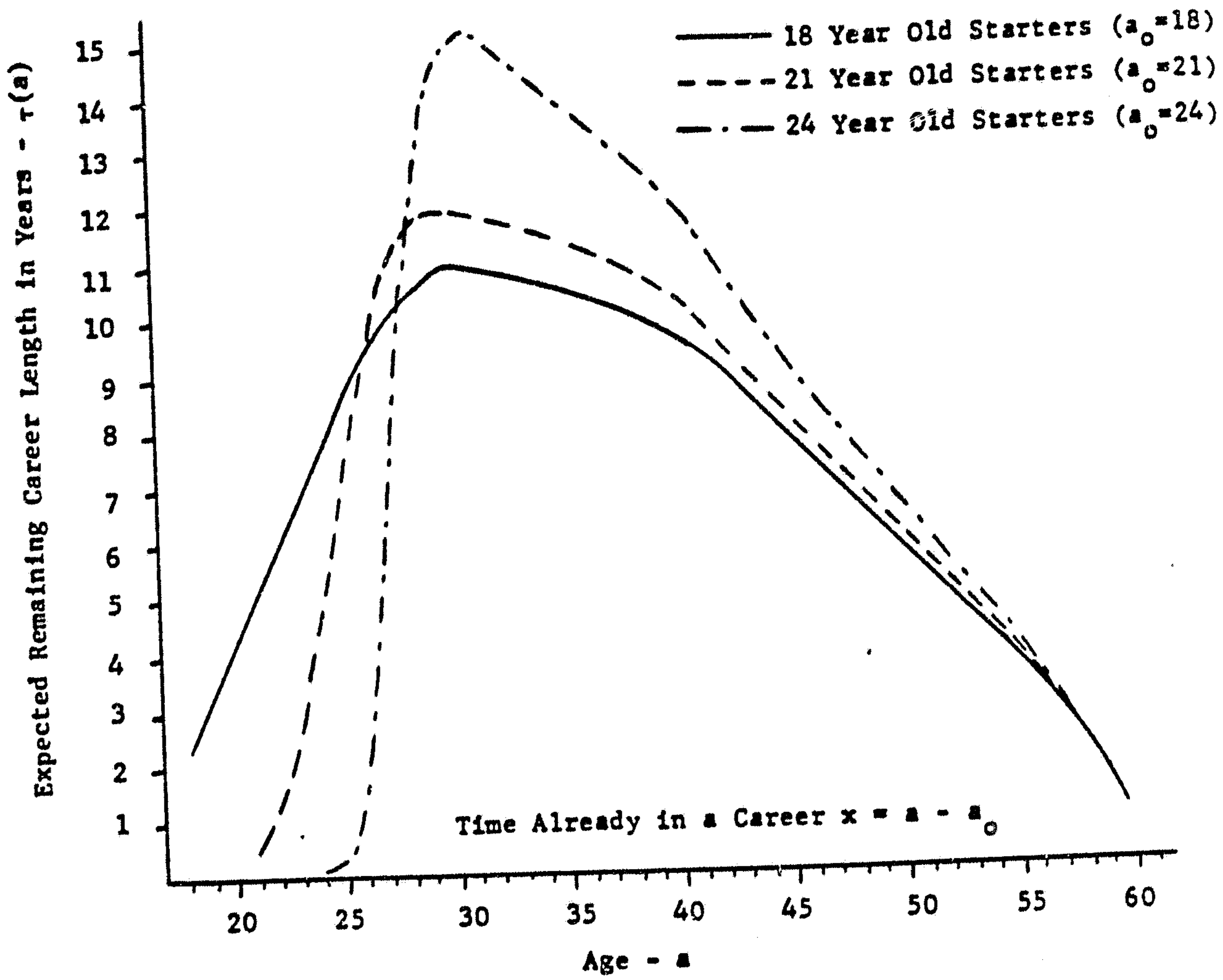

Figure 18

Comparison of Mean Residual Career Length
for Different Ages at First Adult Index Arrest

different starting cohorts. Older starters may engage predominantly in those index crime types characterized by longer careers. In this event, if crime type were controlled, we might expect to find a consistent pattern of residual career length over different starting ages. This issue is explored in the next section.

6.0 VARIATIONS IN CAREER LENGTH BY CRIME TYPE

Significant differences in age have been observed among arrestees for different index crime types (Figure 19). The most dramatic differences are between robbery and aggravated assault, with robbery arrestees being younger, and those arrested for aggravated assault generally older. These age differences could have profound implications for the career lengths associated with different crime types.[33] A predominance of young people in the age distribution for a crime type means that careers for that crime type are likely to be short, while a greater presence of older people suggests longer career lengths. Arrestees for different crime types, however, also differ in the age of their first adult index arrest, with robbery arrestees being the youngest when first arrested, and aggravated assault arrestees being the oldest. These differences in age at first arrest might fully account for the differences in the age distribution for different crime types with older arrestees also starting their careers much later. In this event, there might be no real difference in the time actually elapsed in careers for different aged offenders. Thus, when proper controls for age at the start of career are used, there might be no difference in career length for different type crime types.

The Washington, D.C. data were used to examine career length for each of the index offenses separately. The age distribution of arrestees per population for each crime type (except larceny) are available from the analysis in Section 2.1.[34] The resulting age distributions,

[33]In this crime-specific analysis of career length, the resulting career length by crime type refers to the average period during which offenders engage in a particular crime type. The full index career length for offenders will, in general, be longer than the length for any one index crime type as offenders switch among the different crime types. The career length for robbery, then, refers to the average period during which robberies occur, and not to the total career length of individuals who ever commit robberies.

[34]Larceny is excluded from the crime-specific analysis because the arrest history sample that is the basis for estimating the arrestees from arrests and the late starter correction (P_p) does not include data on all larceny arrestees. Only those larceny arrestees with an additional arrest for some other index crime in 1973 are included in the data, and they may not be representative of larceny arrestees in general.

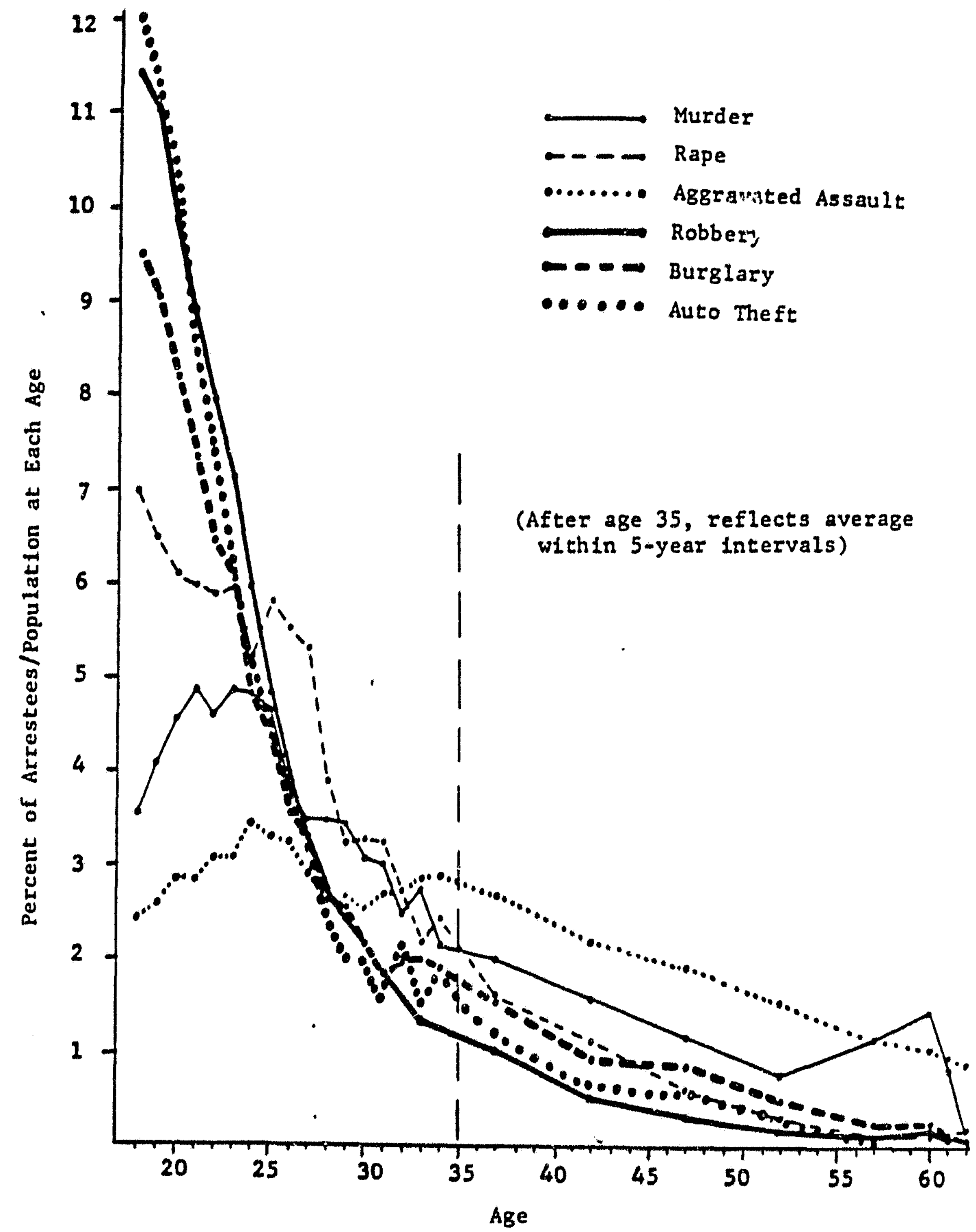

Figure 19

Age Distribution of Arrestees for Individual Crime Types g(a), by crime type are presented in Figure 19,[35] where the greater representation of younger arrestees for the property crimes of robbery, burglary and auto theft, and the higher proportion of older arrestees for murder and aggravated assault are apparent.

To estimate the career-length variables, late-starter adjustments were estimated separately for the arrestees in each crime type using the 1973 arrestee data. The resulting proportions of arrestees for each crime type who had a first adult arrest for any index offense before threshold age b (b = 20, 23 and 25) are presented in Appendix H. Some differences in the starting age are found for different types of offenders. In particular, property offenders (robbery, burglary and auto theft) are more likely than violent offenders (murder, rape and aggravated assault) to begin their adult criminal careers at younger ages.

The resulting mean residual career lengths for each crime type for 18-year-old starters are presented in Figures 20 to 22. Three distinct career-length patterns are evident among the crime types.[36] For the property crimes of burglary, auto theft and robbery, career length is characterized by an early "break-in" period, a period of relative stability, and a "wear-out" period, as was observed for all index offenses combined (Figure 20). In contrast, for the violent crimes of murder and rape there is no "break-in" period; careers start out at a stable level, followed by declines in length at older ages (Figure 21). For aggravated assault, residual careers increase sharply to a peak in the first few years of the career and then steadily decline with age (Figure 22).

Even after controlling for age at the start of careers, significant differences remain among the crime types. Aggravated assault has the longest career of the index crime types with a mean total career length of 10.3 years for offenders who begin their adult careers at age 18. Furthermore, offenders who do not drop out of aggravated assault very quickly have extremely

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[35]Because the number of arrestees at any one age for a crime type is often quite small (N<5), additional data aggregation was necessary to estimate g(a) for ages past 35. The variability in the age distribution at older ages where n(a) often varies from values of 0 to 5 can induce enormous variation in the estimates of the career-length variables. To minimize this variation, the already smoothed age distribution was additionally smoothed past age 35 by breaking ages into 5-year intervals and assigning the average value of n(a) for the interval to the midpoint age in that interval.

[36]Note, the same general career-length patterns were found for different crime types when the adjustment for late-starters is based on having an adult arrest for the same crime type before age threshold b. The resulting residual career lengths, however, do differ in magnitude and are longer for all crime types except robbery. These differences in magnitude are relatively small except for murder which doubles in length when having an adult arrest for murder before age threshold b is used as the first-arrest criterion.

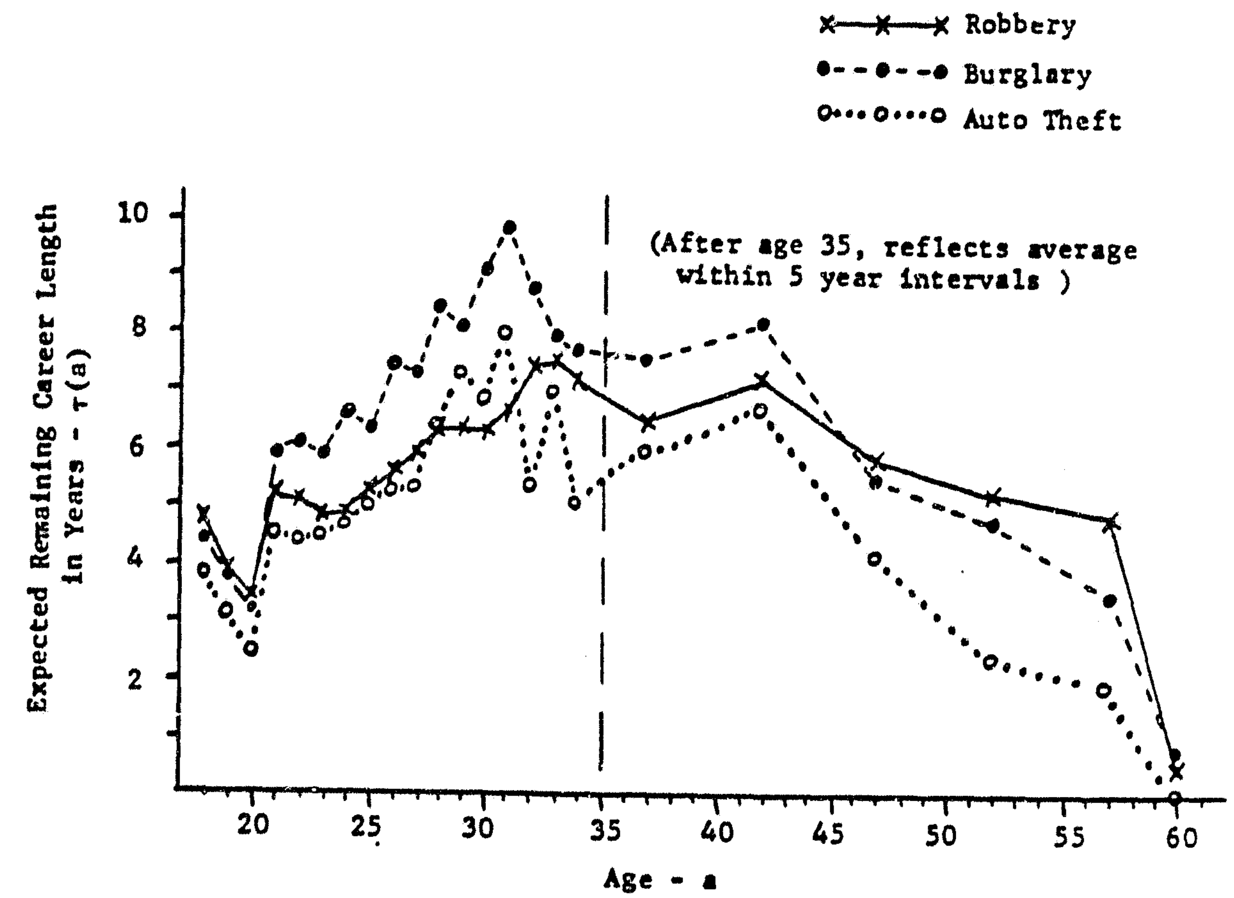


Figure 20

Mean Residual Career Length by Crime Type: Robbery, Burglary and Auto Theft (b = 20)

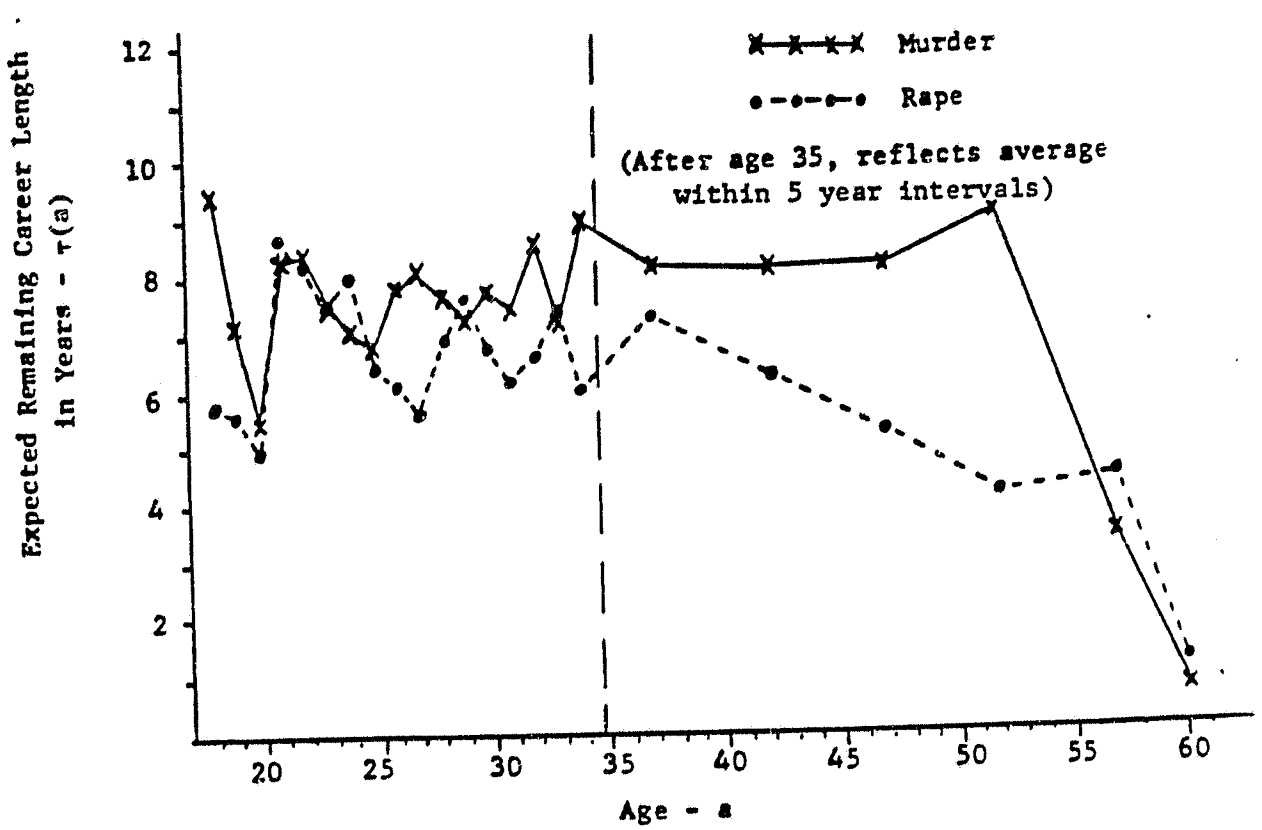


Figure 21

Mean Residual Career Length by Crime Type: Murder and Rape (b = 20)

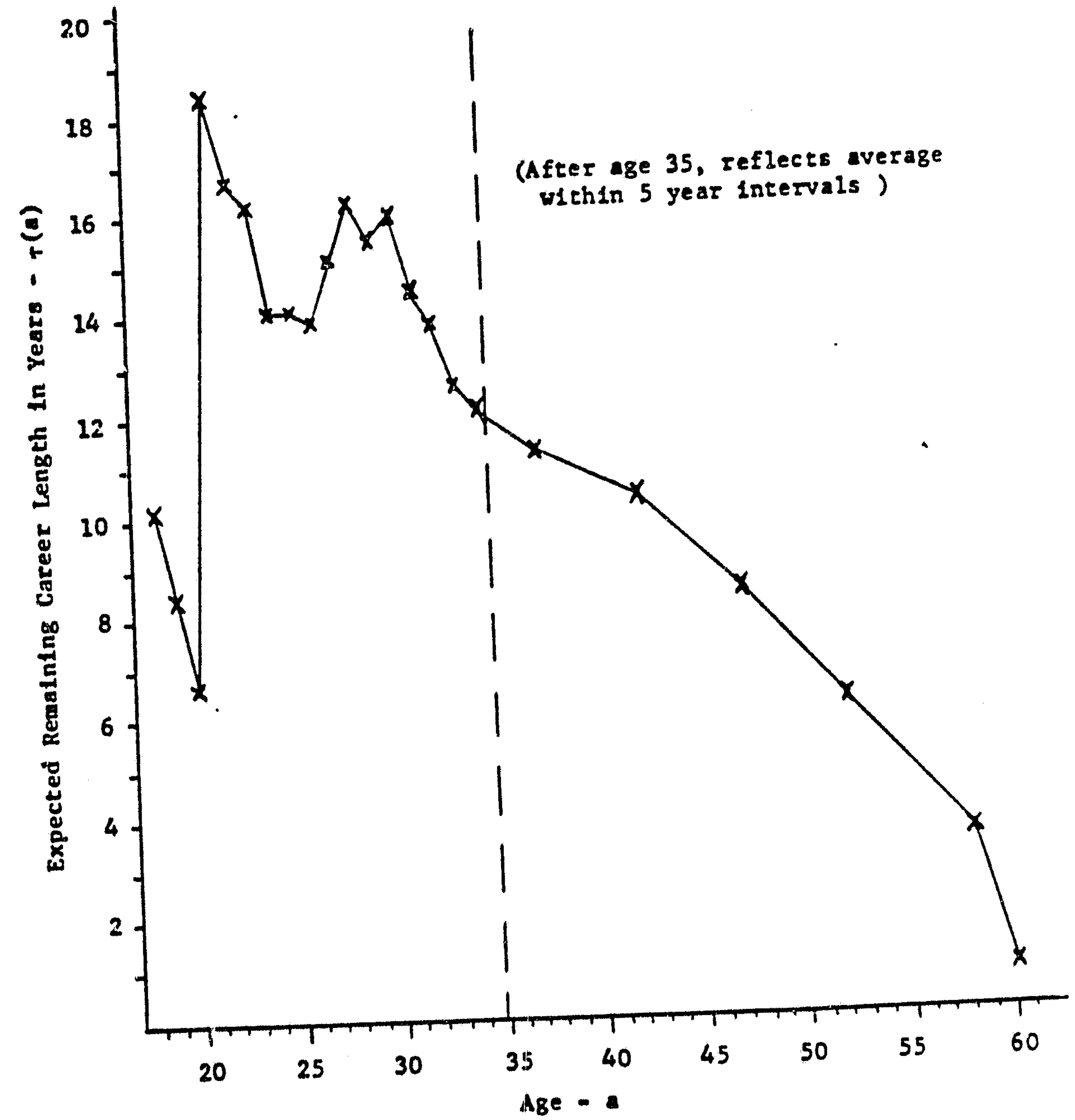


Figure 22

Mean Residual Career Length by Crime Type: Aggravated Assault (b = 20) long assault careers. Eighteen-year-old starters who remain active for at least three years in aggravated assault careers can be expected to last an average of 18.5 more years in those careers. Even when older first-time assaulters are eliminated, then, aggravated assault is the most enduring crime type. Those offenders who begin index careers at age 18 and who are arrested for aggravated assault while young can be expected to have long careers of aggravated assault arrests. These younger assaulters are thus prime targets for crime control strategies to reduce aggravated assault.

