Order Number 9103031

Crime, criminal careers and social control: A methodological analysis of economic choice and social control theories of crime

Britt, Chester Lamont, III, Ph.D.

The University of Arizona, 1990

U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

CRIME, CRIMINAL CAREERS AND SOCIAL CONTROL: A METHODOLOGICAL ANALYSIS OF ECONOMIC CHOICE AND SOCIAL CONTROL THEORIES OF CRIME

by

Chester Lamont Britt, III

A Dissertation Submitted to the Faculty of the

DEPARTMENT OF SOCIOLOGY

In partial Fulfillment of the Requirements
For the Degree of

DOCTOR OF PHILOSOPHY

In the Graduate College

THE UNIVERSITY OF ARIZONA

1 9 9 0

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

As members of the Final Examination Committee, we certify that we have read the dissertation prepared by Chester Lamont Britt III

entitled CRIME, CRIMINAL CAREERS AND SOCIAL CONTROL: A METHODOLOGICAL ANALYSIS OF ECONOMIC CHOICE AND SOCIAL CONTROL THEORIES OF CRIME

and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

Travis Hirschi	10 July 1990
Travis Hirschi	Date
David A. Snow	10 July 1990
David Snow	Date
Richard Curtis	10 July 1990
Richard Curtis	Date
	Date
	Date

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copy of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

Travis Hirschi	10 July 1990
Dissertation Director Travis Hirschi	Date

STATEMENT BY AUTHOR

This dissertation has been submitted in partial fulfillment of requirements for an advanced degree at the University of Arizona and is deposited in the University Library to be made available to borrowers under rules of the Library.

Brief quotations from this dissertation are allowable without special permission, provided that accurate acknowledgment of source is made. Requests for permission for extended quotation from or reproduction of this manuscript in whole or in part may be granted by the copyright holder.

SIGNED: Chester L. Butt, III

ACKNOWLEDGMENTS

I would like to first thank my committee members for their time and effort. For Travis Hirschi, I would like to pass along a special thanks for truly acting as a mentor and teaching me the ropes of academia. For Richard Curtis and David Snow, thank you for sitting on my committee and for your insights during the defense.

I also owe thanks to Mike Gottfredson, Gary Jensen, and Jim Shockey for the guidance they have given me over the last four years.

For Roberto DeAnda, Carol Diem, Kelly Moore, and Ronelle Paulsen, thank you for making life in the Department enjoyable. Without daily contact with all of you, life would have been rather boring on the fourth floor of the Social Sciences Building.

I would also like to thank the National Institute of Justice for providing a Graduate Research Fellowship that made several aspects of writing this dissertation much easier.

And for my best friend, Teri, thank you for all of your support. You and Lucas have helped me to keep this work in perspective. Without the two of you, this work would mean very little.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

This study tests the validity of two theories of crime: economic choice (as manifest in the criminal career paradigm) and social control. The test of these two theories is primarily methodological, in that four types of crime data (official and longitudinal (*Uniform Crime Reports*), official and cross-sectional (Bail Decisionmaking Study), self-report and longitudinal (National Youth Survey), and self-report and cross-sectional (Seattle Youth Study)) and a variety of graphical and statistical techniques are used to compare findings on (1) the stability of the age distribution of crime, (2) the prevalence of offense specialization, and (3) the differences in the causes of participating in crime compared to the causes of frequency of criminal activity among those individuals committing crimes. The findings on the relation between age and crime show the general shape of the age-crime curve is stable across year of the data or curve, type of data, cohort, and age group. The tests for offense specialization reveal that offenders are versatile. An individual's current offense type is not predictable, with much accuracy, on the basis of prior offending. Again, the lack of offense specialization held across type of data, but age, race, and gender distinctions also failed to alter significantly the observed pattern of versatility. Findings on the causes of participation in crime and frequency of criminal activity among active offenders showed only trivial differences in the set of statistically significant predictors for each operationalization of crime and delinquency. Two distinct operationalizations of frequency also showed no substantial difference in the set of statistically significant predictors. Similar to the findings on age and crime, and offense specialization, the pattern of results for the participation and frequency analyses held across type of data. In sum, the

results tended to support the predictions of social control theory over those of the economic choice–criminal career view of crime.

CHAPTER 1

INTRODUCTION

INTRODUCTION

The rational criminal offender is alive and well in the United States. It makes little difference whether one looks at the urban drug dealer, the robber, the embezzler, or the loanshark, many criminal justice policies assume offenders rationally consider the costs and benefits associated with their criminal activity. For example, the recent Federal Sentencing Guidelines (U.S. Sentencing Commission, 1989) establish prison term lengths on the assumption that offenders rationally consider the consequences of their activity. Each additional arrest, the Sentencing Commission suggests, should result in an increasingly severe penalty for the convicted offender. The is that once an offender has been caught and punished, he or she should realize the chances of being caught and punished more severely in the future. As a result of the calculating potential offenders are supposed to do, many are expected to be deterred from committing additional crimes.

As another example, consider President George Bush's "War on Drugs." In a nationally televised speech, he outlined a multi-billion dollar program aimed at reducing the apparent drug problem in the United States. President Bush's plan emphasizes certain and more severe penalties for drug offenders. To accomplish this task, the President is supporting increased prison construction, and hiring more law enforcement personnel, prosecutors, and judges. In short, both the U.S.

Sentencing Commission and President Bush have conceptualized criminal offenders as rational actors who are capable of discerning the potential costs and benefits of their criminal activity, and who can potentially be deterred from committing crimes, once they consider the consequences of their behavior.

The microeconomic theories of crime that motivated much of the deterrence research published in the 1960's and 1970's has more recently produced what Blumstein et al. (1986) call the "Criminal Career Paradigm." Although crime and criminal justice policies have obviously changed in the United States in the last twenty to thirty years, there has remained implicit support for the rational offender notion. Whether solely in terms of deterrence variables (i.e., the certainty, celerity, and severity of punishment), or in terms of the criminal career (the length of time an offender is "criminally active"), offenders are seen – at some level – as rationally committing crimes.

It is then unfortunate, on further examination, to note how scant and uncertain the research findings in this tradition are. Specifically, does microeconomic theory, as it relates to the criminal career paradigm, adequately explain criminal behavior? Are there alternative explanations that may prove useful in explaining crime? While this study cannot provide the definitive answers to these questions – no single study could accomplish such a goal – it will hopefully add to knowledge on criminal behavior and in the process improve both criminological theory and methods of testing these it.