The property crimes of auto theft, burglary and robbery have the shortest mean total careers, ranging from 4 to 5 years. However, individuals with very short property crime careers tend to be weeded out during the early years of the career. Arrestees for property crimes who have already been active from 15 to 25 years (ages 33 to 43 for 18-year-old starters) have the longest expected remaining careers for these crime types, averaging 9.5 additional years. Offenders arrested for property crimes during their 30's are thus prime candidates for strategies to reduce property crimes. Younger and older arrestees for property crimes are more likely to discontinue offending in these crime types more quickly.

Robbery has traditionally been linked with violent offenses.[37] While robbery is properly viewed as violent from the perspective of the victim (because the risk of physical harm is a salient consideration), this characterization appears to be inappropriate from the perspective of the offender, for whom instrumental concerns for monetary gain are more salient. A number of studies have challenged the view that robbery is principally a violent offense. In a review of literature on robbery, Sagalyn (1971, p. 8) cites a number of studies indicating that violence is infrequently used in the commission of the offense, especially in cases of armed robbery. In another study of robberies, Normandeau (1968) is highly critical of the "violent" characterization of robbery, concluding that "robbers...are primarily thieves." The results on career length certainly support this view; the career-length pattern for robbery is virtually identical to the career-length patterns of unambiguous property offenses like burglary and auto theft.

Unlike the residual careers for property crimes which do not reach their maximum until many years into a career, the violent offenses of murder and rape begin at their maximum residual career length of 9.6 and 5.9 years, respectively, and remain there for about 25 years

[37]See, for example, Wolfgang and Ferracuti (1967), Mulvihill, et al (1969), Elliot and Ageton (1980), and the FBI's annual Uniform Crime Report, which has included robbery in the violent index rate since 1968.

(to age 43 for 18-year-old starters). During this long period of stability, knowledge of the past career length provides little information in estimating expected future career lengths in these violent offenses. A violent offender beginning a career at age 18 is just as likely to discontinue violent offenses within the next year as is an offender with 25 years already in the career. The expected remaining career begins to decline with age only after about 25 years already in a career.

When the crime-type-specific mean total career length is compared over the different starting ages (in Table 4), a consistent pattern for each crime type emerges. Older starters have shorter total careers. There are also sharp differences in the incidence of early starting for different crime types. Arrestees for the property crimes (robbery, burglary and auto theft) are predominantly early starters, ranging from 53% of burglary arrestees to 66% of robbery arrestees starting their careers with an index arrest between the ages of 18 and 20 (Table 4). This contrasts with the violent crimes, especially aggravated assault, where only 27% of aggravated assault arrestees start their adult careers between ages 18 and 20.

The differences in career length for different crime types should affect the pattern of crime-type switching between arrests as careers progress. To the extent that aggravated assault is a more enduring offense that is committed over longer periods of time during criminal careers, one would expect to observe more switching into aggravated assault as careers get longer.

To examine the crime-type switching patterns between arrests in a career, the arrest histories for the 1973 arrestees in Washington, D.C. were used. Transition probabilities between crime types were estimated for all adjacent pairs of arrests from these arrest histories where p_{ij} is the probability of switching to an arrest for crime type j after an arrest for crime type i.[38] The impact of longer careers was assessed by partitioning the arrest pairs by the length of time between the first adult arrest in the career and the second arrest in each arrest pair. The resulting transition probabilities are summarized in Table 5. As would be expected from the differences in career length for different crime types, as careers get longer, there is an increasing concentration in aggravated assault and decreasing activity in robbery and burglary.

When comparing residual career lengths for all index offenses combined, among those remaining active for at least seven years, older starters were found to have longer remaining

[38]To avoid the potential biases in crime type switches resulting from the crime-type mix of criterion arrests in the sampling year 1973, only those arrests before the sampling year are included in this analysis.

Table 4

Mean Total Career Length - T
by Crime Type and Starting Age

	Starting Age					
	18*		21**		24***	
Crime Type	Career Length (years)	Proportion Starting At 18	Career Length (years)	Proportion Starting At 21	Career Length (years)	Proportion Starting At 24
Murder (100%)	9.6	36.8%	6.1	15.7%	3.7	9.4%
Rape (100%)	5.9	49.1%	5.7	20.1%	2.9	7.7%
Aggravated Assault (100%)	10.3	26.8%	8.0	16.9%	4.3	8.7%
Robbery (100%)	4.9	66.4%	3.8	16.7%	3.1	6.1%
Burglary (100%)	4.6	53.2%	3.9	17.4%	2.7	6.4%
Auto Theft (100%)	3.9	58.1%	3.9	18.6%	2.6	6.0%

*First adult index arrest between ages 18 and 20

**First adult index arrest between ages 21 and 23

***First adult index arrest at ages 24 or 25

Table 5

Variations in Crime-Type Switching Between
Adjacent Arrests as Criminal Careers Get Longer

Crime Type of Origin in Arrest Pairs	Prior Career Length at Time of Transition (Years)	Transition Probabilities				Crime Type Distribution for Origin in Arrest Pairs
		Diagonal	To Assault	To Robbery	To Burglary	
Robbery	≤ 3	.355	.111	-	.086	13.4%
	> 3 to 10	.256	.121	-	.065	10.1%
	> 10	.143	.152	-	.063	5.7%
	Total	.292	.120	-	.075	10.4%
Burglary	≤ 3	.319	.063	.114	-	12.1%
	> 3 to 10	.283	.085	.074	-	10.5%
	> 10	.237	.126	.026	-	9.9%
	Total	.289	.084	.081	-	11.0%
Aggravated Assault	≤ 3	.277	-	.106	.063	10.4%
	> 3 to 10	.290	-	.078	.063	13.4%
	> 10	.357	-	.043	.043	16.1%
	Total	.306	-	.077	.057	12.8%

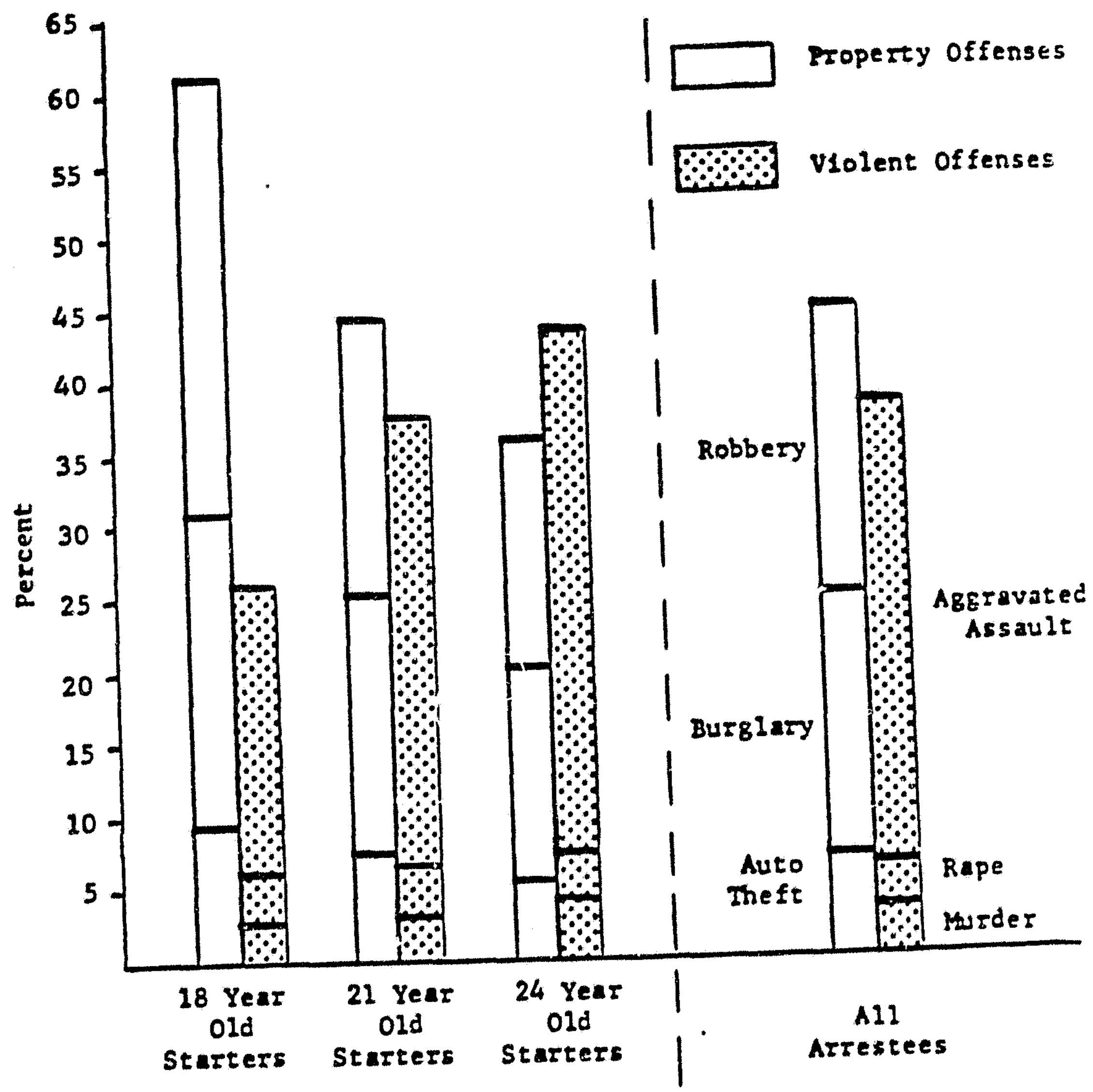


Figure 23

Distribution of Crime Types Characterizing Index Arrestees by Age at Start of Adult Index Career[a]

[a] The figure presents the proportion of index arrestees in an observation period who are arrested for each index crime type during that period. The different crime types are not mutually exclusive. The same arrestee may be arrested for more than one index crime type during the observation period and is counted in each of those crime types in this figure.

careers (as was seen in Fig. 18). It was suggested in Section 5 that this pattern might be due to different crime type mixes among the different starting-age cohorts. In particular, offenders starting at older ages may be more likely to have arrests for violent crime types which, as we have just seen, are characterized by longer careers. This would drive up the index career-length estimates for those older starters. As indicated in Figure 23, offenders with arrests for violent crimes are increasingly represented among index arrestees as the starting age increases.

This difference in crime-type mix for different starting ages, however, does not account for the difference in residual career length observed for total index careers in Figure 18. While not displayed here, when estimated separately for different starting ages, the career lengths for individual index crime types were generally found to exhibit a pattern similar to that found for index careers combined. In particular, for murder, rape, aggravated assault and robbery, older starters who remain active at least seven years tend to have longer remaining careers. It is only in careers for burglary and auto theft that younger starters tend to have longer remaining careers throughout these careers.

The finding that older starters have longer careers among those who remain active at least seven years is produced by differences in the distribution of career lengths within each starting-age group. Younger starters have the longest total careers, as is evident in Figure 24 where younger starters have a greater proportion with careers at least x years long (1-F(x)).[39] As seen in rows 2 and 3 of Table 6, after eliminating those with short careers in each starting-age group, however, a higher proportion of the remaining older starters have long careers. This drives up the residual career length for these older starters who are still active. Thus, the longest average total careers are found among younger starters because older starters tend to have large numbers of offenders with very short careers. Once those offenders with short careers are eliminated, however, the older starters who remain active have greater proportions of offenders with long careers than do persistent younger starters.

The mean residual career length can be modeled separately for each crime type. As was done for all index offenses combined in section 4, a model is first developed for the dropout rate; the mean residual career length is then estimated from that model. The mean residual career lengths estimated from the age distribution and those fit by models for each crime type

[39] The proportion of offenders with careers at least x years long is given by $1-F(x) = g(x)T$. This is estimated here using the observed age distribution of arrestees g(x) and the estimate of total career length, T, for different starting ages.

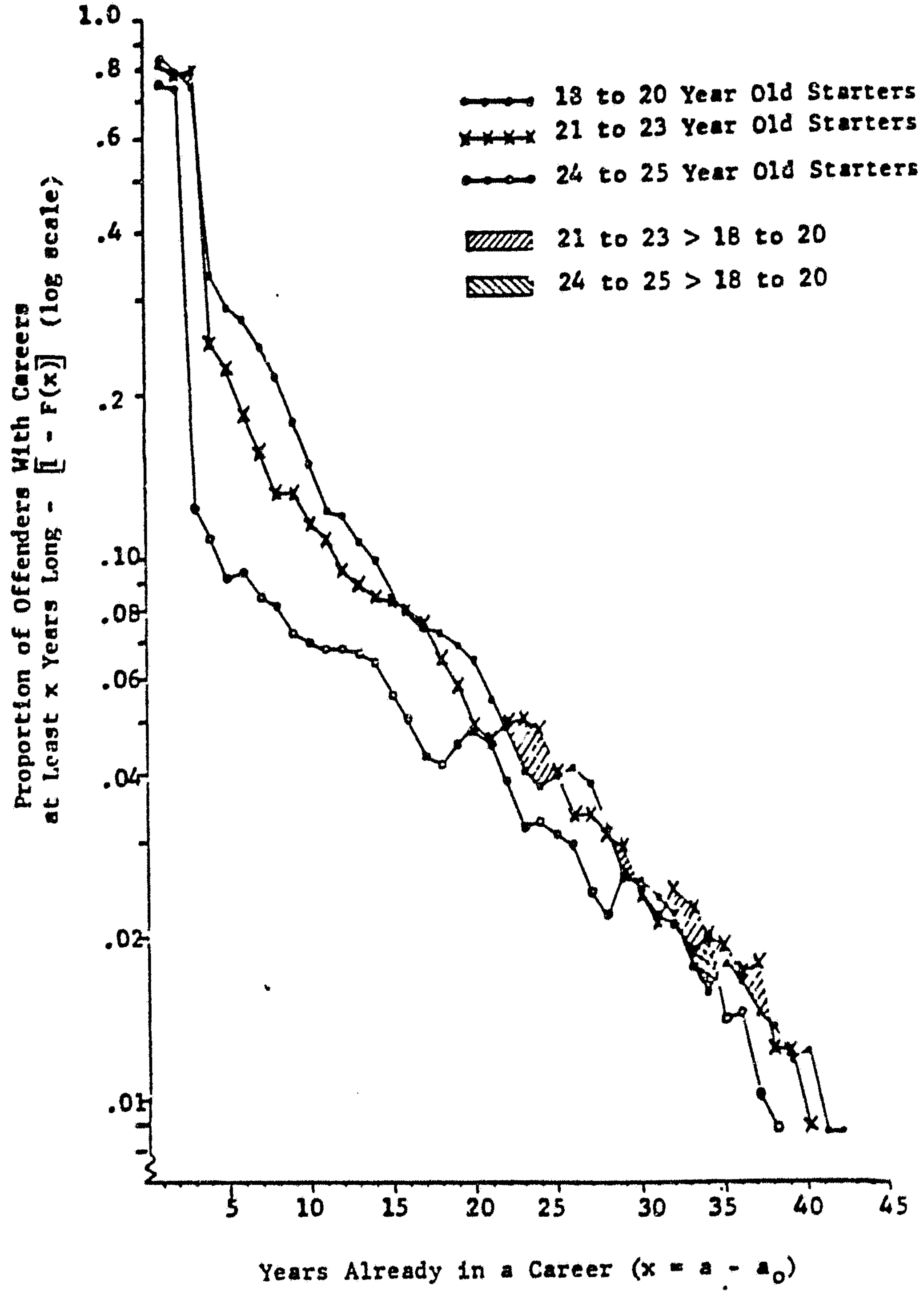


Figure 24

Distribution of Arrestees With Index Careers at Least x Years Long $(1-F(x))^a$ for Different Starting Ages

[a] The proportion of offenders with careers at least x years long is given by $1-F(x) = g(x)T$ in eq.(A1). This is estimated from the observed age distribution of arrestees g(a) and the estimates of total career length, T, for different starting ages.

Table 6

Distribution of Arrestees With Long Index Careers for Different Starting Ages

Proportion of Arrestees With Long Careers	Starting Age 18	21	24
1. Proportion of arrestees who last at least 5 years given they last at least 1 year: $\frac{1-F(5)}{1-F(1)}$ *	34.5%	26.9%	12.2%
2. Proportion of arrestees who last at least 15 years given they last at least 5 years: $\frac{1-F(15)}{1-F(5)}$	29.2%	37.7%	60.2%
3. Proportion of arrestees who last at least 25 years given they last at least 15 years: $\frac{1-F(25)}{1-F(15)}$	47.0%	48.1%	55.7%
4. Proportion of arrestees who last at least 35 years given they last at least 25 years: $\frac{1-F(35)}{1-F(25)}$	45.1%	47.5%	45.2%

* The proportion of arrestees with careers at least x years long is given by $1-F(x) = g(x)T$ in eq. (A1). This is estimated here using the observed age distribution of arrestees, g(x), and the estimates of total career length, T, for different starting ages.

are presented in Figures 25 to 27. All models are special cases of the general model used earlier in which the dropout rate first decreases exponentially, then stabilizes at a constant value and is finally followed by a period of exponentially increasing dropout rates. As seen in Figure 25, the property crimes of burglary, auto theft and robbery follow the basic model very closely. Figure 26 presents the results for the violent offenses of murder and rape where the middle period of a constant dropout rate is extended over the entire career in the underlying model. For aggravated assault, there is no middle period of stable dropout; instead the dropout rate first decreases exponentially and then increases exponentially (Figure 27). These models do reasonably well in representing the mean residual career length for each crime type.

7.0 CONCLUSIONS

A number of distinctive features of adult index criminal careers have been suggested by this analysis of arrest data for Washington, D.C. First, adult criminal careers for index offenses tend to start early, with 44% of adult index arrestees having had at least one arrest for an index offense when they were between the ages of 18 and 20 (Table 3). The extent of early starting also varies somewhat for different crime types. Early starting is especially prevalent among arrestees for property crimes (robbery, burglary and auto theft) where 54% of burglary arrestees and 66% of robbery arrestees started their careers with an index arrest between the ages of 18 and 20 (Table 4). This contrasts with only 27% of aggravated-assault arrestees starting their careers between 18 and 20.

Total adult index careers are also quite short, averaging from only 3.3 years for 24-year-old starters up to 5.6 years for 18-year-old starters (Table 3). Careers are similarly short for individual crime types. Property crimes have the shortest careers averaging only 4 to 5 years for auto theft, burglary and robbery among 18-year-old starters (Table 4). The longest careers are found for murder and aggravated assault which average 10 years among 18-year-old starters.