The goals for the remainder of this chapter are fourfold. First, to describe the criminal career paradigm – its microeconomic roots, current conceptualization, and previous research findings. Second, to describe social control theory as it will be tested here, along with discussing previous research findings. Third, to present the three testable hypotheses that comprise the data analysis section of this study. Fourth, to explain why only two theoretical approaches – economic choice (criminal career paradigm) and social control theories of criminal behavior – will be tested in this study, and not other, more traditional sociological theories of crime.

MICROECONOMIC FOUNDATIONS OF THE CRIMINAL CAREER PARADIGM

Microeconomic Theories of Crime

Microeconomic theory assumes that individuals are rational actors who consider the costs and benefits associated with their actions (Varian, 1984). Economists are quick to note, however, that this does not imply that individuals always make the correct decision. The emphasis is on individuals *generally* acting in a rational, calculating, and utilitarian manner. Further implied by the assumption of individual rationality is the idea that humans are long-term oriented, that they are able to see past some short-term benefit and consider how current activities fit with long-term goals.

There are two broad classes of microeconomic explanations of crime: portfolio and time allocation models (Heineke, 1978a; Pyle, 1983; Schmidt and Witte, 1984). In addition to the rational actor assumption, portfolio models of crime further assume that both the costs and benefits to criminal activity have some inherent economic value. In other words, crimes are seen as having only monetary costs and benefits, or that the non-monetary costs and benefits of crime can be monetized (i.e., given some monetary value). For example, Becker's (1968) economic theory of crime explicitly assumed that all psychic costs and benefits that result from committing crime had some equivalent monetary value. Andersen (1976) also argued that every crime had some monetary value at which a person would either start committing the act or stop committing the act. Andersen's monetizing argument even included crimes such as drug addiction where, he suggested, a drug addict would give up his or her use of drugs once enough money had been offered as an incentive to quit.

From this view of crime, economists have attempted to model the criminal choice based solely on the monetary costs and benefits associated with the illegal activity. Applications of the portfolio model have included property crimes (Ehrlich, 1973), tax evasion (Allingham and Sandmo, 1972; Andersen, 1976), and even homicide (Ehrlich, 1975). Whether the portfolio model is viewed as successful or not will depend on the acceptance of the monetary equivalence assumption. If the assumption is accepted, there appears to be empirical support for this economic theory of crime, since the statistical models proposed by the above researchers were apparently accurate. On the other hand, if this assumption is rejected as unrealistic, the validity of the results is likely more questionable. There are simply too many consequesnces of the commission of crime that cannot be realistically given monetary equivalents. Heineke (1978a) was particularly forceful in pointing out that the idea of monetizing psychic costs and benefits is questionable on a theoretical level. He also proved that it was mathematically intractable to calculate a monetary equivalent in many cases. Furthermore, according to Heineke, the additional assumptions required to compute a monetary value bordered on the unbelievable.

The time allocation model differs considerably from the portfolio model. In this perspective, an individual's time is assumed to be divided among work (legitimate activities), crime (illegitimate activities), and leisure activities. The amount of leisure time an individual has is assumed to be invariable. The individual's time allocation decision thus centers on how much time to spend on legitimate and illegitimate activities, in light of how much wealth can be gained from work and crime, respectively, given the chances of being caught by the authorities if a crime is committed. An additional assumption implied by the time allocation model is that criminal activities are labor intensive, meaning that individuals committing criminal acts will spend substantial time on the planning and committing of crimes.

The most general statements of this type of economic model of crime have been proposed by Block and Heineke (1975) and Heineke (1978b), where they suggest stochastic returns to property crime, rather than assuming a constant rate of return. Specific applications of the time allocation model have included family violence (Long et al., 1983), property crime (Carr-Hill and Stern, 1973, 1977, 1979; Pyle, 1983; Schmidt and Witte, 1984), and recidivism of prison parolees (Witte, 1980), with apparent success. The major question for this approach, however, concerns the assumption of crimes requiring large amounts of planning and execution time. Gottfredson and Hirschi (1990) spend considerable time documenting the "nature of crime." What they clearly demonstrate is that crimes are generally spontaneous and require little knowledge or skill. Feeney (1986) and Carroll and Weaver (1986) also present evidence contrary to the labor intensiveness assumption. Feeney (1986) and Carroll and Weaver (1986) interviewed convicted robbers and shoplifters, respectively, and found that most crimes were spontaneous. In many instances, the offender perceived an opportunity to rob a convenience store or pocket some item in a store, and acted on that apparent opportunity (see, also, Katz (1988) for a similar description of robbers). These two studies raise a serious question about the validity of the time allocation assumption: Do offenders really spend a substantial amount of their time planning and committing crimes? Evidence to this point suggests they do not.

Thus, the appropriateness of conceptualizing criminal behavior as a time allocation problem appears to be as problematic as thinking of crime as a portfolio problem. Both economic models of crime are seemingly unrealistic by failing to square with known facts about crime – the portfolio model's emphasis on monetizing all costs and benefits of crime, and the time allocation model's emphasis on criminal activities being labor intensive. The result is that microeconomic theories of crime may rest on faulty assumptions, calling into question the validity of applying both the portfolio and time allocation models to criminal behavior in the way economists have done in the past.[1]

[1]In addition to these general criticisms of the microeconomic models discussed above, another concern focuses on the use of the Bernoulli probability model to operationalize an individual's expected utility function. With the exception of Block and Heineke (1975), Heineke (1978b), and Schmidt and Witte (1984), all the papers in this tradition have assumed the Bernoulli probability model. The major problem with the Bernoulli assumption, as noted by Block and Heineke (1975) and Heineke (1978b), is it implies the person either always succeeds and is not caught or always fails and is caught and punished. This assumption is so obviously false, it is curious how it can be used with so little critical attention to its validity. Obviously, people who commit criminal acts are not always caught and punished, or conversely, do not always succeed in getting away with the crime unpunished. Block and Heineke (1975), Heineke (1978b), and Schmidt and Witte (1984) attempted to remedy this problem by incorporating more realistic assumptions on the returns to criminal activity. Block and Heineke (1975) and Heineke (1978b) assumed the returns of crime were entirely random. In other words, that the level of gain and the level