Residual index careers, or the expected time remaining in careers, vary considerably with the time already elapsed in a career (Figure 12). Early in index careers the expected time remaining in a career increases as past duration in a career increases. This reflects a weeding out of offenders with high dropout rates (and short total careers). For those index offenders who still remain active after about 12 years (or to age 30 for offenders who begin adult careers at age 18), the expected remaining career reaches a maximum of about 10 more years in an index career. Residual index careers remain stable at about 10 additional years until age 42, (for 18-year-old starters). During this period of stability, past time spent in careers is of little help in distinguishing future expected index careers. A thirty-year-old who has been

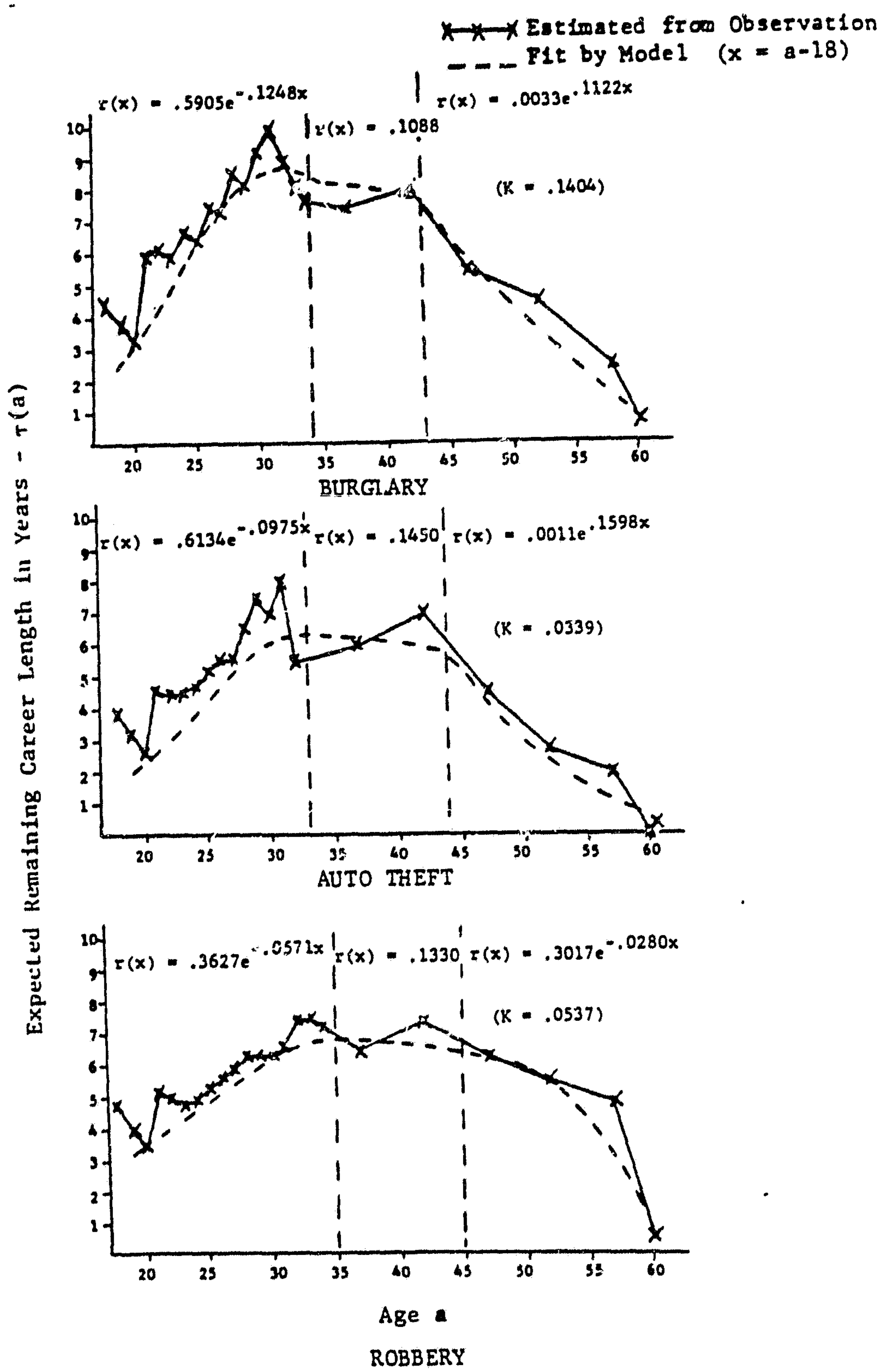
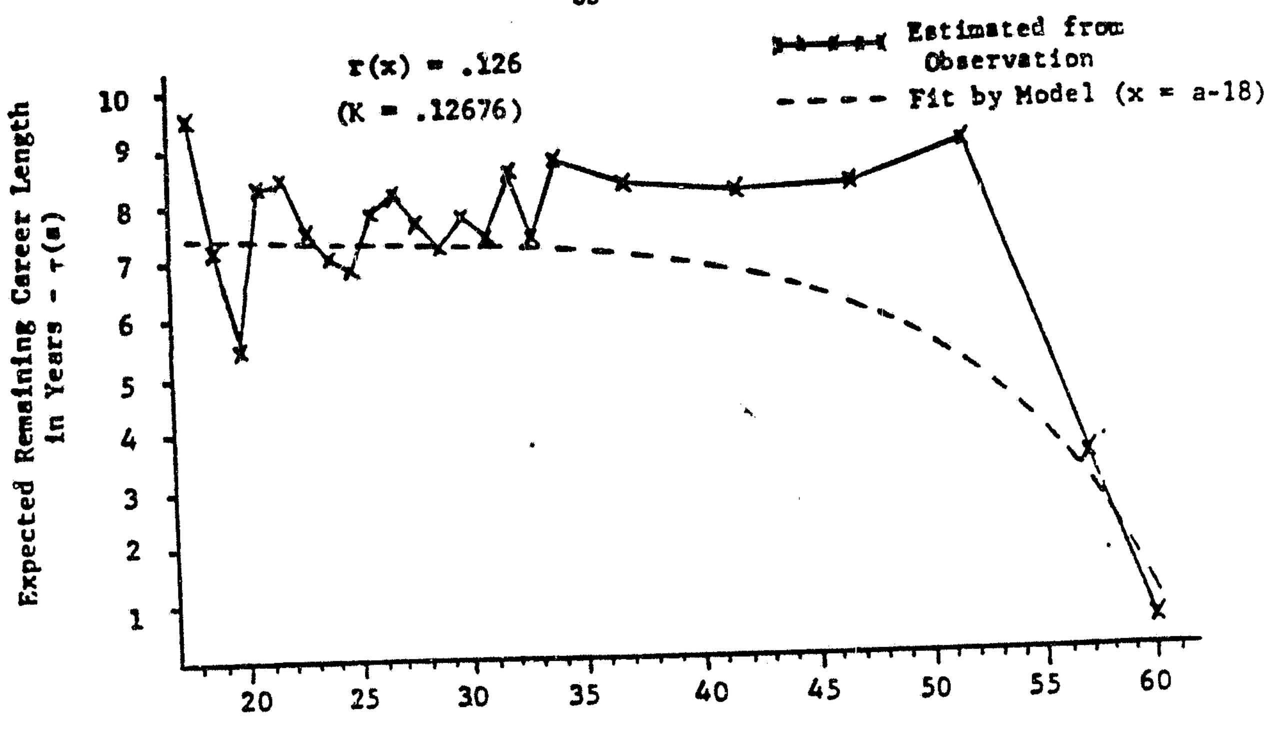
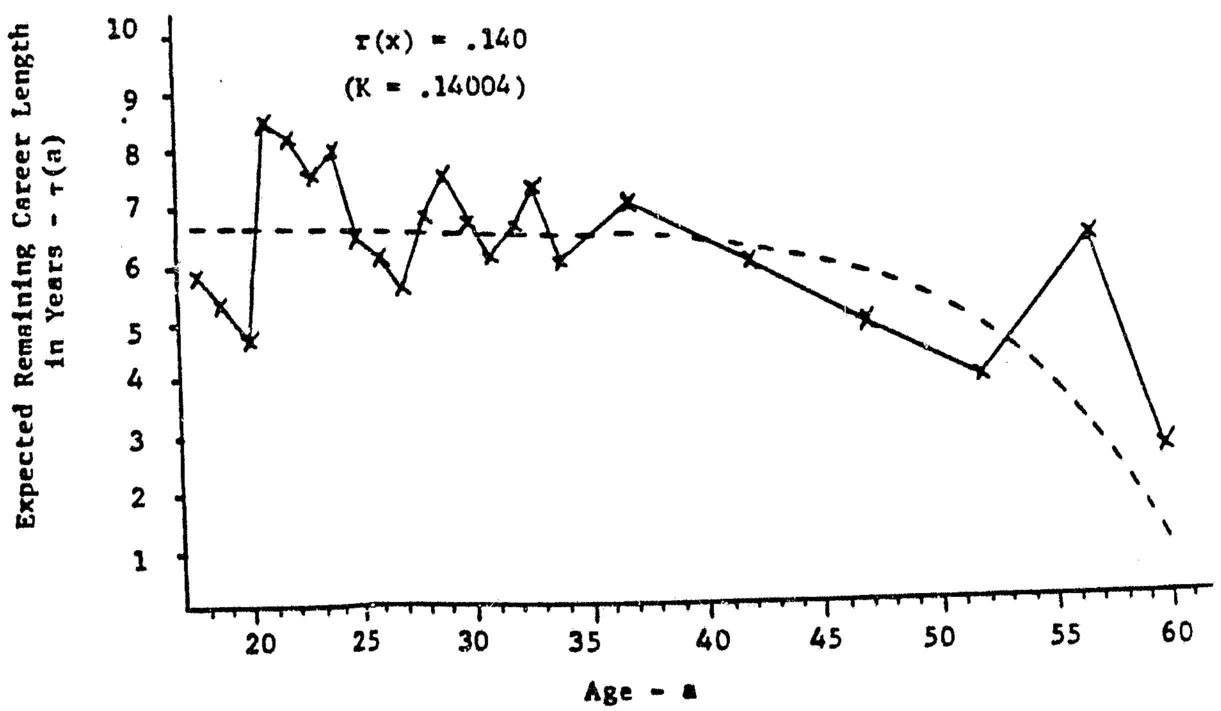


Figure 25

Mean Residual Career Length
Estimated from Observations and Fit by Model
for Property Crimes
(18-Year-Old Starters)



MURDER



RAPE

Figure 26

Mean Residual Career Length
Estimated from Observations and Fit by Model
for Violent Crimes
(18-Year-Old Starters)

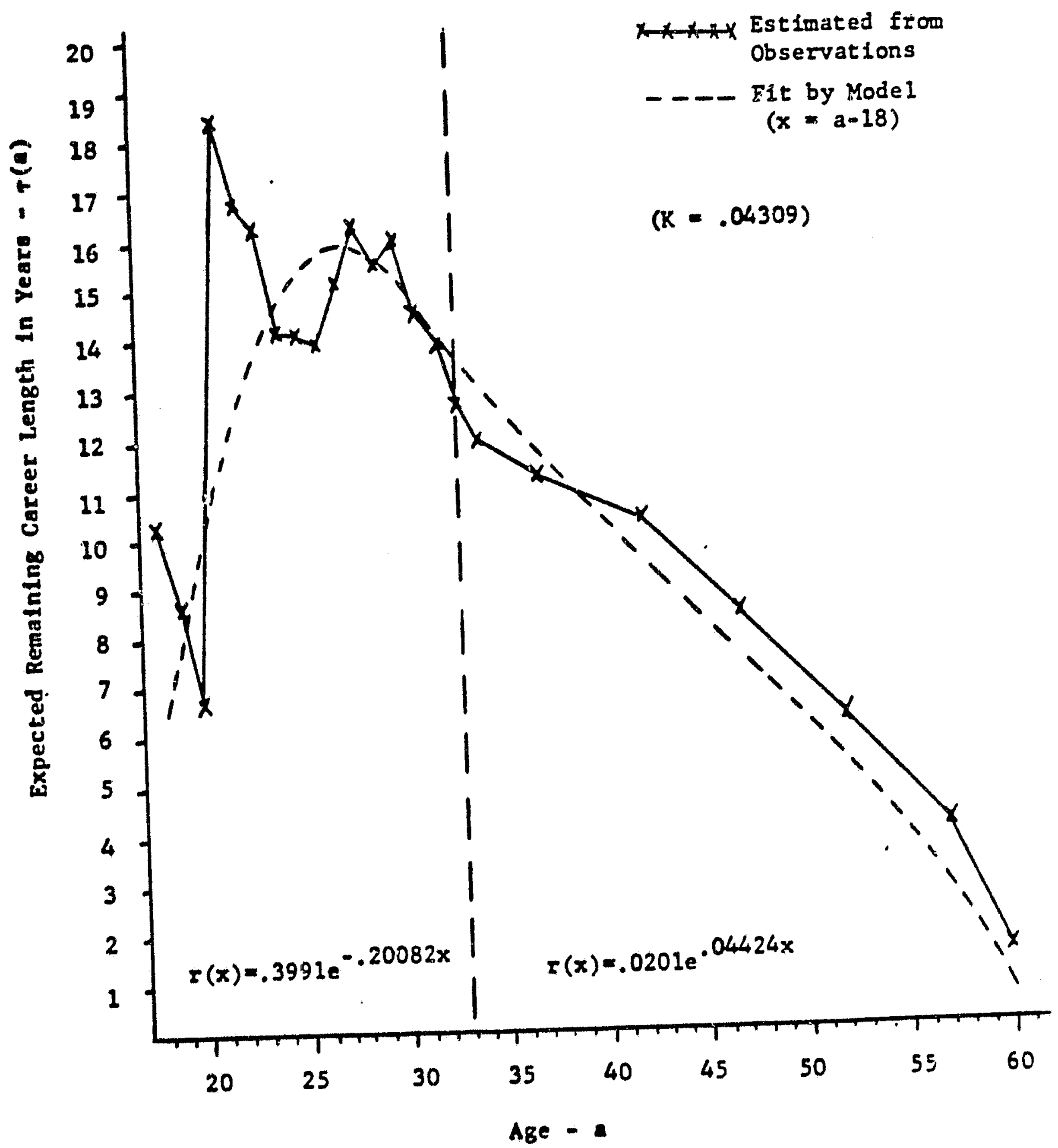


Figure 27

Mean Residual Career Length
Estimated from Observations and Fit by Model
for Aggravated Assault
(18-Year-Old Starters)

active twelve years since age 18 is just as likely to end his career in the next year as is a forty-year-old who has been active for 22 years.[40] After age 42 index careers enter a "wear-out" period in which the remaining career length gets increasingly shorter with advancing age.

This residual career length pattern for the combined index crimes is reflected in the patterns for the individual property offenses of burglary, robbery and auto theft. As with index offenses combined, the residual career lengths for these property crimes reach maximums of from 6 to 8 additional years from 15 to 25 years into a career (i.e., between ages 33 and 43 for 18-year-old starters).

Adult career lengths were also compared for different ages at the start of adult careers. Consistent with previous research on recidivism, younger starters were found to be more persistent offenders; for all index crime types, both separately and when combined, those offenders who begin adult careers at younger ages have longer total careers. The difference in career length for different starting ages is generally small for the property crimes (robbery, burglary and auto theft) and for all index offenses combined, ranging from only a 1.3 year difference for auto theft to a 2.3 year difference for all index offenses combined. Starting age has a more dramatic impact for murder and aggravated assault where careers for 18-year-old starters are about 6 years longer than careers for 24-year-old starters (Table 4).

These characterizations of career length have implications for incapacitation policies. From an incapacitative perspective, incarceration is only effective in averting crimes when it is applied during an active career; incarceration after the career ends is wasted for incapacitation purposes. The estimates of the expected remaining career as a function of time already elapsed in a career are particularly useful in identifying those offenders most likely to remain criminally active during periods of incarceration.

Under existing sentencing policies, offenders at the start of adult careers (i.e., at their first adult conviction) are typically not candidates for incarceration. Based on the analysis of

[40]This stability of dropout rates for different durations of careers is characteristic of the memorylessness property of exponential distributions where the dropout rate remains the same regardless of prior history. After controlling for natural population changes resulting from births, deaths, and migration and for late entry into criminal careers, the length of adult index careers seems to be exponentially distributed only for those index offenders who remain active at least 12 to 24 years (i.e., from 30 to 42 for 18-year-old starters). This thus represents an important refinement to Shinnar and Shinnar (1975) which assumes an exponential distribution for the length of all careers, and to Blumstein and Greene (1978) where without corrections for late starters they find an exponentially distributed career length from ages 18 to 40.

residual career lengths, this prevailing policy is consistent with a strategy of targeting incarceration on offenders when their expected remaining careers are longest. For all index offenses combined and for the property offenses individually, the offender population at the start of careers includes large portions of offenders who will end their careers very shortly. It is only after an offender has remained active for several years (surviving the weeding out process) that the more hard-core committed offenders with the longest remaining careers are more easily identified.

Residual careers for index offenses reach a maximum of ten additional years after 12 to 24 years have already elapsed in those careers. The maximum for the property offenses separately is 6 to 8 additional years reached after 15 to 25 years already in a career. For all index offenses combined and for the property offenses individually, those offenders who remain active into their thirties thus include the most persistent offenders and so represent a prime target group for sanctioning. Earlier and later in careers, sanctions will be applied to many offenders who are likely to drop out shortly anyway.

This finding has implications for the design of special career-criminal programs intended to target resources of the criminal justice system on offenders with serious prior criminal records. Because the selection criteria for special career criminal programs typically involve extensive past criminal records as adults, the average age of target populations tends to be in the late twenties and sometimes the early thirties.[41] Largely informed by the sharp decline with age in aggregate arrest rates illustrated in Figure 1, many people involved in the implementation of career criminal programs have expressed concern about the older age of these target populations because of the presumed greater likelihood that these older offenders will be dropping out of criminal careers shortly anyway.[42]

The findings on career length for index crimes reported here, however, suggest that such concern is misplaced. Indeed, for property crimes, including the frequent target offenses of robbery and burglary, active offenders in their thirties or early forties do represent prime targets for sanctioning. Offenders who have persisted to that point have the longest expected

[41]For example, in the evaluation of California's statewide career-criminal prosecution program, the average age of the career-criminal defendant was 28 in each of three years of program operation. (Office of Criminal Justice Planning, 1981, p. 81.)

[42]This view was expressed by many of the participants at the Special National Workshop on the Career Criminal held by the National Institute of Law Enforcement and Criminal Justice, U.S. Department of Justice in September, 1979, and is noted in Office of Criminal Justice Planning (1981, p. 81).

CONTINUED

1 OF 2

remaining careers. The violent offenses of murder and rape are also still at their maximum remaining careers for offenders in their late twenties and early thirties. Only aggravated assault, which is rarely a target offense of criminal-career programs, has passsed its peak remaining career length by the late twenties.

The average remaining career length tends to be quite short for 18-year-old starters. For all index offenses combined, the maximum is an average of 10 additional years. For property offenses individually, the maximum remaining career averages only 6 to 8 additional years. The generally short length of these remaining careers means that reasonable incapacitative impacts are possible with comparatively short periods of incarceration. Time served in prison on a sentence averages around two years in the United States.[43] Two-year terms of incarceration represent from one-fifth to one-third of the maximum expected remaining careers for index offenses combined and for property offenses individually. To the extent that these careers are not merely postponed by incarceration, reasonably large portions of those careers can be averted (with minimal risk of wasting incapacitation) by two-year prison terms imposed during the period of maximum residual careers. This strategy is particularly attractive because the payoff in reduced crimes by those offenders who are incarcerated is achieved at a reasonable cost in terms of prison resources expended.[44] Because remaining careers for aggravated assault are considerably longer, short prison terms impact a smaller fraction of the remaining careers for persisters in aggravated assault.

[43]In Pennsylvania in 1980, for example, average time served in prison was 2.18 years (Pennsylvania Bureau of Corrections, 1981). Persons released to parole supervision from state and federal institutions in the U.S. in 1977 accounted for 67.8% of all releases. These parole releases had a median time served of 1.43 years and an average time served of about 2.25 years (U.S. Department of Justice, 1980). Since the average time served for unconditional releases is generally lower than that for parole releases, the average time served for all releases in 1977 will be somewhat less than 2.25 years. An approximation of this average time served can be obtained by dividing admissions to state and federal prisons into the daily prison population that year. In 1977 the estimated average time served is 2.17 years. (U.S. Department of Commerce, 1979, Table 332).

[44]Note that the persisters are only a small portion of the total offending population, so the reduction in total crimes committed from incapacitating persisters may not be large. The reduction in crimes is reduced further if the crimes of incarcerated offenders occur anyway, e.g., through recruitment of a replacement for the incarcerated offender of through the continued activity of multiple-offender groups.

APPENDIX A

The Mathematical Model Underlying Estimates of the Duration of Criminal Careers

The general approach to estimating criminal-career length derives directly from the life-table methods developed in Greene (1977) and Blumstein and Greene (1978). This approach uses the observed age distribution of arrestees in a year as the basis for estimating time already elapsed in a career, or the survival time so far in careers. Looking at Figure A-1, the horizontal lines represent the passage of time with the time between the X's representing the duration of complete criminal careers. If we enter the process at some random time t, the heavy solid line is the survival time—or the length of the career elapsed by time t. Under certain well-specified assumptions the distribution of survival times available in a cross-section can be used to estimate the length of complete careers. In other words, total career length can be estimated from the distribution of partially completed careers available from the age distribution of arrestees in a year.[45]

A1. THE AGE DISTRIBUTION OF ARRESTEES

Under various steady-state conditions, the duration of criminal careers for a cohort of offenders beginning their careers at a common age, a_o, in some year y can be empirically estimated by examining the age distribution of arrestees from different cohorts found in a single year. To show this we start with the same assumptions of Greene (1977), namely:

1. The average probability of at least one arrest in a year does not vary with the age of active offenders;
2. The size of the offender population for each age is constant over different cohorts; and
3. All offenders begin their criminal careers at the same age a_o.

When these assumptions are satisfied:

[45]The basic approach applied here to the age distribution can also be used with the distribution of prior arrests to estimate the expected dropout rate and the expected remaining number of arrests after exactly x arrests in a career. The application to prior arrests is illustrated in Appendix I.

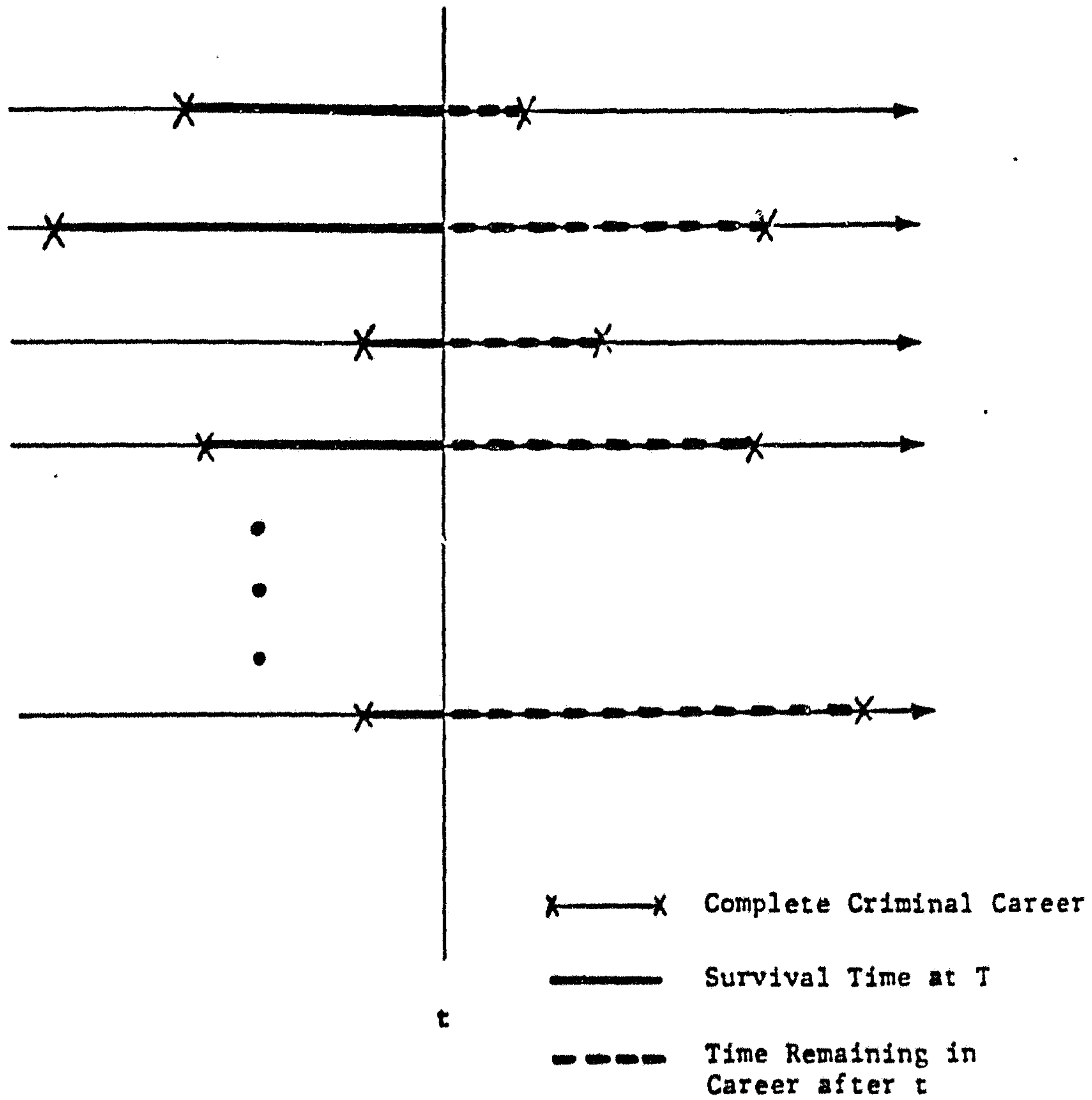


Figure A-1

The "Survivor Distribution" for Criminal Careers.

1. Arrestees are representative of all active offenders with respect to age;[46]

2. All cohorts of offenders are indistinguishable in terms of career lengths;[47] and

3. The age of arrestees in a year, a, directly indicates the length of time already in a career (i.e., $x = a - a_o$).

In this event the observed age distribution of arrestees in a year, $g(a-a_o)$, is just the distribution of time already elapsed in a career, $g(x)$. The distribution for time already elapsed in a career is related to the distribution of total careers, L, as follows:

$$g(x) = g(a-a_o) = [1-F(x)]/T. \tag{A1}$$

where F and T refer to the distribution of total career lengths, L.[48] In particular,

$f(x)$ = probability that careers last exactly x years,

$$1-F(x) = \int_x^\infty f(y)dy$$

= probability that careers last at least x years, and

---

[46]By using arrestees, the career-length variables are estimated from a population of offenders known to be active (i.e., individuals with non-zero λ's in that year). To the extent that arrestees are representative of all active offenders, at least with respect to age, the estimated career-length variables refer to the true career from start at or before the first offense to end at or after the last offense. The career-length variables are not restricted to the career bounded by the first and last arrest.

[47]Cohorts are indistinguishable when the offender proportion in the population that starts in each cohort is the same and when all cohorts are subject to the identical dropout process. Ordinarily the arrestees in any single year reflect the dropout process of the many different cohorts represented among the arrestees. When the different cohorts are indistinguishable, the process reflecting dropout in many different cohorts accurately reflects dropout in any one cohort.

[48]The length of criminal careers may be viewed as a renewal process where the start and end of a career are the renewal events and the time between these events (i.e., the length of a career) is the renewal period, L. We assume that L is independent and identically distributed across individual offenders. Now observing the process at some time t, the time that has elapsed since the last renewal event (i.e., the time already spent in a career) is known as the backward recurrence time. In the limit, the probability density function for the backward recurrence time is given by equation (A1). See Cox (1962) for further details on the derivation of this expression.

$$T = \int_0^{\infty} x f(x)dx = \int_0^{\infty} [1-F(x)]dx$$

= expected (or mean) total career length.

The age distribution $g(a-a_0) = g(x)$, is empirically estimated as:

$$\hat{g}(a-a_0) = N(a)/\Sigma_{i=a_0}^{MAX} N(i) \qquad (A2)$$

where $g(a-a_0)$ simply gives the proportion of total arrestees in a year who are each age a.[49]

A2. THE DROPOUT RATE

The dropout rate from criminal careers reflects the portion of remaining active offenders that end their criminal careers (i.e., permanently cease any criminal activity) each year. The dropout rate at each year in a career, r(x), is a function of the distribution of total career lengths, L, and is defined as:

$$r(x) = f(x)/[1-F(x)] \qquad (A3)$$[50]

Combining the relations in equations (A1) and (A3), the dropout rate can be expressed exclusively in terms of the age distribution of arrestees, namely

$$r(x) = -g'(x)/g(x) \qquad (A4)$$

where $g'(x)$ is the first derivative of $g(x)$.

---

[49]In the most general case $g(a-a_0) = N(a)/\Sigma_{i=a_0}^{\infty} N(i)$. However, since death represents a natural termination of criminal careers, a finite maximum, MAX, can be used as the upper limit for the age distribution of arrestees.

Ideally the value of MAX would itself be estimated from the data. For simplicity in the current estimates, however, we have set MAX = 62 reflecting the usual MAX age at arrest observed in the data. Note that use of a constant MAX means that all careers end by age 62 in the career-length estimates generated here.

[50]Barlow and Proschan (1965).

Using equation (A4), then, the dropout rate at x can be empirically estimated by fitting a regression line through the observed values of the age distribution immediately surrounding g(x) to estimate the slope, g'(x), at x.

A3. THE MEAN RESIDUAL CAREER LENGTH

By analogy with the definition of the dropout rate associated with the career-length distribution f(x) in eq (A3), we can also define the hazard rate (or failure rate) associated with the age distribution, g(x), as:

$$h(x) = g(x)/[1-G(x)] \qquad (A5)$$

which is empirically estimated by:

$$\hat{h}(x) = N(a)/\Sigma_{i=a}^{MAX} N(i) \qquad (A6)$$

Substituting from eq (A1) into eq (A5) we find that:

$$h(x) = \frac{1-F(x)}{T} \Big/ \frac{\int_x^{\infty}[1-F(y)]dy}{T} = \frac{1-F(x)}{\int_x^{\infty}[1-F(y)]dy} \qquad (A7)$$

Equation (A7) is just the reciprocal of the mean residual career length given a career lasts at least x years, i.e., the expected time remaining in a career after x years have already elapsed in a career. Therefore, the mean residual career length at any age, $\tau(a)$, can be estimated from the age distribution of arrestees as:

$$\hat{\tau}(a) = 1/\hat{h}(a) = \Sigma_{i=a}^{MAX} N(i)/N(a) \qquad (A8)$$

A4. THE MEAN TOTAL CAREER LENGTH

The last variable of interest is the mean total career length, T. In general the expected value is given by:

$$T = \int_0^{\infty} [1-F(x)]dx.$$

In this case, the desired expected value can be estimated using equation (A7).

For x = 0 (i.e., at the start of a career), equation (A7) becomes

$$h(0) = [1-F(0)]/\int_0^{\infty} [1-F(x)]dx = 1/T$$

and the mean total career length is given by the mean residual career length at the start of a career, or

$$T = \tau(x) \text{ for } x = 0 \text{ (i.e., at age } a_0\text{)}. \quad (A9)$$

APPENDIX B

Tests for Stationarity of Arrestee-to-Arrest Ratios and Unique-Index-Arrestee Ratios in Michigan Counties

The results from Washington, D.C. pose a relationship of the arrestee-to-arrest ratio or the proportion of unique index arrestees with age. The general form of that relationship is:

Ratio = a + bAge

The parameters, a and b, may vary over time, or over jurisdictions. To test the stationarity of the parameters over time and over jurisdiction, we use data on these ratios for four different years in twelve Michigan counties.

The test for stationarity (either over time, or over counties) uses a standard F-test suggested by Chow to compare the residuals from an <u>unconstrained</u> regression (in which the parameters are estimated separately for different years, or for different counties) with the residuals of a <u>constrained</u> regression (in which the parameters are assumed to be equal in all years, or in all counties.)[51] The F-statistic is computed from the residuals as:

$$F = \frac{(R_c - R_u)/[(N-k) - (N-mk)]}{R_u/(N-mk)}$$

where R_c = sum of squared residuals of the constrained regression;

R_u = sum of squared residuals of the unconstrained regression;

N = total number of observations;

k = number of parameters in the constrained regression; and

m = number of years (or counties) estimated separately in the unconstrained regression.

Table B-1 lists the F-statistic, and the approximate p-value of that statistic, in tests of <u>time</u> stationarity. The arrestee-to-arrestee ratio for each index crime type and the proportion of unique index arrestees were individually regressed on age in each Michigan County. The test compares the residuals in regressions where the parameters are constrained to be equal over time, with those obtained when the parameters are estimated separately for each year. A significant F-value supports rejecting the null hypothesis that a ratio is time stationary (i.e., has

[51]See Fisher (1970) or Rao (1973:281-4) for details of this test.

constant parameters over time). In comparisons for 88 separate ratios across time, only eight were found to have statistically significant time trends.

To test the hypothesis that all ratios in Table B-1 are time stationary, the p_i values in Table B-1 were used to form Pearson's p_λ statistic (Rao, 1973; p. 168-169)

$$p_\lambda = \Sigma_{i=1}^{k} - 2\ell n \; p_i = 192.548$$

which is distributed X^2 with 2k degrees of freedom. The probability of a X^2 value at least this large, with 166 degrees of freedom, is .076.

To test for jurisdictional stationarity, the ratios for the four years combined were regressed on age. The residuals when the parameters for different jurisdictions were constrained to be equal are then compared to the residuals when the parameters are estimated separately in each jurisdiction. The variations in age patterns across counties are more substantial, with significant (or near significant) differences found for every ratio in Table B-2. As is evident in Table B-3, while statistically significant, the absolute magnitude of the differences across counties is not very large. In part this reflects the excessive power of the statistical test with very large samples.

To assess the sensitivity of the career-length estimates to variations in the arrestee-to-arrest ratios and the unique-index-arrestee ratios, career length for Washington, D.C. was estimated separately first applying the Washington, D.C. ratios and then applying selected ratios for Michigan counties to the Washington, D.C. arrests. The Michigan ratios were selected to be most different from those found in Washington, D.C. Typically the alternative ratios were larger in value and had flatter slopes (if there was a trend detected). The alternative ratios are listed in Table B-4.

The resulting mean residual career lengths are presented in Figures B-1 and B-2. Using only the arrestee-to-arrest ratios for individual crime types yields total index arrestees with multiple counting of arrestees. The resulting career-length estimates for "multiple" index arrestees in Washington, D.C. are compared in Figure B-1. Using the larger ratio (i.e., fewer multiple arrests for the same crime type) found in Michigan reduced the total career length based on Washington, D.C. arrests by less than one-half of a year (or by 3.7%) from the estimate found using the Washington, D.C. ratios.

In Figure B-2, both the arrestee-to-arrest ratios and the unique-index-arrestee ratios were

Table B-1

Tests of Time Stationarity: F-Statistics and Approximate p-Values

Michigan County	Proportion Unique Index Arrestees	Arrestee-to-Arrest Ratio by Crime Type						
		Murder	Rape	Robbery	Aggravated Assault	Burglary	Larceny	Auto Theft
Berrien	F= .377 (6,149) p= .875	N/A[(a)]	F=1.326 (6,52) p= .26	F=6.930 (6,51) p= .0005***	F= .754 (6,126) p= .60	F= .732 (6,77) p= .60	F= .455 (6,55) p= .83	N/A
Calhoun	F= .496 (6,128) p= .80	F=1.318 (6,25) p= .29	F=2.208 (6,43) p= .07	F=1.014 (6,54) p= .45	F= .921 (6,105) p= .50	F=1.721 (6,77) p= .125	F= .682 (6,52) p= .66	F= .535 (6,31) p= .78
Genessee	F= .854 (6,176) p= .51	F=1.439 (6,83) p= .20	F=2.147 (6,91) p= .06	F=2.588 (6,90) p= .03*	F=1.746 (6,165) p= .11	F=2.009 (6,112) p= .065	F=1.421 (6,79) p= .19	F=1.365 (6,54) p= .23
Ingham	F= .838 (6,141) p= .525	N/A	F= .912 (6,48) p= .50	F= .419 (6,67) p= .85	F= .433 (6,103) p= .82	F= .556 (6,85) p= .80	F=1.078 (6,61) p= .42	F= .686 (6,45) p= .64
Jackson	F= .408 (6,138) p= .85	N/A	F= .268 (6,46) p= .95	F= .615 (6,56) p= .75	F= .738 (6,113) p= .62	F= .581 (6,84) p= .80	F=1.508 (6,61) p= .17	F= .672 (6,28) p= .65
Kalamazoo	F=1.745 (6,127) p= .11	N/A	F= .744 (6,38) p= .55	F=3.736 (6,56) p= .003**	F=2.292 (6,103) p= .04*	F= .907 (6,71) p= .50	F=2.600 (6,57) p= .025*	F=1.149 (6,25) p= .49
Kent	F= .639 (6,157) p= .69	F= .818 (6,43) p= .55	F=1.643 (6,89) p= .13	F= .313 (6,66) p= .93	F= .286 (6,124) p= .94	F= .732 (6,94) p= .63	F= .443 (6,70) p= .825	F= .778 (6,51) p= .525
Macomb	F= .500 (6,150) p= .80	F= .792 (6,58) p= .62	F= .619 (6,76) p= .73	F= .600 (6,72) p= .74	F= .581 (6,138) p= .75	F= .476 (6,104) p= .85	F= .650 (6,69) p= .67	F=2.714 (6,48) p= .025*
Oakland	F= .233 (6,166) p= .96	F=1.035 (6,77) p= .42	F=2.833 (6,82) p= .015*	F=1.377(6,82) p= .25	F=1.093 (6,142 p= .45	F= .923 (6,97) p= .45	F=1.316 (6,71) p= .27	F= .427 (6,63) p= .875
Washtenaw	F= .812 (6,125) p= .49	F= .788 (6,38) p= .58	F=1.729 (6,56) p= .31	F=2.123 (6,58) p= .06	F=1.039 (6,109) p= .43	F= .183 (6,71) p= .98	F= .617 (6,58) p= .75	F= .965 (6,31) p= .48
Wayne	F=1.596 (6,192) p= .14	F= .362 (6,151) p= .85	F= .432 (6,117) p= .85	F=1.464 (6,126) p= .18	F= .738 (6,181) p= .54	F= .467 (6,143) p= .84	F=1.464 (6,89) p= .18	F=2.706 (6,88) p= .02*

(a) Not applicable – there is no variation in the ratio at all.
* Significant at .05 level
** Significant at .01 level
*** Significant at .001 level

Table B-2

Tests of Jurisdictional Stationarity -- F-Statistics

Proportion Unique Index Arrestees	Arrestee-to-Arrest Ratio						
	Murder	Rape	Robbery	Aggravated Assault	Burglary	Larceny	Auto Theft
F=4.206*** (22,548)	F=3.076*** (22,328)	F=1.603* (22,385)	F=2.016** (22,319)	F=1.716* (22,520)	F=2.850*** (22,389)	F=1.603* (22,303)	F=1.510+ (22,242)

+Significant .10 level
*Significant .05 level
**Significant .01 level
***Significant .001 level

Table B-3

Jurisdictional Differences in the Regressions on Age
for the Arrestee-to-Arrest and Unique Arrestee Ratios

Jurisdiction	Proportion Unique Index Arrestees	Arrestee-to-Arrest Ratio						
		Murder	Rape	Robbery	Aggravated Assault	Burglary	Larceny	Auto Theft
Wash. D.C.	$.759+.00368^{***}$ Age	r = .917	r = .934	$.619+.00816^{***}$ Age	$.910+.0007^{+}$ Age	r = .878	.574+.0082 Age	r = .914
Berrien	$.928+.00171^{***}$ Age	r = 1.000	r = .992	$1.021-.00538^{**}$ Age	r = .991	r = .979	r = .926	r = 1.000
Calhoun	$.867+.00371^{***}$ Age	r = .979	r = .964	$.877+.00447^{*}$ Age	$.938+.00182^{**}$ Age	$.860+.00396^{*}$ Age	r = .931	r = .968
Genessee	$.875+.00311^{***}$ Age	$.583-.00344^{***}$ Age	r = .940	$.869+.00241^{+}$ Age	$.924+.00106^{+}$ Age	r = .881	$.763+.00496^{*}$ Age	r = .970
Ingham	$.910+.00218^{***}$ Age	r = 1.000	r = .991	r = .975	r = .985	r = .950	$.880+.00439^{+}$ Age	r = .992
Jackson	$.895+.00275^{***}$ Age	r = 1.000	r = .977	r = .979	r = .982	$.894+.00344^{**}$ Age	r = .924	r = .983
Kalamazoo	$.906+.00087^{+}$ Age	r = 1.000	r = .971	r = .941	r = .982	r = .952	$.853+.00509^{*}$ Age	r = .962
Kent	$.924+.00155^{***}$ Age	r = .993	r = .974	r = .977	$.959+.00105^{+}$ Age	r = .966	r = .957	r = .994
Macomb	$.915+.00187^{***}$ Age	r = .989	r = .966	$.881+.00338^{+}$ Age	r = .966	$.882+.00335^{**}$ Age	r = .909	r = .960
Oakland	$.954+.00109^{**}$ Age	r = .992	r = .986	r = .955	r = .995	r = .972	r = .945	r = .979
Washtenaw	$.905+.00248^{***}$ Age	r = .989	r = .970	r = .973	r = .981	$.873+.00381^{*}$ Age	r = .891	r = .981
Wayne	$.937+.00131^{***}$ Age	r = .931	r = .978	$.919+.00179^{+}$ Age	r = .979	r = .955	$.868+.00341^{+}$ Age	r = .987