Systems Analyses of Crime and Criminal Justice

At the same time microeconomic theories of crime begin with assumptions of *individual* rationality and some form of utility maximization, data analyses have looked at crime at the *societal* level. Manski's (1978a,b) discussions of the need for individual level data to test microeconomic theories of crime, and Witte's (1980) analysis are the only papers to discuss how an individual level theory should use individual level data. Every other paper purporting to test a microeconomic model of crime uses data on units of analysis no smaller than a city. There developed from this type of research a focus on what may generally be called "systems analysis." The idea was to look at the mutual interaction of the crime rate in society and the operation of the criminal justice system. Figure 1.1 displays this model in its simplest form.

of punishment an offender receives from criminal activities are unknown to the potential offender. Schmidt and Witte (1984) move away from the Bernoulli assumption included assuming four possible outcomes of criminal activity: (1) no crime and no punishment, (2) crime committed but no punishment, (3) crime committed and person caught, and (4) crime committed, person caught and then convicted. Unfortunately, while these changes from the Bernoulli assumption provide a welcome dose of reality to microeconomic theories of criminal behavior, these papers invariably fall back on the notion that fines can serve as proxies for psychic costs. Thus, while the change in probability models was a step forward, the overreliance on fines subjects these papers to the same criticisms as portfolio models.

Figure 1.1: Relationship between the crime rate and criminal justice system.

CRIME $\longrightarrow$ CJS
RATE $\longleftarrow$ OPERATION

The relationship between systems analysis and microeconomic theory comes through assessing the deterrent effects of certainty, celerity, and severity of punishment, which are characteristics of the criminal justice system. The microeconomic theories of crime developed by the researchers noted above suggested negative relationships between crime and certainty, celerity, and severity of punishment. Thus, when the criminal justice system is catching and prosecuting more offenders, the crime rate should become lower, as potential offenders will rationally consider the increased chances of being caught and punished. If more offenders are being caught and punished, other individuals should see that crime is not economically profitable, and then also be deterred from committing future offenses. However, researchers using this approach also argued that the criminal justice system is influenced by the level of crime in society. In those years when a high crime rate is observed, for example, there should be a corresponding increase in criminal justice expenditures and resources in future years, as the society attempts to deal with a higher crime rate through increased law enforcement. Conversely, if the crime rate appears to be declining, cutbacks in criminal justice resources become more likely, raising the probability of crime in the future. Keep in mind, however, that this type of research assumes that individuals rationally consider their chances of being caught, and that the criminal justice system makes a difference.

The research aimed at testing the model displayed in Figure 1.1 has shown little in the way of deterrence by the criminal justice system (Zimring and Hawkins, 1973; Gibbs, 1975; Blumstein et al., 1978; Nagin, 1978; Greenberg et al., 1979). In summarizing the field research on deterrence, Blumstein et al. note

> Our reluctance to assert that the evidence warrants an affirmative conclusion regarding deterrence derives from the limited validity of the available evidence and the number of competing explanations for the results (1978:47).

The report's conclusions on experimental and quasi-experimental deterrence research were even more critical, arguing that the design of these studies was so flawed that it became almost impossible to determine if a finding was indicative of deterrence or some quirk in the experimental design.[2] Interestingly, the only systems properties found to be consistently statisticall y significant in predicting the crime rate of a community involved traditional sociological variables, such as age structure and racial composition (Ehrlich, 1973, 1975; Fox, 1978; Witte, 1980; Pyle, 1983; Schmidt and Witte, 1984).

In recognition of little or no deterrent effect of the criminal justice system, researchers shifted the emphasis of the systems analysis approach from deterrence of all potential offenders to control of exceptionally "high-rate" offenders through selective incapacitation (Blumstein et al.,

[2]Zimring and Hawkins (1973) and Gibbs (1975) reached similar conclusions in regard to the deterrence research they reviewed, although deterrence was still viewed as a viable possibility in both of these studies.

1978, 1986; Greenwood, 1982, 1983; Chaiken and Chaiken, 1983). This shift in focus was further facilitated by the now famous finding of Wolfgang et al. (1972) that 18 percent of the sample accounted for approximately 50 percent of all offenses. If these high-rate offenders could be identified and incapacitated, systems analysts argued, there should be some corresponding decrease in the overall crime rate. Recently, Blumstein et al. (1986) have summarized this work under what is now referred to as the "criminal career paradigm."

The Criminal Career Paradigm

Blumstein et al. (1986) define a criminal career as

> ... the longitudinal sequence of crimes committed by an individual offender (1986:12).

Four parameters, or characteristics, of the criminal career were suggested in this report: participation, frequency, seriousness-specialization, and career length (1986:1). Participation simply refers to whether a person has committed a crime in some time period. Frequency is the number of crimes committed in the same time period, denoted in the literature by λ (lambda).[3] Seriousness, or specialization in offending, was suggested by Blumstein et al. as a way of describing trends in offending patterns over an individual's life course. The idea being that the more crimes committed by an individual, the more likely the individual is to repeat those same types of crime at some future time. Career length is the time between an individual's first offense and last offense.

[3] A problem Blumstein et al. have created for the career paradigm involves the restriction that only "active" offenders can have a value for frequency of offending. This restriction introduces censoring to the sample, since the offenders a researcher will study have been chosen based on some minimum value of the dependent variable (offending frequency). This issue is discussed in more detail in Chapter 5.

Again, to make clear the theoretical roots of the criminal career perspective, recall that research on criminal careers, and high-rate offenders, grew out of systems analyses of the crime rate and criminal justice system, which were grounded in microeconomic theory. Although not always obvious, microeconomic theory's assumption of individual rationality is consistent with the major elements of the criminal career paradigm. First, by attempting to describe an individual's offending frequency with a constant (λ), the career view implies that individuals will offend at the same rate throughout life.[4] Pyle's (1983) microeconomic analysis shows how offenders who commit crimes at some rate would be expected to continue offending at the same rate. If an individual's utility is maximized by offending at a rate of, say, five crimes per year, then it is perfectly rational for that person to continue committing crimes at the same rate, so long as the economic benefits associated with the activity continue to exist.