+ Significant at .10 level
* Significant at .05 level
** Significant at .01 level
*** Significant at .001 level

Table B-4

Alternative Arrest-to-Arrestees Conversion Ratios

Ratio	Washington, D.C.	Michigan
Unique Index Arrestees	r = .759 + .00368 Age	r = .954 + .00109 Age
Arrestees-to-Arrests:		
Murder	r = .917	r = .993
Rape	r = .934	r = .986
Robbery	r = .619 + .00816 Age	r = .877 + .00447 Age
Aggravated Assault	r = .910 + .0007 Age	r = .995
Burglary	r = .878	r = .979
Larceny	r = .574 + .0082 Age	r = .853 + .00509 Age
Auto Theft	r = .914	r = .992

Mean Total Career Length:

10.33 Using Washington, D.C. Ratios
9.95 Using Michigan County Ratios

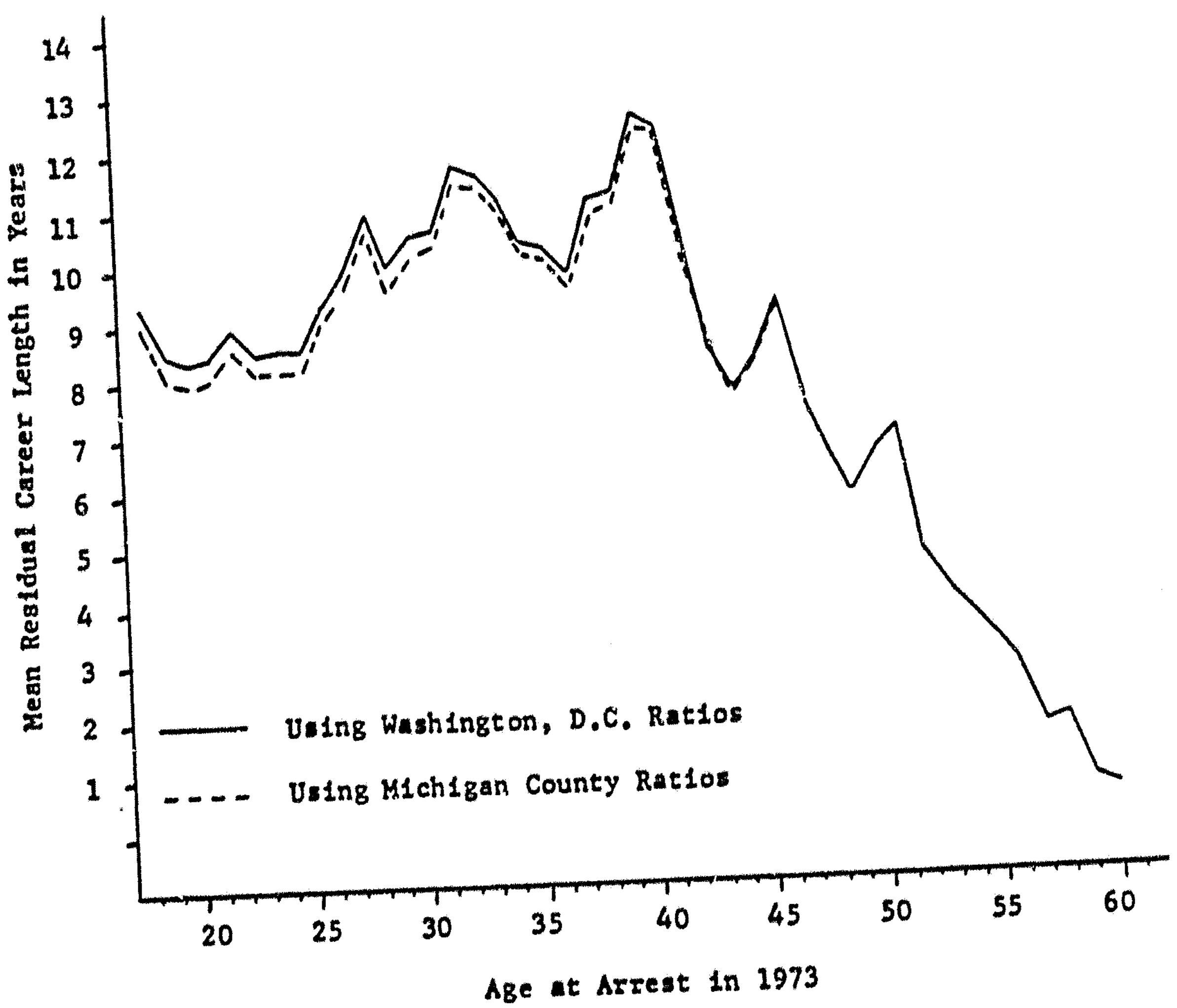


Figure B-1

Sensitivity of Mean Residual Career Length Estimates to Variations in Arrestee/Arrest Ratios: Career Length Estimates for Index Arrestees With Multiple Counting

<u>Mean Total Career Length</u>:
10.80 Using Washington, D.C. Ratios
10.06 Using Michigan County Ratios

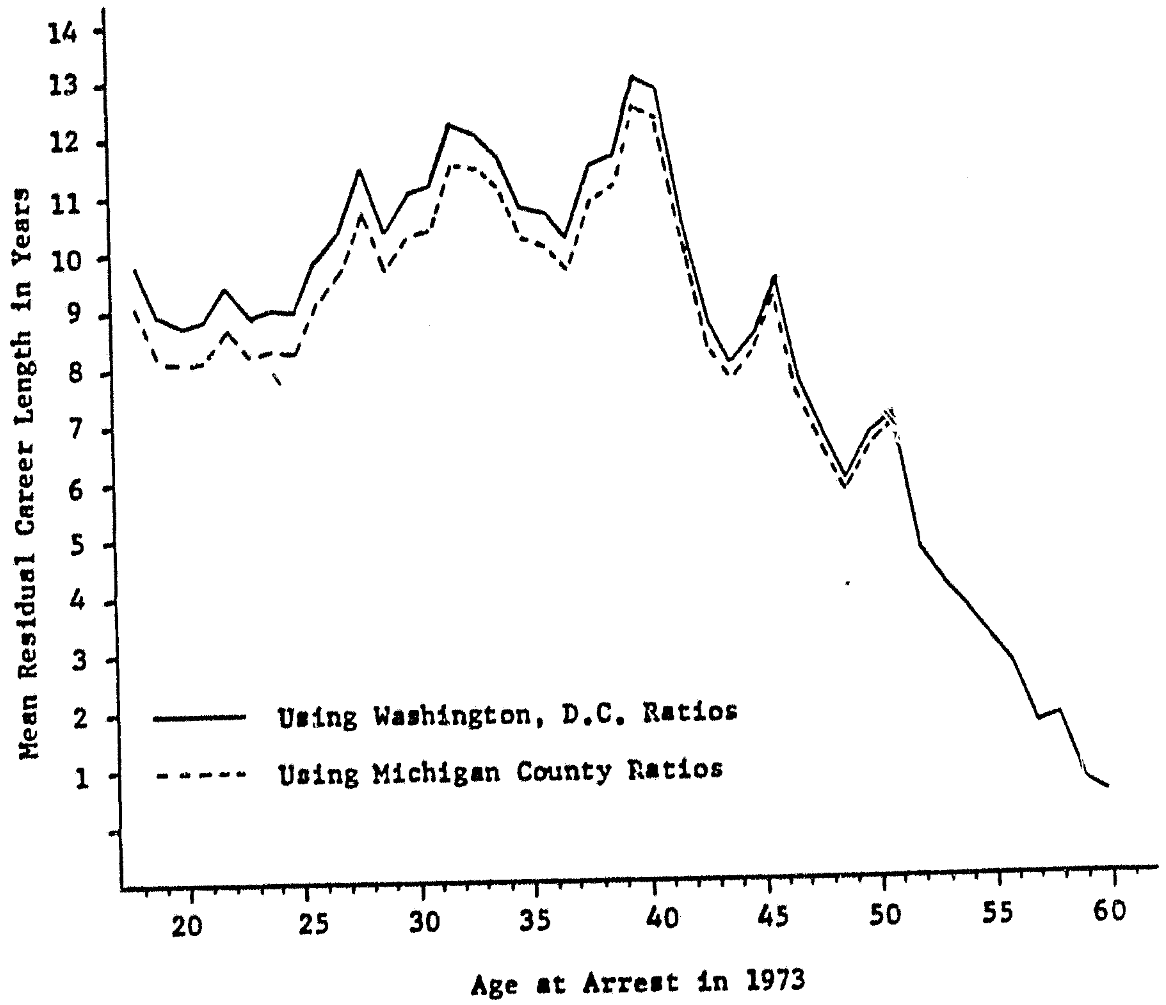


Figure B-2

Sensitivity of Mean Residual Career Length Estimates to Variations in Both Arrestee-to-Arrest Ratios and Unique Index Arrestee Ratio: Career Length for Unique Index Arrestees

applied to index arrests in Washington, D.C. to yield total unique index arrestees. The combined effect of the two Michigan conversion factors was a reduction of about 3/4 of one year (or 6.9%) from the estimate found using the Washington, D.C. ratios.

The most noteworthy finding is that the use of different slopes for trends in the ratios did not alter the pattern of age variation in the mean residual career-length. Thus, within the range of jurisdictional differences in the ratios observed in Michigan and Washington, D.C., the impact of different ratios on career-length estimates is small, especially when compared to the role of the other correction factors indicated in Figure 9 and Table 2.

APPENDIX C

Estimating Age-Specific Numbers of Arrests from Age-Grouped Arrest Data

The annual arrest data for Washington, D.C. were only available for the age groups identified in Table C-1. The 1973 arrestee data contain the number of arrests for each index offense type at each age for adults (≥18) arrested in 1973. The more detailed 1973 arrests can be used to partition the reported arrests over each age within an age group. In particular, we estimate:

$$p_{ik}(j) = \frac{n_{ijk}}{N_{ik}} \text{ for } \begin{cases} i = \text{crime type} \\ k = \text{age group (e.g., 25 to 29)} \\ j = \text{individual age within} \\ \quad \text{age group } k \text{ (e.g., 26)} \end{cases}$$

where N_{ik} is the number of arrests for offense type i in age group k, n_{ijk} is the number of arrests for offense type i at age j in group k, and $N_{ik} = \Sigma_{j \in k} n_{ijk}$. These proportions, $p_{ik}(j)$, are multiplied by the number of arrests reported in each age group k available for each year 1970 to 1976 to yield estimates of the annual number of arrests for each individual age.

The 1973 arrestee data are complete for all index offenses other than larceny. In the case of larceny, the age-specific numbers of arrests are available only for adults arrested for larceny in 1973 and also arrested for some other index offense that year. Since younger offenders are more likely to have arrests for multiple crime types (section 2.1.1), this requirement of multiple arrests tends to over-represent younger age groups and under-represent older age groups among larceny arrests in 1973. The age-specific estimates, however, are calculated separately within each age group. If the resulting proportion at each age within an age group more closely represents the age distribution within age groups for all larceny arrests, the age-specific estimates of larceny arrests are not likely to be seriously biased.

Note also that we use the age-specific proportions for 1973 to derive estimates of arrests for each year 1970 to 1976. While this assumes stationarity in the age distribution within age groups, it still permits year-to-year variations in the overall age distribution of arrests reflected in changes in the distribution over the different age groups.

Table C-1

Age Groups Available in Washington, D.C. Arrest Data

Years

1970-74	1975,76
Age Groups:	Age Groups:
	≤ 10
	11-12
≤15	13-14
	15
16	16
17	17
	18
18-20	19
	20
21-22	21
	22
23-24	23
	24
25-29	25-29
30-34	30-34
35-39	35-39
40-44	40-44
45-49	45-49
≥ 50	≥ 50

APPENDIX D

Estimating the Annual Age-Specific Population Distribution for Non-White Males in Washington, D.C.

With the exception of the decennial census in 1970, the annual age-specific population distribution for non-white males in Washington, D.C. from 1971 to 1976 must be estimated. The available population data for Washington, D.C. are:

- The annual total population over race, sex, and age for 1970 to 1976 (last row of Table D-1):
- The annual population subtotals for ten age groups for non-white males from 1972 to 1975 (Table D-1)[52]; and
- The age-specific non-white male population for 1970 (Table D-2).

There are two basic elements to the population estimates, first estimating the <u>proportion</u> of the total population at each age for non-white males, $P_a(t)$, and then estimating the <u>absolute number</u> of non-white males each age, $M_a(t)$. Slightly different procedures are used for the years 1972 to 1975 when age-group data are available, and for the years 1971 and 1976 when only total population figures are available. The resulting estimates for $M_a(t)$ are presented along with the 1970 census data in Table D-3.

D.1. Estimating $P_a(t)$

(1) <u>Years:</u> <u>1972</u> - <u>1975</u>

The estimates for these years make use of the available age-group population data by first estimating the proportion of the total population at the "mid-age" of each age group as:

$$P_{m_i}(t) = \frac{A_i(t)}{T_t} \qquad \text{(D1)}$$

where:

[52]The inter-census year population figures were provided by the D.C. Government, Office of Planning and Development, Statistical Services Division, Demographic Unit. These population estimates are generated using a basic cohort method with adjustments for births (from vital statistics), deaths (using life-table estimates), and migration. Migration is estimated using data on school enrollment for younger ages, supplemented by social security data to estimate migration of older age groups.

$P_{m_i}(t)$ = proportion of the total population at "mid-age" m_i of age group

$P_{m_i}(t)$ = proportion of the total population at "mid-age" m_i of age group i in year t;

$A_i(t)$ = $S_i(g)/5$, i.e., the simple average population each age within age group i in year t where $S_i(t)$ is the population subtotal for age group i; and

T_t = total population over race, sex and age in year t (t = 1970, 1972, ..., 1975).

Equation (D1) enables us to obtain ten "mid-age" proportions for each of the years 1970, 1972, 1973, 1974, and 1975.

$P_a(t)$ is the proportion of the total population at each age a. This proportion is estimated for the intermediate ages between two "mid-age" proportions by using the linear interpolation with:

$$\frac{P_a(t) - P_{m_i}(t)}{a - m_i} = \frac{P_{m_j}(t) - P_{m_i}(t)}{m_j - m_i} \qquad \text{(D2)}$$

where

$m_j \le a \le m_j$, j = i + 1

m_i = the "mid-age" of age group i in year t;

$P_{m_i}(t)$ = the proportion of the total population at "mid-age" m_i of age group i in year t (from eq (D1));

t = Years 1970, 1972, ..., 1975

(2) <u>Years:</u> <u>1971 and 1976</u>

The $P_a(t)$ are estimated for the two years without age-group data (1971 and 1976) by a linear regression model applied to the estimates derived for the years 1970, and 1972 through 1975 for each age a:

$$P_a(t) = \alpha_a + \beta_a t, \quad 18 \le a \le 62 \qquad \text{(D3)}$$

D.2. Estimating $M_a(t)$

(1) Years: 1972 - 1975

For those years where age-group subtotals are available, the absolute number of non-white males, $M_a(t)$, are computed as follows:

Step 1: Compute the proportion each age within an age group, $P_a^i(t)$, as:

$$P_a^i(t) = \frac{P_a(t)}{\sum_{a \in i} P_a(t)} \qquad \text{(D4)}$$

where i = age group and t = years 1972 to 1975.

Step 2: Compute the absolute number of non-white males each age for each age group separately as:

$$M_a(t) = P_a^i(t) \cdot S_i(t) \qquad \text{(D5)}$$

for age a in age group i;

and $S_i(t)$ = the subtotal population of age group i in year t (Table D1); and

t = years 1972 to 1975.

(2) Years: 1971 and 1976

In these years $M_a(t)$ is simply estimated as:

$$M_a(t) = P_a(t) \cdot T_t \qquad \text{(D6)}$$

for t = years 1971 and 1976.

Table D-1

Annual Non-White Male Population in Washington, D.C. for Selected Age Groups*

Age Group	Year						
	1970	1971	1972	1973	1974	1975	1976
15-19	24,549	NA**	26,100	27,000	27,600	28,500	NA**
20-24	22,719	•	22,900	22,900	23,300	24,000	•
25-29	20,904	•	21,800	22,200	22,000	22,000	•
30-34	16,965	•	18,100	19,200	19,500	19,700	•
35-39	15,119	•	15,200	15,100	15,300	15,800	•
40-44	15,025	•	14,500	14,400	14,100	14,000	•
45-49	14,373	•	15,200	13,900	13,300	13,600	•
50-54	12,267	•	14,300	13,100	13,000	12,600	•
55-59	10,711	•	10,400	10,200	9,900	10,400	•
60-64	8,031	.	8,600	8,500	8,500	8,600	.
Total All Races, Sexes, Ages	756,510	753,600	752,700	739,600	729,100	721,800	700,000

*Prepared by: Office of Planning and Management, Research and Statistics Unit, Washington, D.C.

**NA: Not available

Table D-2

1970 Age-Specific Population for Non-White Males in Washington, D.C.*

AGE	POP'N	AGE	POP'N	AGE	POP'N	Age	POP'N	Age	POP'N
15	5374	25	4460	35	3217	45	2888	55	2407
16	5008	26	4180	35	2985	46	2844	56	2124
17	4866	27	4422	37	3100	47	3096	57	2091
18	4646	28	3888	38	2660	48	2796	58	1999
19	4655	29	3954	39	3157	49	2749	59	2090
20	4543	30	4020	40	3302	50	3063	60	1929
21	4389	31	3457	41	2876	51	2504	61	1612
22	4832	32	3171	42	2977	52	2347	52	1644
23	4688	33	3044	43	2985	53	2189	63	1362
24	4267	34	3273	44	2975	54	2164	64	1466

*From Table 19, <u>1970 Census of Population, District of Columbia</u> (Washington, D.C.: U.S. Bureau of the Census).

Table D-3

Annual Age-Specific Population Estimates
for Non-White Males in Washington, D.C.

	YEAR						
AGE	1970	1971	1972	1973	1974	1975	1976
18	4646	4850	5007	5196	5314	5488	5651
19	4655	4749	4881	5033	5143	5310	5437
20	4543	4726	4783	4822	4928	5096	5106
21	4389	4623	4657	4661	4758	4919	4898
22	4832	4520	4530	4500	4589	4741	4689
23	4688	4466	4487	4472	4538	4662	4633
24	4267	4412	4443	4445	4487	4583	4577
25	4460	4445	4513	4553	4534	4567	4625
26	4180	4389	4468	4524	4481	4487	4568
27	4422	4334	4423	4496	4429	4407	4511
28	3888	4183	4273	4374	4328	4315	4432
29	3954	4031	4123	4253	4228	4223	4354
30	4020	3797	3895	4108	4143	4165	4342
31	3457	3649	3748	3987	4042	4072	4262
32	3171	3500	3601	3867	3941	3979	4182
33	3044	3399	3485	3701	3771	3821	3984
34	3273	3298	3370	3536	3602	3664	3787
35	3217	3168	3216	3260	3318	3418	3442
36	2985	3068	3102	3100	3154	3264	3253
37	3100	2968	2988	2941	2990	3110	3063
38	2660	2955	2961	2913	2943	3040	2989
39	3157	2943	2933	2886	2896	2969	2914
40	3302	2980	2922	2931	2906	2909	2864
41	2876	2967	2894	2903	2858	2838	2789
42	2977	2954	2867	2875	2810	2767	2714
43	2895	2944	2894	2855	2779	2751	2695
44	2975	2934	2922	2835	2747	2735	2676
45	2888	2957	3022	2827	2712	2767	2684
46	2844	2947	3051	2807	2680	2751	2665
47	3096	2936	3079	2787	2648	2735	2646
48	2796	2876	3042	2755	2636	2694	2638
49	2749	2816	3006	2723	2624	2654	2629
50	3063	2753	3008	2737	2694	2630	2705
51	2504	2693	2971	2704	2681	2690	2696
52	2347	2632	2934	2671	2669	2549	2688
53	2189	2530	2774	2553	2542	2460	2562
54	2164	2428	2614	2435	2414	2371	2436
55	2407	2296	2335	2240	2183	2246	2196
56	2124	2195	2183	2126	2061	2158	2076
57	2091	2094	2031	2012	1940	2070	1956
58	1999	2005	1960	1945	1885	1999	1907
59	2090	1915	1890	1878	1830	1927	1859
60	1929	1873	1929	1904	1892	1929	1944
61	1612	1781	1855	1833	1833	1855	1891
62	1644	1690	1780	1763	1775	1780	1839

APPENDIX E

Assessing Stability of Recruitment to Adult Criminal Careers

To test for the presence of a trend (either toward increased, or decreased recruitment of adult offenders) in the Washington, D.C. data, the numbers of arrestees per capita, $N_t(a)$, at ages a = 18, 19 and 20 were examined in each year t = 1970 to 1976. If all adult offenders begin their careers at age 18, then as one looks beyond age 18, the number of arrestees per capita includes the combined effects of changes with time in both recruitment and dropout. Since the relative influence of dropout increases with age, we do not compare "recruitment" rates beyond age 20. Figure E-1 shows arrestees per capita in adjacent years for ages 18, 19 and 20. In each case, the observed values are distributed evenly around the line representing a constant rate of arrestees per population from year to year.