Second, Blumstein et al. (1978, 1986) and Blumstein and Nagin (1978) directly assume that criminal sanctions influence the level of crime in society through deterrence or incapacitation. Additionally, Blumstein et al. and Blumstein and Nagin show an individual's offending frequency to be a function of the probability of arrest. Blumstein et al. assume this with the following relationship

$$\mu = \lambda q,$$

where μ is the individual's arrest rate, λ is the individual offense rate, and q is the probability of arrest (1986:59). Simple algebraic manipulation

[4]Blumstein et al. say "... λ is relatively stable over age for those offenders who remain active" (1986:5).

shows that

$$\lambda = \frac{\mu}{q}.$$

This relationship says that an individual's offense rate is a function of the chances of being arrested.[5] Recall that in the traditional microeconomic approach, the chances of being arrested influenced the likelihood that crime would be the chosen act, and that the lower the chances of being caught, the more likely criminal behavior becomes. Thus, there is very little difference between the key criminal career parameter (λ) and the implications of microeconomic theories of crime.

Third, Blumstein et al. also argue that specialization (the tendency to repeat the same offense) is likely as the offender commits more crimes (1986:5,81). Pyle's (1983) analysis again demonstrates how specialization in offending is a "corner solution" to a person's expected utility function. In other words, if criminal activities provide any economic benefits, Pyle argues that they would likely be chosen over legal activities, providing the chances of being caught remained low (1983:17-19). The same logic implies specialization. Individuals who have committed a specific crime in the past will have that much more knowledge to work with in the future, making a repeat occurrence of a past offense more likely, and increasing the chances for success. Thus, the most rational course of behavior for offenders is to specialize in particular offenses, thereby minimizing

[5]Segments of the Blumstein et al. discussion (1986:59-61) on the relationship between μ and λ are seemingly contradictory. They first assume q and λ are independent (1986:59). The independence assumption, however, is immediately relaxed when Blumstein et al. discuss several ways in which q and λ *are* related (1986:61). For example, observed estimates of λ are dependent on people reporting crimes to the police – an arrest cannot be made without the crime having been reported. If the crime is not reported, $q = 0$, and, therefore, $\lambda = 0$. If the crime is reported, $q > 0$ (even if very low), which then implies that $\lambda > 0$. Thus, there is no escaping the fact that an individual's offending frequency is a function of the probability of arrest.

information and start-up costs involved in changing criminal activities.

In sum, microeconomic theory and the criminal career paradigm see the offender as an individual who, at some level, rationally considers the chances of being caught and punished by the criminal justice system.[6] Blumstein et al.'s (1978, 1986) and Blumstein and Nagin's (1978) systems analyses make little sense without these assumptions.

SOCIAL CONTROL THEORY

Social control theory begins with the assumption that individuals will violate the law if they are not controlled by the community of which they are members. Or, as Hirschi notes,

> Control theories assume that delinquent acts result when an individual's bond to society is weak or broken (1969:16).

This assumption is firmly grounded in the works of Durkheim (1951) and Hobbes (1962), where individuals are seen as pursuing their own self-interests – legal and illegal pursuits – and the way for society to prevent the illegal acts is to regulate, or control, individual pleasure seeking.

Using the assumption that individuals are pleasure oriented, Hirschi's (1969) version of social control theory emphasized an individual's bond to

[6]Supporters of the criminal career perspective may contest the notion of the probability of arrest as a salient issue for most offenders. This does not detract from the relationship with microeconomic theory, however. Varian (1984) notes how individuals are expected to act rationally most of the time. But since many people do not have perfect information about their choices, they cannot estimate probabilities and act entirely based on those measures. Rather, prior experiences will tend to have a greater influence on a person's subsequent behavior, giving the appearance that they are acting in their best interests. Similarly for the criminal career view, individuals are assumed, at some level, to consider potential sanctions, and to act accordingly. Paternoster (1989) has recently produced some evidence to support this view.

conventional society. Where the social bond was weak, crime was expected to be more likely. Conversely, where the social bond was stronger, crime was expected to be less likely. Hirschi suggested the social bond was comprised of four primary elements: (1) attachment, (2) commitment, (3) involvement, and (4) belief. Attachment to conventional society was conceptualized as reflecting whether an individual was sensitive to the opinions and expectations of others (1969:18). The more sensitive an individual is to others' expectations, the less likely that individual is to commit an illegal act. Commitment was defined as the rational component of the social bond, where individuals are expected to consider the potential social costs involved in illegal activity (1969:20). As illegal acts become increasingly risky to an individual's investment in conventional society, the occurrence of those illegal acts becomes less and less likely. Involvement is the simplest concept in this theory, and it refers directly to how much time an individual spends involved in conventional activities. Obviously, the more time an individual spends with his or her family, or at school, the fewer opportunities there are for any kind of criminal activity. Belief is perhaps the most difficult element of the social bond to conceptualize. It refers to the level at which an individual has accepte d a common value system existing in society. If a common value system exists in society, then to the extent that an individual has accepted it, the chances that the individual will commit an illegal act are lower.

More recently, Gottfredson and Hirschi (1990) have commented on the substantial similarity across both offenders and offenses. Crimes, they argue, are events in time and space that involve the use of force and/or fraud. Crimes are not limited to those behaviors proscribed by the state, but also include other activities that still involve forceful and fraudulent behavior (e.g., lying to one's spouse or parents). Additionally, crimes as events are oriented toward some short-term gain, involving little planning since most crimes are relatively simple and uncomplicated, and likely to occur spontaneously (see, also, Feeney, 1986; Carroll and Weaver, 1986).

In the Gottfredson and Hirschi view, offenders are also seen to exhibit similar characteristics. Namely, the lack of self-control. They argue that the more self-control an individual has, the less likely that person is to be attracted to short-term gains, and more oriented to long-term gains. This implies that people with greater self-control will be less likely to commit criminal acts, because crimes are aimed primarily at short-term gains. Along the same line of thought, Herrnstein (1983) has argued that some traits of individuals are more "criminogenic": when offenders are matched with an equivalent non-offender population, they tend to exhibit more of such characteristics as aggressiveness, short-term gratification, and low self-control. Rowe and Osgood's (1984; see also Rowe et al., 1990) argument for a latent trait approach follows a similar logic – that all individuals have more or less of some characteristic that makes the individual more or less likely to commit criminal or delinquent acts. This is not to argue, however, that there is some deterministic process at work. Rather, whether one looks at self-control, aggressiveness, or some other "latent trait", it is a way of talking about how *every* individual is, at some level, prone to crime commission. Then, given some latent individual tendency, the social context influences the chances of a crime occurring. Persons high on self-control can still commit crimes, although they are very unlikely, and something unusual about the situation would be required to account for them. Conversely, persons low on self-control can avoid committing criminal acts if the social situation is such that the person is restrained from following natural impulses.