The ratio $N_{t+1}(a)/N_t(a) = k_t(a)$ was also computed as a measure of the rate of growth (or decline for $k_t(a) < 1$) in recruitment between t and t+1. A value of unity for this ratio indicates stable recruitment rates from year to year. As is evident in Table E-1, the ratio for ages 18, 19 and 20 assumes values slightly below and above unity over the period 1970 to 1976. The mean value of the recruitment ratio for each age is never significantly different from unity at .990 for 18-year-olds, .993 at age 19 and 1.000 at age 20. Also, regressions of $k_t(a)$ against time for each age found no statistically significant time trend coefficients. Thus, the recruitment rate appears to be reasonably stable over the seven years 1970 to 1976.

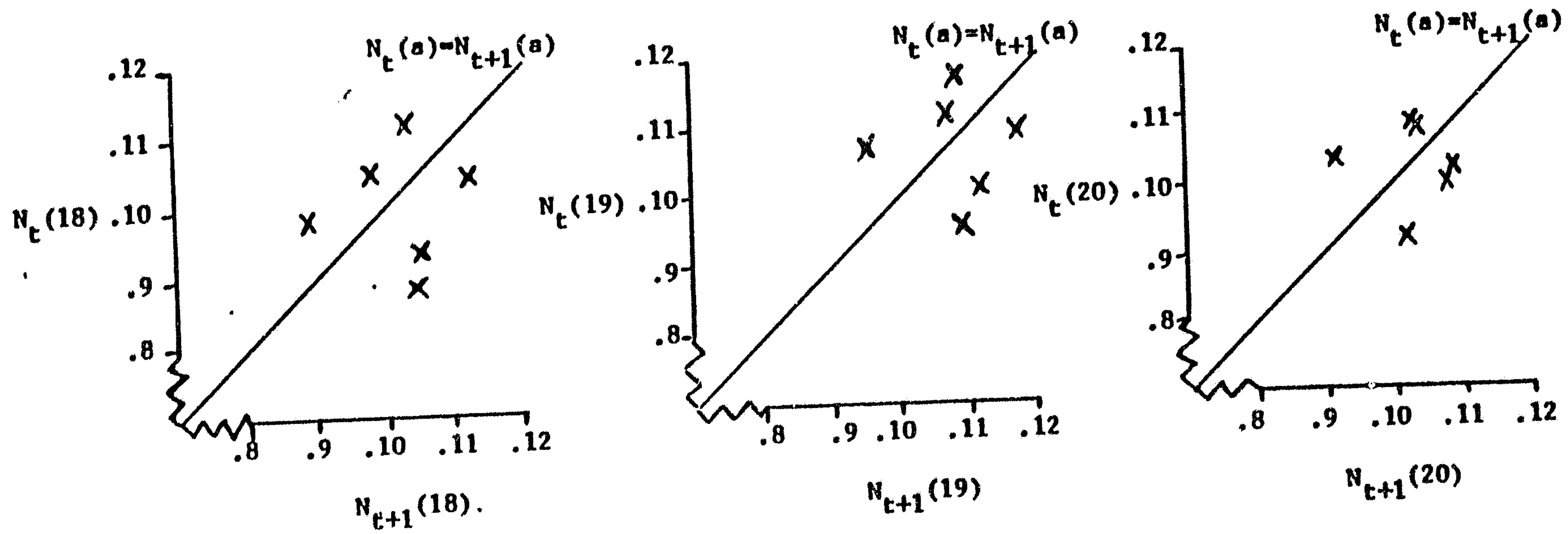


Figure E-1

Arrestees Per Capita, $N_t(a)$, in
Adjacent Years for Ages 18, 19, and 20

Table E-1

Recruitment Ratio, $k_t(a)$,
For Ages 18, 19 and 20

t	$k_t(a) = N_{t+1}(a)/N_t(a)$		
	a=18	a=19	a=20
1970	1.088	1.085	1.058
1971	.931	.932	.941
1972	.855	.873	.898
1973	1.103	1.117	1.135
1974	1.067	1.047	1.039
1975	.894	.902	.927
Mean k(a)	.990	.993	1.000
(Standard Deviation)	(.099)	(.094)	(.084)
Regression Against Time $k_t(a) = b_o + b_1 t$	$\hat{b}_o$ = 1.021, $\hat{b}_1$ = -.00898 (t=-.312)	$\hat{b}_o$ = 1.025, $\hat{b}_1$ = -.00926 (t=-.342)	$\hat{b}_o$ = 1.012, $\hat{b}_1$ = -.00356 (t=-.145)

APPENDIX F

Deriving the Age Distribution g(x) Associated with a Three-Piece Dropout Rate Function

The proposed dropout rate function is:[53]

$$r(x) = \begin{cases} b_1 e^{a_1 x}, & 0 \le x \le x_1 \\ b_2, & x_1 \le x \le x_2 \\ b_3 e^{a_3 x}, & x_2 \le x \le \text{MAX} \end{cases}$$

where MAX is the maximum age observed among index arrestees, which in our case is set to 62. From eq. (A4),

$$r(x) = \frac{-g'(x)}{g(x)} = \frac{-dy/dx}{y} \quad \text{for} \quad y = g(x)$$

So

$$r(x) = \frac{-dy}{ydx} = \begin{cases} b_1 e^{a_1 x}, & 0 \le x \le x_1 \\ b_2, & x_1 \le x \le x_2 \\ b_3 e^{a_3 x}, & x_2 \le x \le \text{MAX} \end{cases}$$

and

$$\frac{dy}{y} = \begin{cases} -b_1 e^{a_1 x} dx, & 0 \le x \le x_1 \\ -b_2 dx, & x_1 \le x \le x_2 \\ -b_3 e^{a_3 x} dx, & x_2 \le x \le \text{MAX} \end{cases}$$

[53]The authors wish to acknowledge the helpful assistance of Daniel M. Rosenblum in deriving this result.

Integrating both sides[54]

$$\int_0^x \frac{dy}{y} = \ln y = C + \begin{cases} -\int_0^x b_1 e^{a_1 x}\,dx \\ -\int_0^{x_1} b_1 e^{a_1 x}\,dx - \int_{x_1}^{x} b_2\,dx \\ -\int_0^{x_1} b_1 e^{a_1 x}\,dx - \int_{x_1}^{x_2} b_2\,dx - \int_{x_2}^{x} b_3 e^{a_3 x}\,dx \end{cases}$$

or,

$$\ln y = C + \begin{cases} -b_1/a_1 e^{a_1 x} + b_1/a_1 \\ -(b_1/a_1 e^{a_1 x_1} - b_1/a_1) - b_2 x + b_2 x_1 \\ -(b_1/a_1 e^{a_1 x_1} - b_1/a_1) - b_2(x_2 - x_1) - b_3/a_3 e^{a_3 x} + b_3/a_3 e^{a_3 x_2} \end{cases}$$

Exponentiating both sides

$$e^{\ln y} = y = g(x) = \exp\left[C + \begin{cases} -b_1/a_1(e^{a_1 x} - 1) \\ -b_1/a_1(e^{a_1 x_1} - 1) - b_2(x - x_1) \\ -b_1/a_1(e^{a_1 x_1} - 1) - b_2(x_2 - x_1) \\ \qquad -b_3/a_3(e^{a_3 x} - e^{a_3 x_2}) \end{cases} \right]$$

[54]The integral for each succeeding piece includes the values of the full integral of previous pieces to assure continuity of g(x) at the break points x_1 and x_2 (e.g., $\int_0^{x_1} b_1 e^{a_1 x}dx$ is included in the integral of the second piece). The constant of integration, C, assures that g(x) is a proper probability density function with $\int_0^{MAX} g(x)dx = 1$.

Letting $K = \exp[C - b_1/a_1(e^{a_1 x_1} - 1) + b_2 x_1]$

$$g(x) = K \cdot \begin{cases} \exp(-b_1/a_1 e^{a_1 x} + b_1/a_1 e^{a_1 x_1} - b_2 x_1) \\ \exp(-b_2 x) \\ \exp(-b_3/a_e e^{a_3 x} + b_3/a_3 e^{a_3 x_2} - b_2 x_2) \end{cases}$$

in the appropriate ranges of x. Integrating over g(x) to evaluate K,

$$\int_0^{MAX} g(x)dx = 1 = K \cdot \Big[\int_0^{x_1} \exp(-b_1/a_1 e^{a_1 x} + b_1/a_1 e^{a_1 x_1} - b_2 x_1)dx$$
$$+ \int_{x_1}^{x_2} \exp(-b_2 x)dx$$
$$+ \int_{x_2}^{MAX} \exp(-b_3/a_3 e^{a_3 x} + b_3/a_3 e^{a_3 x_2} - b_2 x_2)dx\Big]$$

APPENDIX G

Assessing the Impact of Age Variations in the Probability of Arrest for an Offender

G1. Age Variations in the Arrest Probability for Offenders

Among the factors that may influence the arrest probability of offenders at different ages are variations in time served with age and a cohort effect with more recent cohorts of offenders (the younger offenders in year t) having higher arrest probabilities.

Figure G–1 displays the general pattern of time served observed for the 1973 Washington, D.C. arrestees. Time served decreases from age 18 and then increases again reaching another peak around age 30. The impact of this time served pattern on the arrest probability is depicted in Figure G–2. As time served decreases, the probability of at least one arrest in a year for an offender increases; and conversely, as time served increases, the arrest probability decreases.

The analysis of variations in individual arrest rates for Washington, D.C. arrestees in Blumstein and Cohen (1979) suggests that arrest rates are stable over age within a cohort of offenders, but have increased for more recent cohorts. Such variations in the arrest rate would introduce age dependencies into the arrest probability for offenders of different ages in any year t. In particular, younger offenders in year t (who represent more recent cohorts) would be expected to have higher arrest probabilities in that year. Figure G–3 depicts such a cohort effect on arrest probabilities. The impact of the cohort effect is greater for more recent cohorts (younger ages in year t) to reflect a more pronounced cohort effect for the post-World War II baby boom cohorts who reached adulthood in the late 1960's and were in their twenties in 1973.

Figure G–4 combines the impact of age variations in time served and cohort differences on the arrest probability for an offender. The increasing probability associated with times served from ages 18 to about 23 decreases the arrest probability somewhat in these ages, while the sharp decrease in the arrest probability as a result of time served from ages 23 to 30 accentuates the decline in the arrest probability for these ages.

G2. Impact of Age Variations on Career-length Estimates

Age variations in the probability of arrest in a year for an offender will distort the

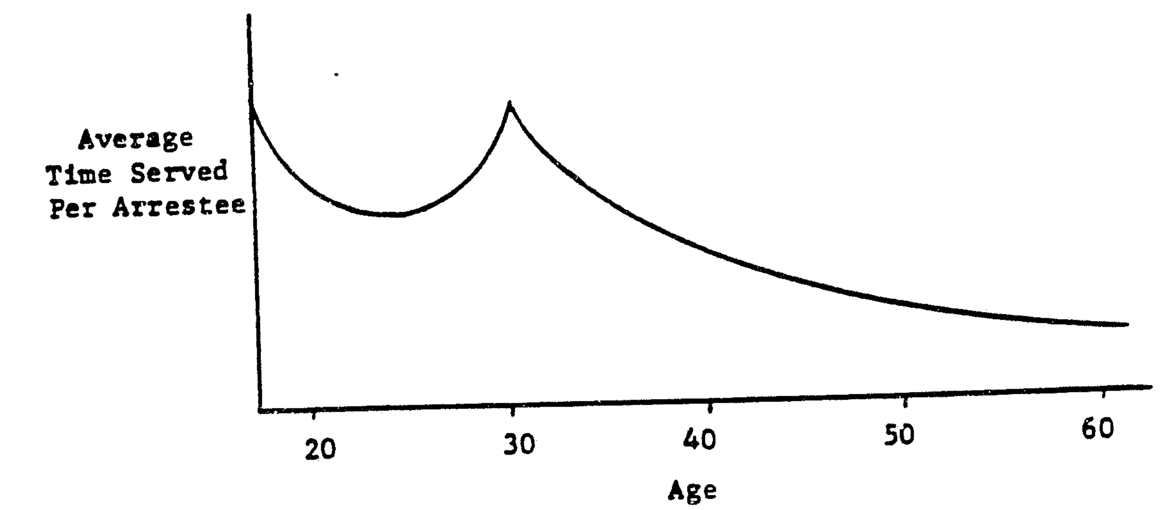


Figure G-1

Age Variations in Time Served
for 1973 Washington, D.C. Arrestees

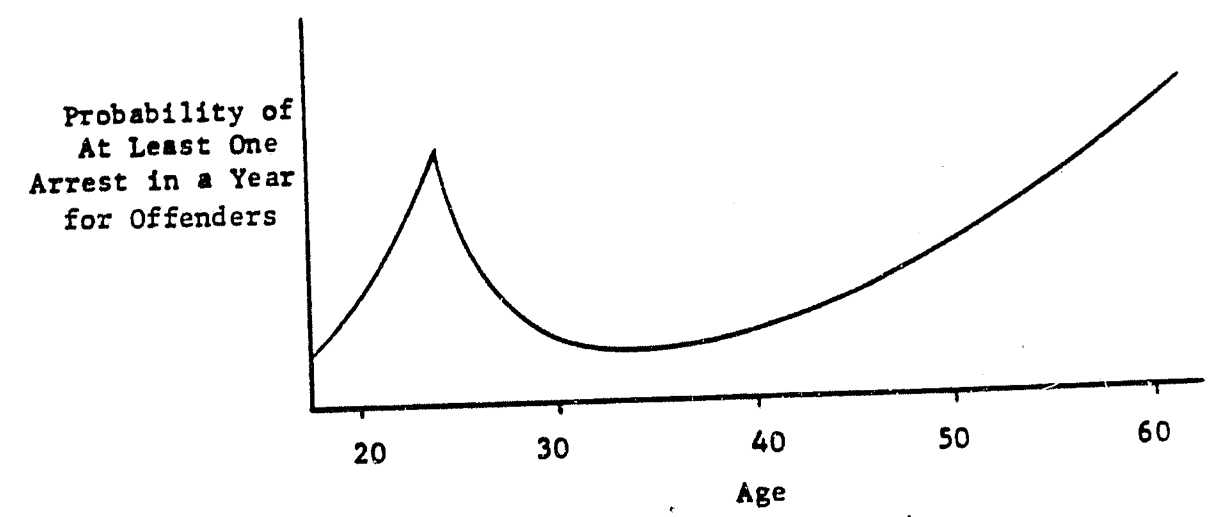


Figure G-2

Age Variations in the Arrest Probability
for Offenders Associated With Time Served Variations

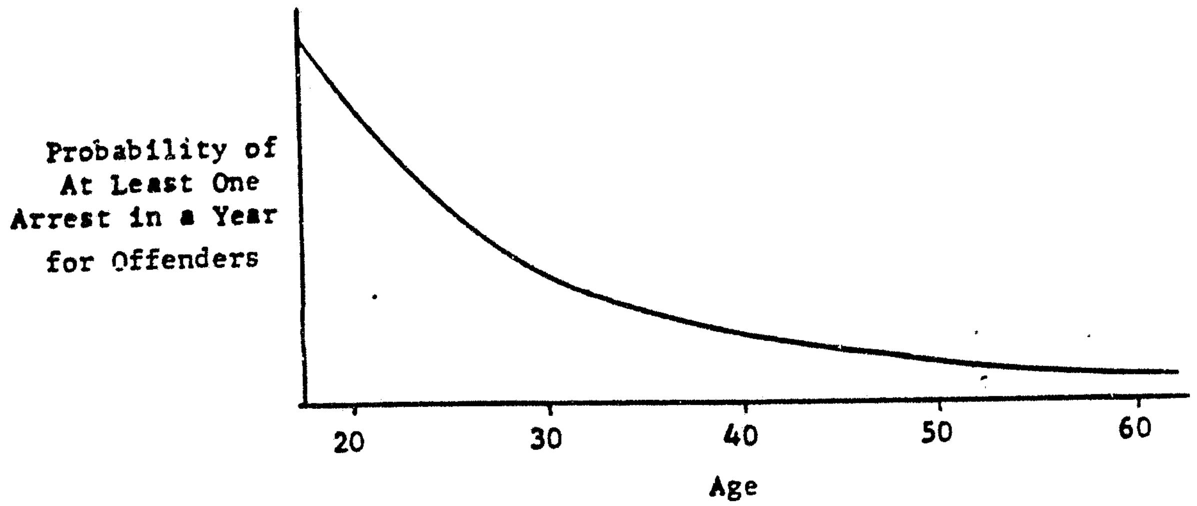


Figure G-3

Age Variations in the Arrest Probability for Offenders Associated With a Cohort Effect on Individual Arrest Rates

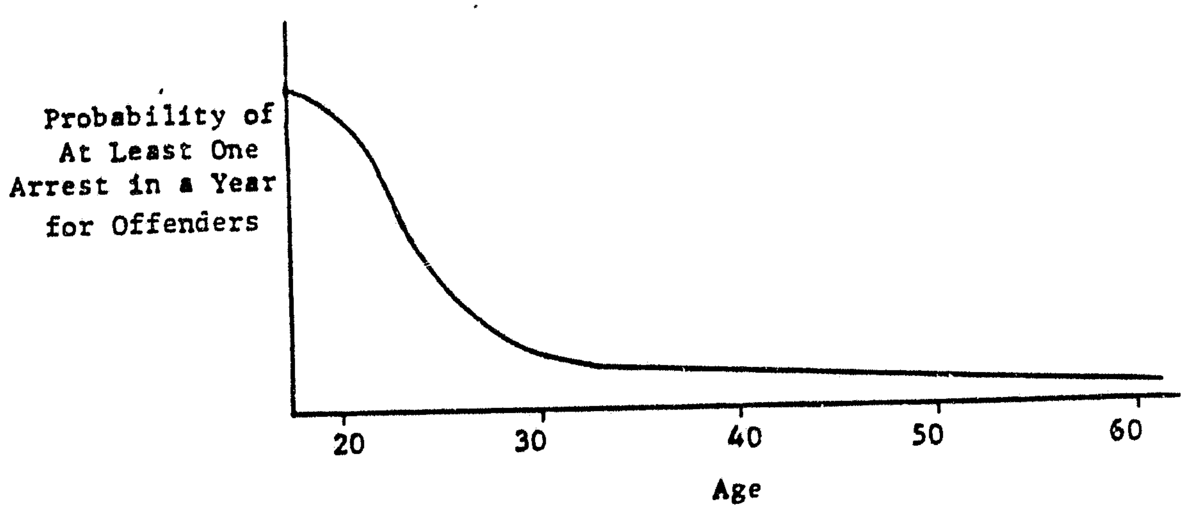


Figure G-4

The Combined Effects of Time Served and Cohort Differences on Age Variations in the Arrest Probability for Offenders

representation of some age groups among arrestees as those offenders with higher arrest probabilities are more likely to be sampled through an arrest. If the arrest probability decreases for older ages, more recent cohorts (younger offenders in year t) are more likely to be arrested and older offenders (earlier cohorts) will be under-represented among arrestees.