In sum, Gottfredson and Hirschi's social control theory claims that society has some influence on a person's moral and psychological development. Out of that moral and psychological development should emerge some ability for a person to control their desires – what they call self-control. Interacting with each individual's self-control is society's ability to monitor and regulate its members' behavior. Figure 1.2 displays this relationship.

Figure 1.2: Theoretical Relationship
Between Crime and Self-Control.

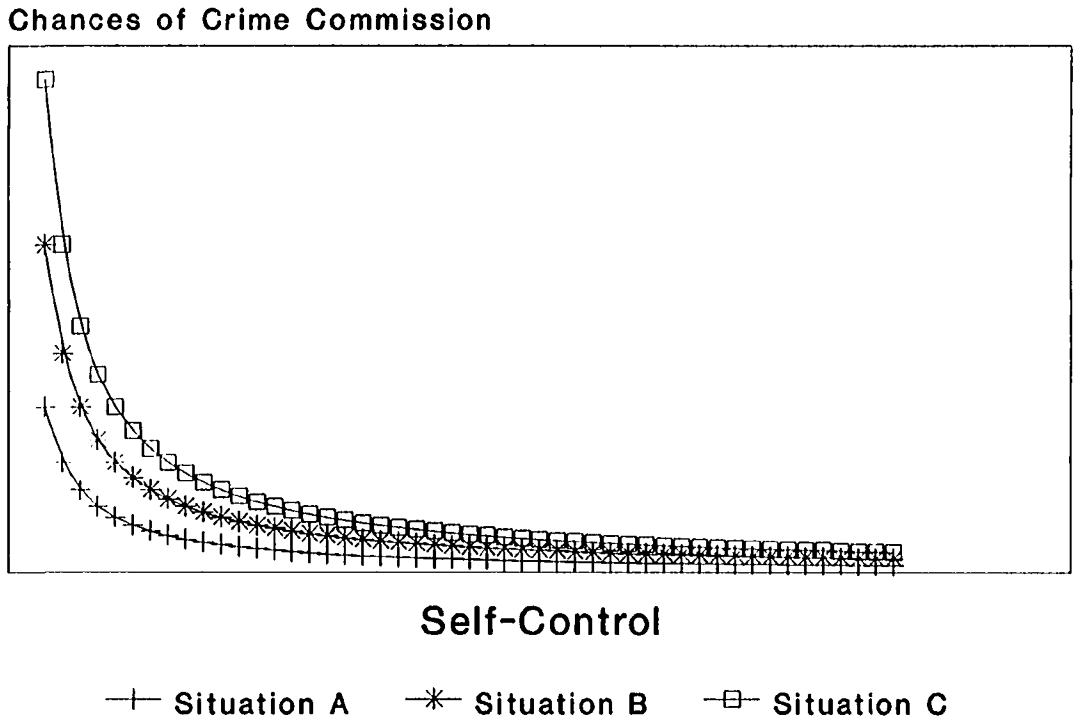


Figure 1.2 may be interpreted in the following way. Assuming a reciprocal relationship between crime and self-control gives curves A, B, or C, where higher levels of self-control should result in lower probabilities of crime commission, and vice versa. If an interaction between self-control and social control is also assumed, then curves A, B, and C each represent decreasing levels of social control. For example, curve A represents a high level of social control, since the individuals with low self-control in Situation A are less likely to commit crimes than if they were in Situations B or C, which are indicative of increasingly lower levels of social control. Another interesting aspect to Figure 1.2 involves those individuals with higher levels of self-control. It seems reasonable to argue, given that there is an interaction between self-control and social control on the chances of crime occurring, that the situation has much less of an effect on those people with high self-control. In other words, there is a convergence in the probability that a person with high self-control will commit a crime. This is also consistent with social control theories that emphasize the social bond–those individuals with strong bonds to conventional society have low chances of committing crimes regardless of the social setting.

HYPOTHESES

Based on the preceding discussion highlighting the major ideas and findings of the criminal career and social control perspectives on crime, several hypotheses are generated and tested in this study. The three hypotheses to be examined are: (1) the stability of the age distribution of crime, (2) the prevalence of offense versatility among offenders, and (3) the correlates of participation and frequency of offending. (More detailed descriptions of the logic underlying the different tests is presented in the respective chapter.)

The meaning of the age distribution of crime has generated a substantial amount of debate in recent years (e.g., Hirschi and Gottfredson, 1983,1985; Greenberg, 1985; Farrington, 1986; Shavit and Rattner, 1988; Steffensmeier et al., 1987, 1989). At issue has been the stability or invariance of the age distribution of crime. Hirschi and Gottfredson (1983) argue that the age distribution of crime is invariant to social and cultural conditions. Although they use the term "invariance" loosely, which has caused some confusion in the field (see, for example, Steffensmeier, 1989), invariance is here defined as similar shape (This definition is consistent with that later proposed by Gottfredson and Hirschi (1988)). Conversely, Blumstein et al. (1986, 1988a) argue that the age-crime relationship is variable due to unique age, period, and cohort effects that can alter the shape of the curve in any year. Others claim that many factors change across a person's life course that will either encourage or inhibit criminal activity (Farrington, 1986), again implying the shape of the age-crime curve will change. Thus, this first hypothesis may be stated as:

> H1: The age distribution of crime has the same shape, regardless of social and cultural conditions.

Chapter 3 presents the results of the test of this hypothesis.

Blumstein et al.'s (1988) assertion that older offenders tend to exhibit more specialization in offending than younger offenders provides an issue on which to evaluate these two views of crime. Early studies on specialization seemed to indicate that there was very little predictability of one's future offense based on prior illegal activity. Yet, more recent work claims to show just the opposite. Adding to the discussion, then, is Blumstein et al.'s claim that we may observe even higher levels of specialization should older offenders be observed. In general, the notion of offense specialization is directly contrary to control theory propositions. Recall that social control theories of crime see crime as a general phenomenon that satisfies some need for immediate pleasure and is a result of low self-control. Thus, crimes are acts that provide short-term gains or pleasure that do not require specific skills or knowledge. The second hypothesis to be tested in this study is the following:

> H2: Specialization in offending will be more prevalent among older offenders.

Chapter 4 presents the results of the test of this hypothesis.

Blumstein et al. (1988a) have also argued that participation and frequency of offending require different causes. Specifically, they argue that the factors

> leading to an individual committing any criminal act (participation) should be substantially different from the factors leading individuals to commit more than one criminal act per year (frequency).

Again, this contradicts social control theory, providing another clean hypothesis test. Since social control theory assumes that crime is a general phenomenon, the distinction between participation and frequency is arbitrary. Yet social control theory would predict that the factors having the strongest relationship with participation will also have the strongest relationship with frequency. The third hypothesis to be tested may be stated as:

> H3: The independent variables having the strongest relationship with participation will have the strongest

relationship with individual offending frequency.

Chapter 5 contains the results from the analyses testing this hypothesis.

WHITHER THE OTHER THEORIES OF CRIME?

Several popular sociological theories of crime will not be tested in this study. I have purposely avoided social learning, strain, and conflict theories of crime. My rationale for rejecting these approaches is based on (1) lack of supporting evidence, (2) logical problems with the theory, or both (1) and (2).

Social learning theory, as described by Akers and colleagues (Akers, 1985; Akers et al., 1979), has failed clearly to demonstrate that a reinforcement process for learning criminal behavior exists. Current social learning approaches, in an attempt to deal with earlier criticisms, have focused on integrating social learning theory and social control theory. The development of "social process models" (Krohn et al., 1989; Massey and Krohn, 1986) has been the result of this effort. The emphasis of this approach has been on describing the process through which an individual goes from being a conforming member of society to a non-conforming member. In general, this process involves the conforming individual's social bond to conventional society becoming weakened. As the bond weakens, the individual becomes more likely to associate with others who commit crimes. Then, through some type of reinforcement process, the individual learns that some acts defined as illegal in larger society are requisite behavior for the group. Thus, the reinforcement for criminal behavior by the group leads to the individual being more likely to commit crimes. This end-to-end integration of social learning theory and social control theory poses some problems (Hirschi, 1979). Foremost among these problems is that the primary assumptions of social control theory and social learning theory do not match, implying different views of human nature. Social control theory, as noted above, assumes that individuals will commit crimes unless somehow prevented. Social learning theory, in contrast, assumes that individuals will not commit criminal acts until they learn what criminal acts are appropriate for their group. These two assumptions are wholly incompatible, implying that this social process theory has serious flaws on logical grounds.

Attempts to empirically test this theory have also run into trouble. Social learning theory implies that a longitudinal study of some sample of individuals should be conducted to test the theory. However, some researchers in this tradition have discovered that it is empirically impossible to sort out the effects of an individual's delinquency from that of their friends by using longitudinal data (Akers, 1988). The major problem to result from this finding is the implication that the causal order question *cannot* be sorted out with longitudinal studies. The problem for social learning theory is that the theory cannot be validly tested, since there are no current measures known to do what social learning proponents would like.

In sum, the theoretical and empirical evidence does not bode well for social learning theory. Since the problems associated with this theory are beyond the purview of this study, social learning theory is not tested. If theoretical and measurement problems can be resolved at some later time, social learning theory could provide an interesting alternative to economic choice and social control theories.

Strain theory has also received much attention in the criminological literature. Although Merton (1938) is often credited with establishing this perspective, Cohen's *Delinquent Boys* (1955) and Cloward and Ohlin's *Delinquency and Opportunity* (1960) have provided the framework from which most contemporary research on strain theory comes. Simply put, the argument behind strain theory says that all individuals are socialized to accept middle class values of economic achievement. However, some segments of the population (assumed to be the poor) realize that their aspirations of achieving economically have been blocked by social structural constraints. The recognition of blocked aspirations is then said to lead to some sense of frustration, or strain, within the individual. In response to this frustration, the individual is expected to be more likely to become involved with a delinquent subculture and then to commit criminal acts as an illegitimate means of achieving economic success.

Unfortunately for strain theorists, any serious test of the theory has failed to produce much evidence supporting the theory. There are instances where strain theory has received mild support, but this has come at the expense of either manipulating the data or misinterpreting the results (see, for example, Blau and Blau, 1982; Elliott et al., 1985; Farnworth and Leiber, 1989). Three decades of research on strain theory show little hope for the theory to accurately describe criminal behavior. Therefore, I see no reason to provide redundant findings against a theory that has already accumulated three decades of similar findings.

Conflict theory, as constructed by Quinney (1970), Chambliss (1974, 1988), and Chambliss and Seidman (1972), focuses on why society defines some behaviors as illegal, rather than commenting on what leads people to violate the law. This is a purpose vastly different from the focus of my study, and to debate the issue of why some behaviors are proscribed by laws, and others are not, detracts from the initial issue of focusing on factors that make criminal behavior more or less likely. In other words, the question: "Why do people commit law violations" is not answered by conflict theory. Since there is then no way to make this theory comparable to the theories tested in this analysis, conflict theory is also excluded.

CHAPTER 2

DATA AND METHODS

INTRODUCTION

Four separate data sets are used in the following analyses. Each data set represents one of four possible types of data collected on delinquent and criminal behavior: official and longitudinal (*Uniform Crime Reports*), official and cross-sectional (Bail Decisionmaking Study), self-report and longitudinal (National Youth Survey), and self-report and cross-sectional (Seattle Youth Survey). The rationale for using these four data sets is twofold. First, there has been substantial recent debate in criminology over the usefulness of longitudinal as opposed to cross-sectional data (Blumstein et al., 1986, 1988a, 1988b; Gottfredson and Hirschi, 1986, 1987, 1988; Farrington, 1979, 1986; Steffensmeier et al., 1989). These four data sets will shed light on whether the findings from longitudinal studies may differ substantially from cross-sectional studies. Second, and related to the first reason, findings that are consistent across type of data will have increased validity because they cannot be solely an artifact of the technique or source of data collection. The remainder of this chapter describes the four data sets as well as their potential pitfalls and limitations. A brief comment on methods of data analysis concludes the chapter.