Let $k > 1$ be a constant rate of growth in the number of arrestees in each successive cohort as a result of the age variation in the arrest probability. The dropout rate estimated from the observed age distribution of arrestees in year t, $n_t(a)$, can be approximated by

$$\hat{r}(a) = \frac{n_t(a) - n_t(a+1)}{n_t(a)} \tag{G1}$$

With decreasing arrest probabilities with age, the arrestees age (a+1) in year t must be increased to reflect the growth in numbers of arrestees already present in the more recent cohort $n_t(a)$. The true dropout rate would then be approximated by

$$\tilde{r}(a) = \frac{n_t(a) - kn_t(a+1)}{n_t(a)} \tag{G2}$$

The ratio of the biased estimate of the dropout rate, r(a), to the unbiased estimate, r(a) is given by

$$R = \frac{\hat{r}(a)}{\tilde{r}(a)} = \frac{n_t(a) - n_t(a+1)}{n_t(a)} \cdot \frac{n_t(a)}{n_t(a)-kn_t(a+1)} = \frac{n_t(a)-n_t(a+1)}{n_t(a)-kn_t(a+1)} > 1 \text{ for } k>1 \tag{G3}$$

and the estimate r(a) <u>overestimates</u> the dropout rate. Correspondingly, for another point a^*, where $a < a+1 < a^* < a^*+1$

$$R^* = \frac{n_t(a^*) - n_t(a^*+1)}{n_t(a^*) - kn_t(a^*+1)} > 1 \tag{G4}$$

For $k = 1+C$, the error ratio, R, can be transformed to

$$\frac{1}{R} = \frac{n_t(a)-n_t(a+1)-Cn_t(a+1)}{n_t(a)-n_t(a+1)} = 1 - \frac{Cn_t(a+1)}{n_t(a) - n_t(a+1)} = 1 - \frac{C}{\left[\frac{n_t(a)}{n_t(a+1)} - 1\right]} \qquad \text{(G5)}$$

Likewise,

$$\frac{1}{R^*} = 1 - \frac{C}{\left[\frac{n_t(a^*)}{n_t(a^*+1)} - 1\right]} \qquad \text{(G6)}$$

Now, if $r(a) > r(a^*)$ (i.e., the dropout rate is <u>estimated</u> to be decreasing with age), then

$$\frac{n_t(a)-n_t(a+1)}{n_t(a)} > \frac{n_t(a^*)-n_t(a^*+1)}{n_t(a^*)}$$

$$1 - \frac{n_t(a+1)}{n_t(a)} > 1 - \frac{n_t(a^*+1)}{n_t(a^*)}$$

$$\frac{n_t(a+1)}{n_t(a)} < \frac{n_t(a^*+1)}{n_t(a^*)} \qquad \text{(G7)}$$

$$\frac{n_t(a)}{n_t(a+1)} > \frac{n_t(a^*)}{n_t(a^*+1)}$$

and substituting (G7) into (G5) and (G6), $\frac{1}{R} > \frac{1}{R^*}$ and $R < R^*$. So, when the dropout rate is <u>estimated</u> to be decreasing (as in period I in Figure 11), the overestimate of the dropout rate reflected by R is less at younger ages as depicted in Figure G-5. Correspondingly, the mean residual career length is increasingly underestimated as age increases.

Using the same logic, if the dropout rate is estimated to be increasing with age ($\hat{r}(a) < \hat{r}(a^*)$) as observed in period III in Figure 11, $R > R^*$. In this case, the overestimates of dropout rates are worse at younger ages, while mean residual career length is increasingly underestimated for younger offenders. These biases are illustrated in Figure G–6.

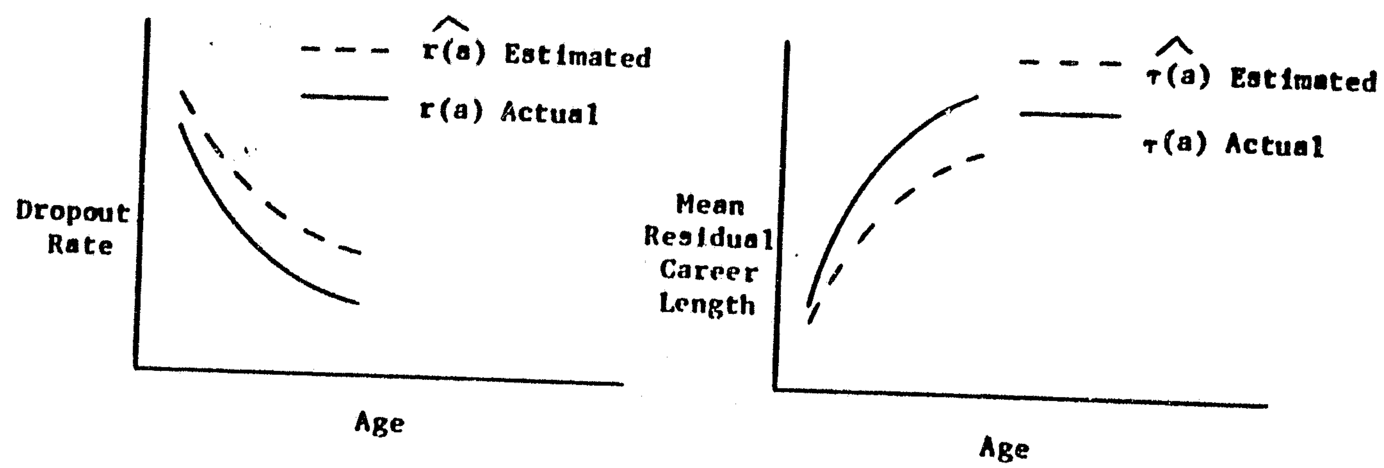


Figure G-5

Nature of Bias in Career Length Estimates
When the Arrest Probability of Offenders is
Decreasing With Age for Decreasing Dropout Rates

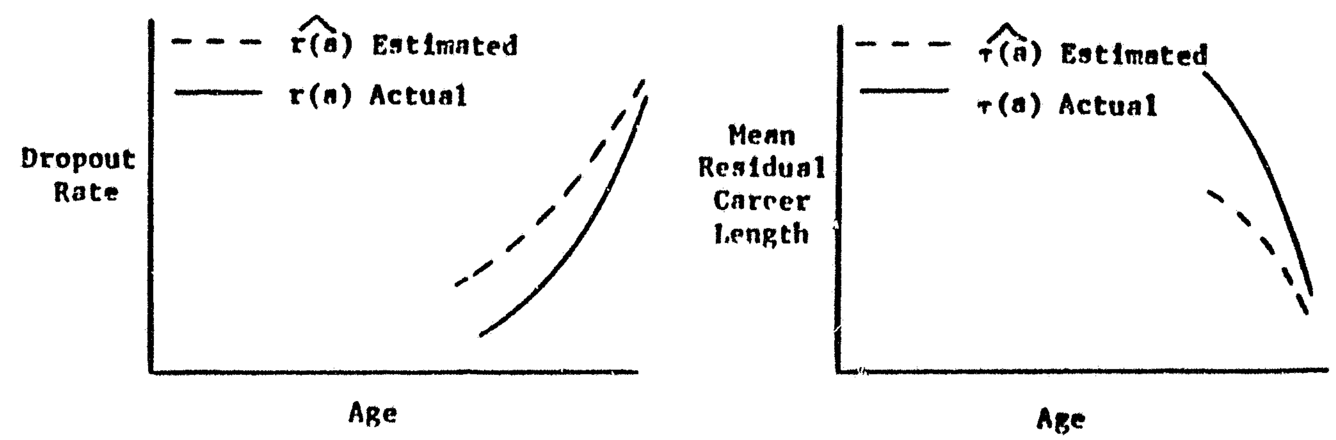


Figure G-6

Nature of Bias in Career Length Estimates
When the Arrest Probability of Offenders is
Decreasing With Age for Increasing Dropout Rates

Figure G–7 combines the results in Figures G–5 and G–6. When the age variation in the arrest probabilities for offenders is associated with a constant growth rate, k, in size for more recent cohorts, the dropout rate will always be overestimated with the worst overestimates in the middle age range. In this case, the true dropout rate (and mean residual career length) has even sharper periods of decline and increase than estimated.

We now explore the nature of the bias when the growth rate is not constant, but rather is increasing for more recent cohorts, i.e., $k(a) > k(a^*)$ for $a < a^*$. The dropout rate at any age a is estimated as in eq. (G1). Because of the growth in the numbers of arrestees in more recent cohorts, however, the true dropout rate is better approximated as

$$\tilde{r}(a) = \frac{n_t(a) - k(a+1)n_t(a+1)}{n_t(a)} \tag{G8}$$

For $k(a+1) = 1 + C(a+1)$, the error ratio of $R(a)$ is given by

$$R(a) = \frac{n_t(a) - n_t(a+1)}{n_t(a) - n_t(a+1) - C(a+1)n_t(a+1)} \tag{G9}$$

and

$$\frac{1}{R(a)} = 1 - \frac{C(a+1)}{\left[\frac{n_t(a)}{n_t(a+1)} - 1\right]} \tag{G10}$$

For $a^* > a$, $r(a^*)$, $R(a^*)$ and $1/R(a^*)$ are defined similarly with a^* replacing a in eqs. (G8) to (G10).

Suppose $C(a+1) > C(a^*+1)$, or there is a larger growth rate in arrestees for more recent cohorts (i.e., for younger offenders in year t). This would be a manifestation of the more rapid decline in the arrest probability between ages 23 and 30 illustrated in Figure G–4. Now, for $\hat{r}(a) > \hat{r}(a^*)$ (i.e., the dropout rate is <u>estimated</u> to be decreasing with age), $R(a) < R(a^*)$ when

$$\frac{C(a+1)}{C(a^*+1)} < \frac{\left[\frac{n_t(a)}{n_t(a+1)} - 1\right]}{\left[\frac{n_t(a^*)}{n_t(a^*+1)} - 1\right]}$$

As long as the growth rate in the numbers of arrestees for more recent cohorts (i.e., younger ages in year t) reflected in $C(a+1)$ is not increasing faster than the estimated dropout rate is increasing for more recent cohorts, the estimated decreasing dropout rate will increasingly overestimate the dropout rate at <u>older</u> ages.

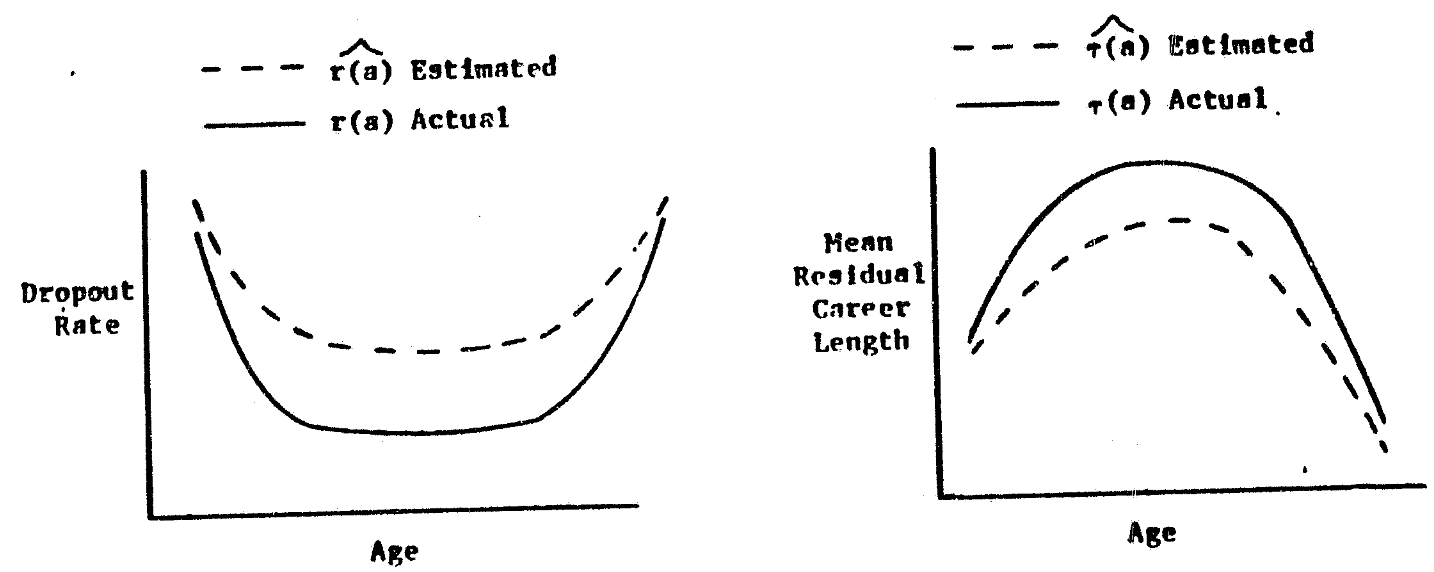


Figure G-7

Nature of Bias in Career Length Estimates
When the Arrest Probability of Offenders
is Decreasing With Age

For $\hat{r}(a) < \hat{r}(a^*)$ (i.e., the dropout rate is estimated to be increasing with age),

$$\frac{n_t(a)}{n_t(a+1)} < \frac{n_t(a^*)}{n_t(a^*+1)} \text{ and } R(a) > R(a^*) \text{ for all values of } a < a^*.$$

In this case, the results in Figure G-6 always hold and the estimated increasing dropout rate will increasingly overestimate the dropout rate at younger ages.

Based on this analysis for a declining arrest probability with age (as in Figure G-4), the true dropout rate and mean residual career length have sharper periods of decline and increase than are estimated as long as more recent cohorts of arrestees do not increase in size faster than the estimated dropout rate is increasing for those same cohorts.

APPENDIX H

Late-Starter Corrections by Crime Type

The 1973 data for Washington, D.C. arrestees provide the basis for estimating the proportion of arrestees each age for each crime type who had a first adult arrest for index crime type before age b. This was done separately for each of the index crime types (excluding larceny) for b = 20, 23, 25.[55] To eliminate much of the noise in the observed proportion starting with an index arrest before age b for each crime type, weighted least squares (weighted by the number of arrestees at each age for a crime type) was used to fit:

$$P_b(x) = \beta e^{\alpha x}, \text{ where } x = a - b.$$

Figures H-1 through H-6 present the fit between the predicted and observed $P_b(x)$ for each index crime type.

There are some differences in $P_b(x)$ between violent and property crimes. For the property crimes of burglary, auto theft and robbery, $P_b(x)$ starts out high and then falls off sharply with age indicating a strong age effect on $P_b(x)$. There is a greater likelihood that younger offenders in these crime types began their adult careers with an index arrest at young ages, while older offenders in these crime types are much less likely to have had an index arrest at young ages. In contrast $P_b(x)$ varies less with age for the violent crimes of rape and aggravated assault. In comparing young and old offenders for these violent offenses, the younger offenders are only slightly more likely to have begun their adult careers with an index arrest at young ages than are older offenders.

[55] The arrest history data is not available for all arrestees for larceny in 1973. Only those larceny arrestees who are also arrested for some other index offense in 1973 are included in the data. Since these offenders may not be representative of larceny offenders in general, larceny is not included in the crime-specific analysis.

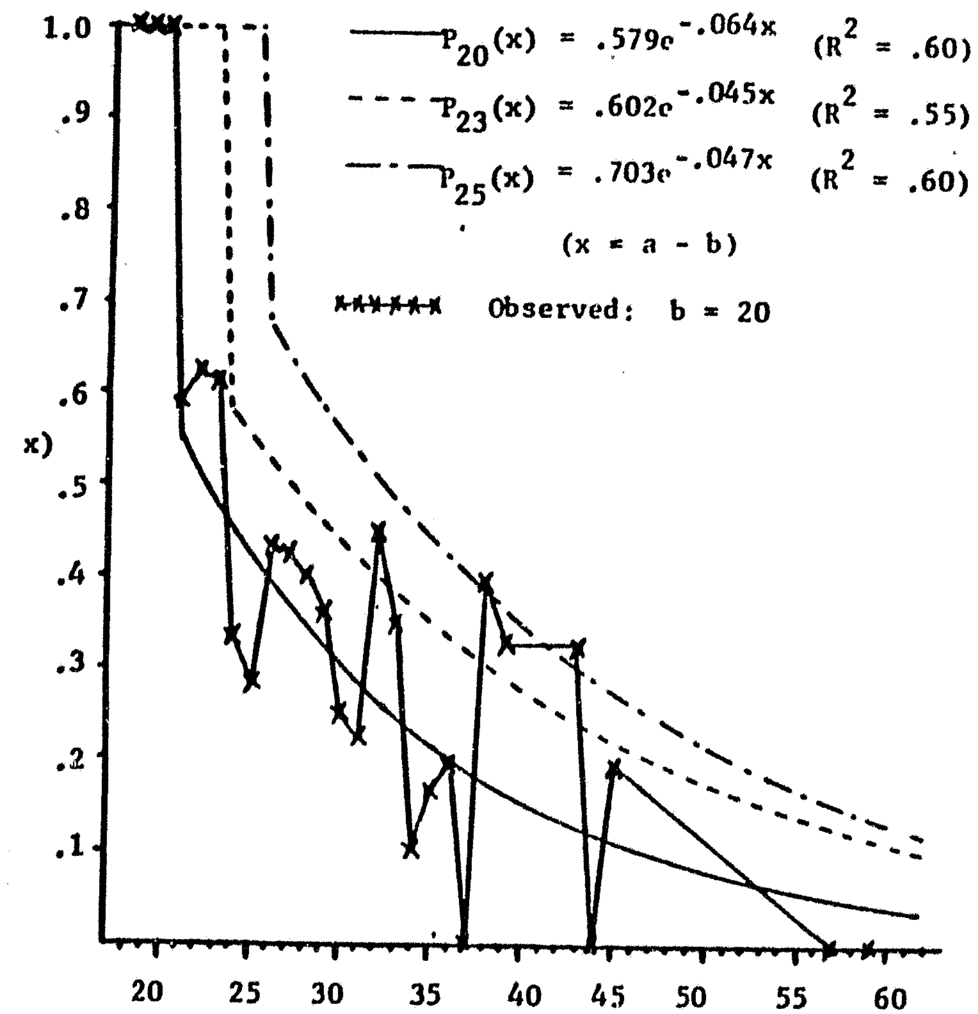


Figure H-1

Proportion of Murder Arrestees in 1973 With a First Index Arrest Before Age b - $P_b(x)$

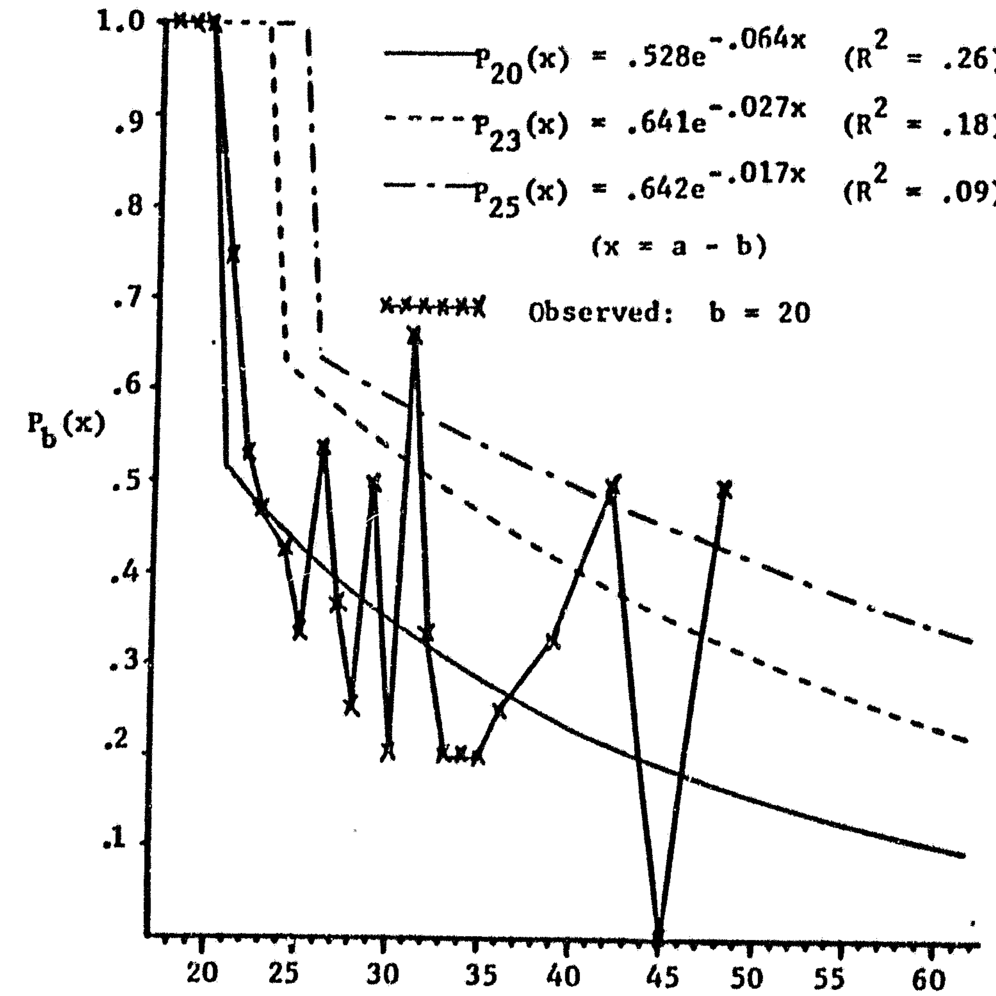


Figure H-2

Proportion of Rape Arrestees in 1973 With a First Index Arrest Before Age b - $P_b(x)$