THE DATA SETS

Uniform Crime Reports

The *Uniform Crime Reports* (*UCR*) are published annually by the Federal Bureau of Investigation (FBI). The information to be used in the following analyses focuses on the nature and distribution of arrests in the United States from 1952 to 1987. The FBI publishes information on 27 unique offenses, further categorizing these statistics by age of offender.[1] Since 1952, the FBI has used arrest reports on which to base its aggregated arrest statistics, as opposed to the fingerprint cards used from the 1930s to 1951 (Steffensmeier and Cobb, 1981). Thus, the 1952-1987 time period relies on data collected in the same way.

Although periodic concern has been expressed over using the *UCR* as a source of data (e.g., Hindelang, 1981), other studies have demonstrated that official statistics are representative of the "true" crime rate in society (Hindelang, Hirschi, and Weis, 1981). This is not to say that arrest statistics provide a perfect indicator of crime in the United States. Rather, the social distribution of arrests indicated by the *UCR* has been confirmed with self-report (Hindelang et al., 1981) and victimization (Hindelang, 1981) studies.

Bail Decisionmaking Study

The Bail Decisionmaking Study (BDS) was conducted by John S. Goldkamp and Michael R. Gottfredson in 1978. The original purpose of

[1]Since 1981, the FBI has published age-specific arrest data by gender category. This distinction will not be used in this study, however, because it would only permit a comparison over seven years, as opposed to the 35 given by the 1952 to 1987 comparison. Additionally, the FBI also publishes arrest information by race, but the age categories are "Under 18" and "18 and Older". This distinction is meaningless for the analyses proposed in the following chapters.

this study was to assess the process judges in Philadelphia use in making a bail decision on recently arrested offenders. The sample selected for this study was stratified on the basis of the bail setting judge and the severity of the offense. There were twenty such judges, and six levels of offense severity, resulting in 120 strata. Goldkamp and Gottfredson used a quota sampling design to collect 40 cases per stratum. This produced a final sample of 4,800 cases. Although this sampling scheme did not produce a simple random sample that could have been generalized to the population of offenders who participate in the Philadelphia criminal justice system, a representative, comparison sample of defendants was collected by Goldkamp and Gottfredson in 1981 to validate the BDS sample and its findings. Most of the BDS sample was collected from 1 February 1978 to 30 November 1978. However, two judges were short cases in some strata so the sampling was extended back to 1977 and forward to 1979 to draw enough cases to fill the quotas (Goldkamp and Gottfredson, 1981:126-129).

Although the BDS was originally collected for purposes different from those of this study, the data will still are suitable for the analyses below. Information was gathered on the legal, demographic, and social (community ties) characteristics of all offenders. Thus, tests of the age-crime relationship (Chapter 3), the specialization-versatility in offending debate (Chapter 4), and the causes of frequency of offending (Chapter 5) can all be conducted with the BDS data.

The primary problem with the BDS is the nature of the sample design. Since offenders were included on the basis of the severity of their offense, sample selection bias may be a problem (see Berk, 1983; Heckman, 1976,1979). However, the findings will not be used to generalize to all offenders. Rather, the findings will be used for comparative purposes, with the main emphasis being the similarity of results across different types of data.

National Youth Survey

The National Youth Survey (NYS) was conducted by the Behavior Research Institute at the University of Colorado. The data used in the analyses below consist of the first four waves of the NYS. The NYS consists of a sample of 1,725 individuals aged 11 to 17 in 1977. This same group of youths was reinterviewed annually in 1978, 1979, and 1980.[2] The analyzable sample of 1,725 is a result of a national probability sample of all households in the United States in 1976, using a multistage, cluster design. Elliott et al. (1985:92) note that they began with seventy-six primary sampling units, which had a probability of selection proportional to population size. The initial selection produced 67,266 households, of which 8,000 were chosen for the NYS sample. Of these 8,000 households, a sample of 2,360 youths aged 10 to 17 was found. Out of the 2,360 youths, "635 (27 percent) did not participate in the study due to (1) parental refusal, (2) youth refusal or (3) an inability to make contact with the respondent" (Elliott et al., 1985:92). Age sex, and race comparisons with the general U.S. population indicated that the NYS sample was indeed representative of the U.S. population (1985:92-93).

The principal problem with the NYS involves sample attrition that appears to be related to the race, social class, and area of residence of the youth. Through Wave 3, 99 participants had been lost. While this attrition is potentially a very serious problem, Elliott et al. (1985:92-93) argue that the sample is still mostly representative of the U.S. adolescent

[2]A follow-up interview was conducted in 1983, but these data are not yet available to the public.

population. Furthermore, they note that those individuals droppi ng out of the study did not have higher reported rates of delinquency, so that the remaining sample is not biased toward being the least delinquent of the original participants.

Seattle Youth Study

The Seattle Youth Study (SYS) was conducted by Michael J. Hindelang, Travis Hirschi, and Joseph G. Weis in 1978 and 1979. The original purpose of the SYS was to assess the impact of method of survey administration on the validity of individuals' responses. The four conditions of the quasi-experiment (the methods of administration) were anonymous interview, anonymous questionnaire, non-anonymous interview, and non-anonymous questionnaire. Since the method of administration had only trivial, non-statistically significant effects on the respondents' answers, individuals are pooled across method of administration for the analyses below.

The sample selected by Hindelang, Hirschi, and Weis was aimed at (1) being representative of the general adolescent population in Seattle and (2) maximizing the variance on delinquency (Hindelang et al., 1981:31). To accomplish this, three separate Seattle populations were sampled, with each population representing an increasing level of delinquency. The first population was an official non-delinquent sample was selected by randomly selecting names from a list of students attending Seattle public schools. Individuals's names were then used to search Seattle police files for an arrest record. If the student had record of contact with the Seattle police, they were excluded from the sample. The second population included all individuals who had Seattle police contact, but none with the King County (Seattle) Courts, and was used to represent a sample of "moderate" delinquents. The third population included youths referred to the King County Division of Youth Services, and represented a sample of more serious delinquents. Each of these three populations was considered mutually exclusive. The result of this sampling design was a sample of 1,611 Seattle youths.