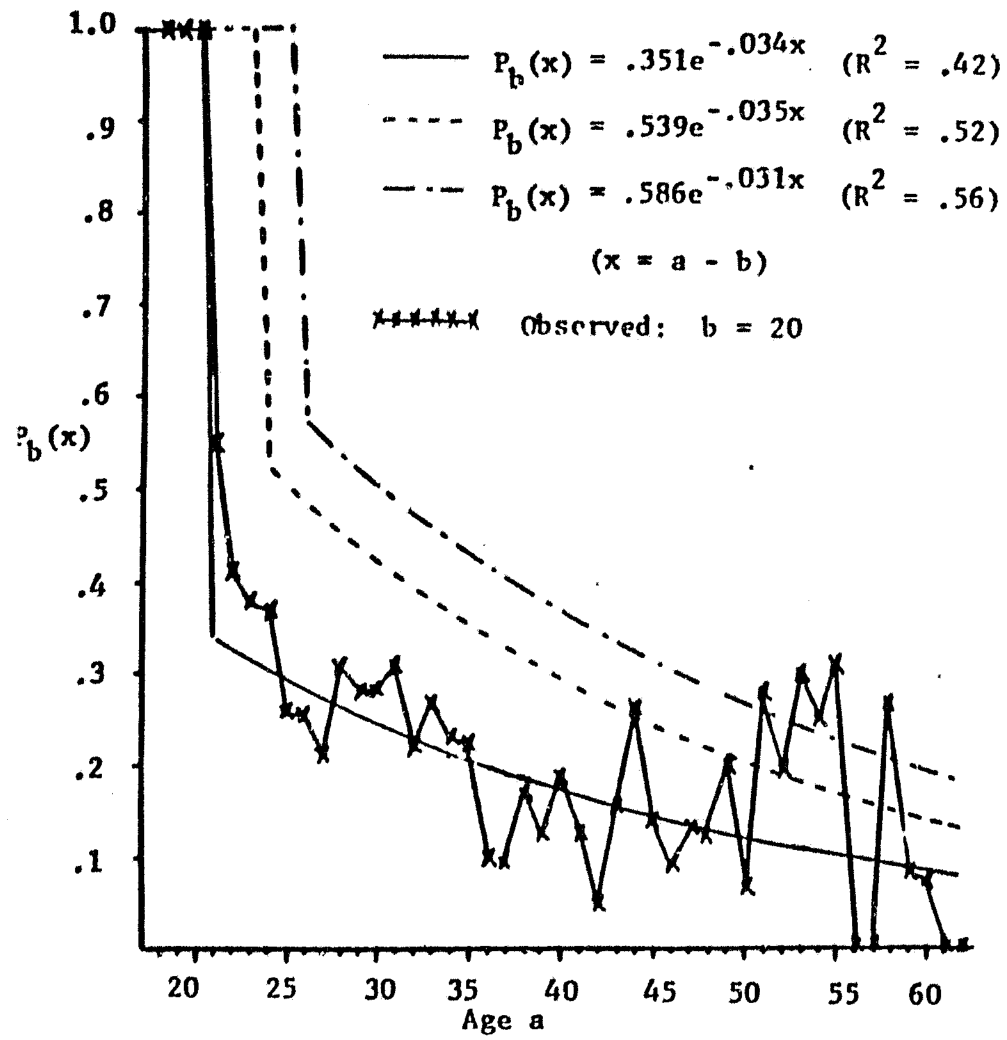


Figure H-3

Proportion of Aggravated Assault Arrestees in 1973
With a First Index Arrest Before Age b - $P_b(x)$

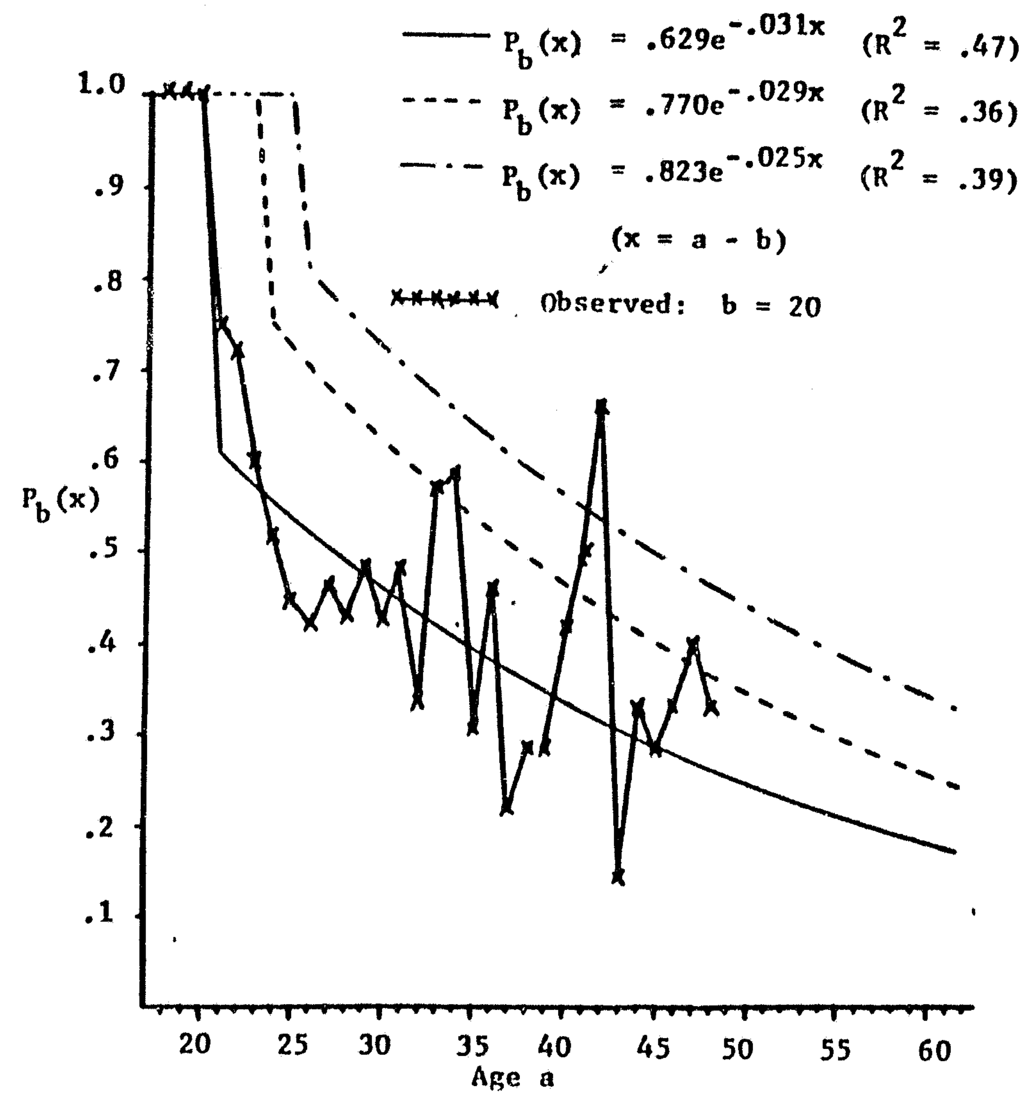


Figure H-4

Proportion of Robbery Arrestees in 1973
With a First Index Arrest Before Age b - $P_b(x)$

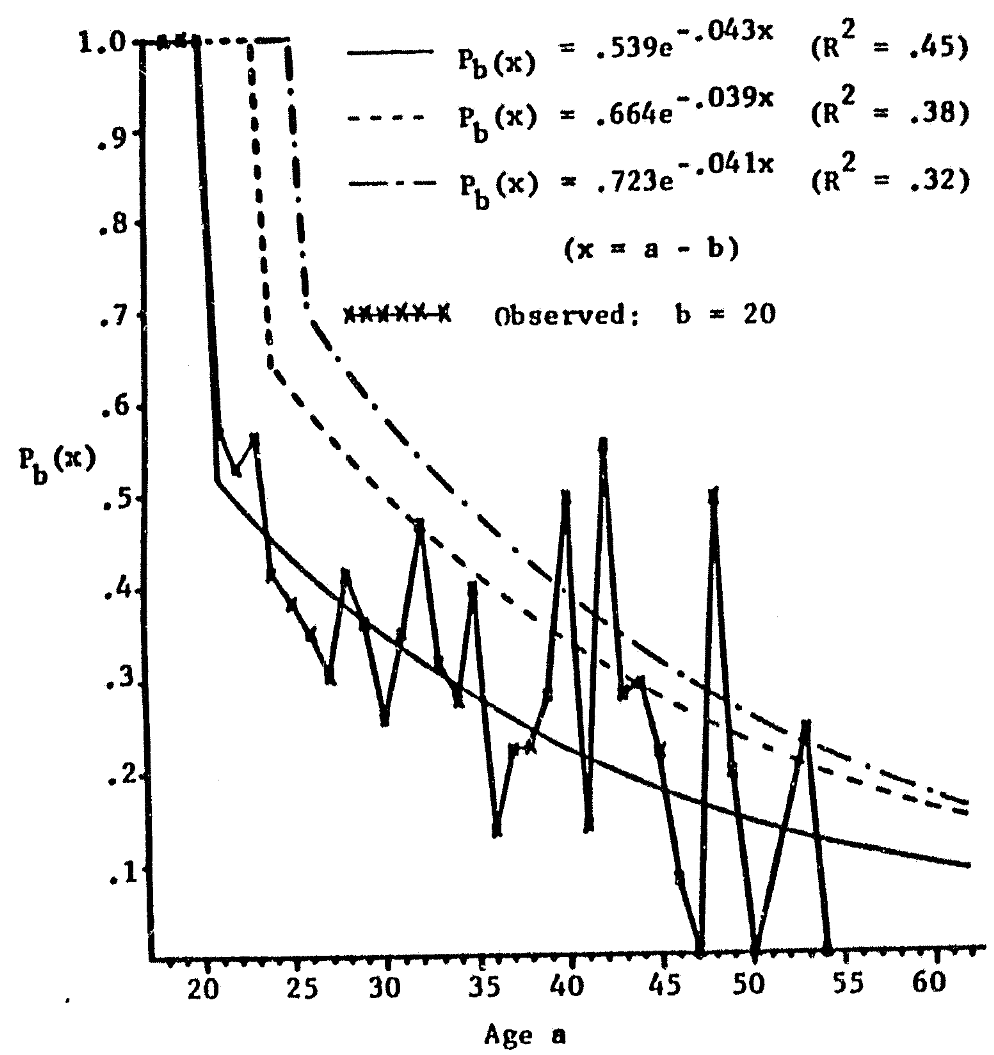


Figure II-5

Proportion of Burglary Arrestees in 1973
With a First Index Arrest Before Age b - $P_b(x)$

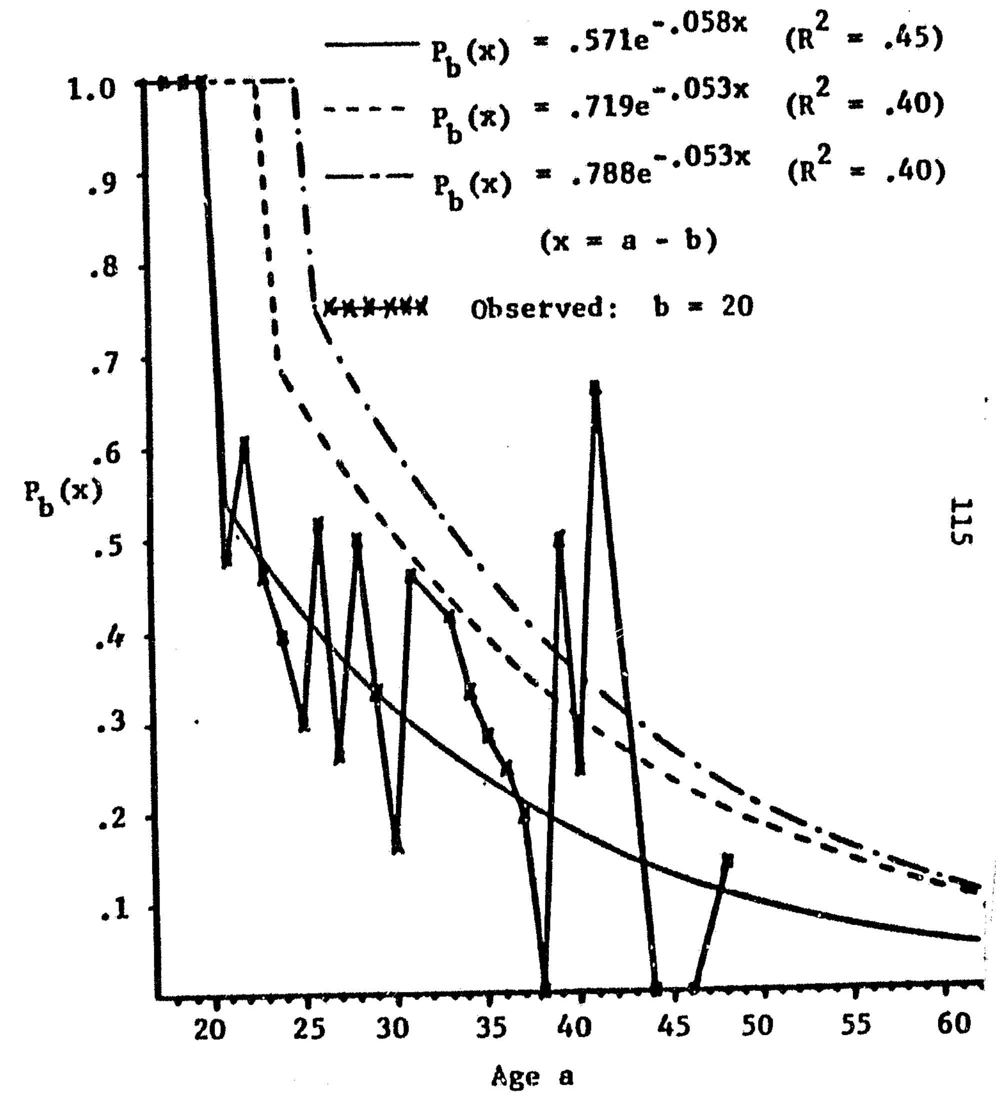


Figure II-6

Proportion of Auto Theft Arrestees in 1973
With a First Index Arrest Before Age b - $P_b(x)$

APPENDIX I

Estimating Dropout Rates After First Arrest

The basic life-table approach described in Appendix A can also be applied to the distribution of arrestees over the number of prior arrests in a record. Using the fall-off in the number of arrestees as the number of prior arrests increases in a cross-section of arrestees, the dropout rate after each arrest and the expected residual number of arrests can be estimated.

Table I-1 presents the distribution of arrestees for zero and one prior adult arrest in Washington, D.C., and Franklin County, Ohio, for 1973. Taking the number of arrestees with zero priors as an estimate of the total number of offenders starting in a cohort, those with exactly one prior arrest gives the proportion of arrestees who remain active after their first arrest. Using this relationship, the dropout rate after the first adult index arrest is estimated at 52.3% for index careers in Washington, D.C. The corresponding dropout rate after the first adult felony arrest is 57.3% for felony careers in Franklin County, Ohio. Using the relationship in equation (A9), the expected future number of arrests after the first arrest in the adult career is estimated as 1.50 additional index arrests in Washington, D.C., and 1.61 additional felony arrests in Franklin County.

Table I-1

Dropout Rate After
First Arrest and Expected
Future Arrests in Adult Careers

Number of Prior Arrests for Arrestees	Washington, D.C. 1973 (Prior Index Arrests As Adults)	Franklin County, Ohio 1973 (Prior Felony Arrests As Adults)[a]
1. 0	2,035 (40.0%)	131 (38.3%)
2. 1	970 (19.1%)	56 (16.4%)
3. Total Arrestees	5,088 (100.0%)	342 (100.0%)
Dropout Rate After First Arrest (1-2/1)	52.3%	57.3%
Expected Future Arrests After First Arrest in Adult Careers (1-1/3)/(1/3)	1.50	1.61

[a] Van Dine, et al (1979, Table 3-10)

APPENDIX J

Assessing Stability in Residual Career Length and in Arrestees per Capita

To test for the presence of time trends in residual career length, the mean residual career length was estimated separately for each year from 1970 through 1976. The resulting $\tau_t(a)$ at each age a were then regressed against time. The regression results are reported in Table J-1. To assure that the data smoothing process does not suppress any time trends, the regression analysis is performed on estimates of arrests per capita, $n_t(a)$, and mean residual career length, $\tau_t(a)$, derived from <u>unsmoothed</u> data. The results are discussed in Section 3.0 of the main text.

Table J-1

Stability Over Time for $\tau_t(a)$ and $n_t(a)$: Results of Regressions Against Time

Age	Mean Residual Career Length (b=20) $\tau_t(a) = c_o + c_1 t$ (n = 7)			Arrestees per Capita $n_t(a) = d_o + d_1 t$ (n = 7)		
	c_o	c_1	(t-value)	d_o	d_1	(t-value)
18	5.187	.237	(2.555)	.1076	-.0017	(-1.246)
19	3.978	.196	(2.493)	.1123	-.0013	(- .962)
20	3.349	.157	(1.948)	.1031	-.0002	(- .187)
21	8.919	.212	(1.978)	.0736	.0015	(1.564)
22	7.966	.025	(.181)	.0768	.0032	(2.263)
23	10.066	-.346	(- 1.706)	.0563	.0057	(2.206)
24	9.715	-.347	(- 1.836)	.0539	.0057	(2.328)
25	9.879	-.410	(-11.511)*	.0493	.0054	(7.414)*
26	10.675	-.454	(- 6.632)*	.0436	.0045	(5.352)*
27	14.590	-.737	(-11.175)*	.0311	.0035	(6.027)*
28	11.984	-.519	(- 4.793)*	.0367	.0033	(5.428)*
29	15.069	-.704	(- 5.378)*	.0284	.0026	(5.976)*
30	9.808	-.195	(- 1.380)	.0434	.0013	(2.114)
31	11.409	-.111	(- .805)	.0358	.0006	(.905)
32	11.414	.070	(.441)	.0343		(- .001)
33	10.443	.055	(.332)	.0355	.0001	(.094)
34	10.662	-.128	(- .844)	.0332	.0006	(.922)
35	11.142	-.087	(- .725)	.0305	.0004	(.398)
36	8.872	-.059	(- .590)	.0358	.0004	(.342)
37	9.735	-.226	(- 2.027)	.0307	.0009	(.926)
38	9.869	-.077	(- .510)	.0289	.0002	(.233)
39	12.825	-.441	(- 2.669)	.0214	.0008	(1.036)
40	8.887	.096	(.649)	.0288	-.0004	(- .561)
41	11.458	.418	(1.989)	.0210	-.0006	(-1.234)
42	9.950	.095	(.467)	.0233	-.0002	(- .484)
43	5.414	.140	(1.494)	.0373	-.0007	(-1.290)
44	7.291	.129	(.885)	.0255	-.0003	(- .649)
45	7.982	.310	(1.417)	.0212	-.0004	(- .561)
46	5.690	.318	(1.914)	.0261	-.0006	(- .768)
47	9.972	.479	(1.016)	.0145	-.0002	(- .366)
48	5.048	.333	(1.772)	.0241	-.0005	(- .646)
49	4.362	.405	(2.232)	.0235	-.0006	(- .910)
50	10.015	-.009	(- .035)	.0102	.0004	(1.082)
51	8.081	.113	(.664)	.0117	.0003	(.923)
52	5.472	-.003	(- .031)	.0154	.0006	(1.282)
53	3.742	.027	(.359)	.0186	.0005	(1.013)
54	6.331	.189	(1.217)	.0096	.0001	(.549)
55	4.865	-.056	(- 2.656)	.0108	.0006	(2.442)
56	2.323	-.029	(- .653)	.0165	.0009	(1.956)
57	6.610	-.006	(- .052)	.0053	.0002	(1.298)
58	1.747	-.049	(- .788)	.0130	.0009	(1.933)
59	2.329	-.049	(- 5.148)*	.0072	.0003	(1.327)
60	1.547	-.026	(- 3.332)	.0069	.0001	(.941)

*Significant at .01 level or better for two-tailed t-test.

APPENDIX K

Age-Specific Arrest Rates for Different Crime Types

Data on the number of arrests by age and sex were made available by the FBI for the fifty-five U.S. cities with populations over 250,000 reporting to the FBI for 1970. These arrest figures were combined with census data on population by age and sex in each city to yield arrest rates within each age category. Table K-1 reports the average population arrest rates for males by age in the fifty-five largest cities.

Table K-1

Average Age-Specific Arrest Rates for Males in Fifty-Five U.S. Cities in 1970

Age Category (years)	Arrests per 100,000 Male Population for: Property* Offenses	Violent** Offenses	Robbery
≤ 10	263.0	6.7	8.0
11-12	2,460.5	74.4	134.2
13-14	6,096.7	248.7	433.1
15	8,479.5	461.0	742.5
16	8,695.6	632.0	985.7
17	7,458.6	754.0	1,079.2
18	5,486.6	710.7	1,005.9
19	4,654.2	731.5	959.5
20	3,511.6	667.2	783.8
21	3,009.2	662.7	693.4
22	2,740.8	663.1	625.1
23	2,404.3	655.0	577.3
24	1,918.8	561.2	454.0
25-29	1,548.7	536.3	327.4
30-34	1,160.4	478.8	195.8
35-39	883.7	400.1	110.6
40-44	666.6	284.6	61.8
45-49	463.5	210.9	36.2
50-54	335.9	148.4	18.8
55-59	241.1	111.7	13.5
60-64	172.7	79.7	4.2
≥ 65	93.5	42.1	3.5

*Property crimes include the F.B.I. index offenses of burglary, larceny and auto theft.

**Violent crimes include the F.B.I. index offenses of murder, rape and aggravated assualt.

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