Hindelang et al. (1981:33-36) comment on the potential problems with the SYS. The major threat to the representativeness of the SYS sample is the participation rate for higher delinquency samples was lower than for lower delinquency samples. This also threatens the internal validity of the sample if those individuals who participated in the study are also the most "honest" within that population, which implies some sort of self-selection. Since this question cannot be answered with this data set, or any other currently available, a representative subgroup is assumed, while at the same time realizing the need to be cautious in interpreting the findings.

NOTE ON DATA ANALYSIS

Due to the great diversity of indicators in all four data sets – of both independent and dependent variables – the discussions of specific measures of crime and delinquency are postponed to the relevant chapter in the interest of clarity. Furthermore, each hypothesis has a slightly different orientation, and will require an assortment of techniques to evaluate the data. Thus, in Chapter 3 (age and crime), the emphasis is on graphical analysis, while Chapter 4 (versatility-specialization) relies on graphical, logistic regression, and latent class analyses, and Chapter 5 (participation and frequency of offending) uses probit and tobit methods of data analysis.

CHAPTER 3

AGE AND CRIME

INTRODUCTION

Recently, there has been an interesting debate over the meaning of the age-crime curve in the sociological and criminological literature (see, for example, Farrington 1986; Greenberg 1985; Hirschi and Gottfredson 1983, 1985; Steffensmeier, Allan, Harer, and Streifel 1989). At the heart of the controversy is whether the age distribution of crime is stable across a variety of social conditions. Greenberg (1985) and Steffensmeier et al. (1989), for example, argue that the transition from youth to adulthood has become more problematic in the United States following World War II. The nature of this transition may be found in the access to employment for young people. Greenberg (1985) and Steffensmeier et al. (1989) both argue that it has become increasingly difficult for adolescents to obtain jobs, and therefore adulthood. As a result, they expect the age distribution of crime to shift to younger individuals as a reflection of these employment difficulties. Farrington similarly expects to see a variable age distribution of crime, but his reasoning is slightly different. Farrington claims that social institutions have age-graded effects, where, for example, peers are more important for adolescents, and spouses and families are more important for individuals in their 20s and 30s. Further, Farrington argues that the impact of these social institutions may change over time. From the criminal career perspective, Blumstein et al. (1988a) argue that many causes of crime are unique to age groups and to periods and cohorts. If the causes of crime vary by age, period, and cohort, Blumstein et al. (1988) claim, then the age distribution of crime must also be variable as a reflection of this fact.

In contrast, Hirschi and Gottfredson (1983) argue that the causes of criminal behavior are the same regardless of age, period, and cohort. Recall from Chapter 1 that Gottfredson and Hirschi (1990) claim self-control has a direct effect on the chances of criminal behavior. Those individuals with low levels of self- control, they assert, are more likely to commit crimes. The effects of self-control on criminal behavior, are not expected to vary by age, period, or cohort. In other words, regardless of other factors, self-control is expected to have the same type of effect on the chances of criminal behavior. This reasoning leads Hirschi and Gottfredson (1983) to claim that the age distribution of crime should be stable over time, since the causes of crime will not have changed for any age group, or varied by year.

Prior research on the stability of the age-crime curve, discussed in more detail below, motivates the analyses in this chapter. The analyses attempt to estimate the stability of the age distribution of crime in the four data sets described in Chapter 2. More specifically, the following series of graphs will focus on assessing whether the age distribution of crime, when considered by year (in the *Uniform Crime Reports* and National Youth Survey) or by data set, has approximately the same shape. In other words, do cross-sectional plots of the age distribution of crime appear to be similar over time and across data set? The two longitudinal data sets permit two other types of analysis that can shed light on the stability of the age and crime relationship. First, does each age group account for a stable level of illegal activity over time? Second, do different cohorts have similar (or variable) age specific offending patterns?

RECENT RESEARCH

Hirschi and Gottfredson (1983) argue that the shape of the age distribution of crime is similar for different social contexts, which they define as invariance. Although this is far from a precise definition of "invariance," the emphasis on the *shape* of the distribution does convey the key idea behind Hirschi and Gottfredson's effort. Namely, that age distributions of crime all show a characteristically sharp increase in offending in the early to mid-teens, a peak in the late-teens or early twenties, and following an initially sharp decline, a more gradual decrease in criminal activity across the older age groups. In support of their claim that the shape of the age distribution of crime was approximately the same, regardless of social and cultural conditions, Hirschi and Gottfredson present a series of graphs from different countries, for different historical periods, ranging from 1842 for England to 1977 for the United States. Neither the peak nor the rate of decline are identical in all their graphs. However, the general shape was quite similar across graphs (Gottfredson and Hirschi (1988) reiterate this specific claim).[1] Additionally, Hirschi and Gottfredson present graphs that distinguish age-specific criminal activity by race and gender. Again, the curves have approximately the same shape, with the only substantial difference being the absolute values of the age-specific rates. These graphs, collectively, suggest that social and cultural conditions do not influence the shape of the age distribution of crime.

[1]Blumstein and Cohen's (1979) comparison of age-specific arrest rates in the U.S. for 1965 and 1976 can be taken as additional support for Hirschi and Gottfredson's claim.

Farrington (1986) observes a similar pattern of arrest rates for males and females in England; yet his conclusion is vastly different from that of Hirschi and Gottfredson. Farrington looks at the distribution statistics (mean, mode, median, skewness and kurtosis) for both male and female arrest distributions. Based on differences in the values of these statistics for the two distributions, Farrington argues that different social processes must be operating on males and females. The implication Farrington's study holds for the invariance proposition is the claim that the age distribution is not invariant to different social conditions (i.e., gender). In other words, males and females have had different experiences, and as a result, commit crimes at different rates at different ages, meaning the age distribution of crime is not invariant across gender.

Interestingly, Farrington's conclusion that the age distribution of crime is not invariant across gender make his attempt to mathematically fit the two age distributions of crime somewhat puzzling. In this curve fitting exercise (1986, pages 240-243), Farrington fit four common probability density functions–Poisson, Chi-Square, Gamma, and Logistic. Without reporting any goodness-of-fit statistics, the logistic curve is claimed to have the best fit for both distributions, based on visual inspection. These results are problematic for Farrington, however, as one of the independent parameters is identical for males and females (c=.15), while the other parameter is trivially different (a=.0287 for males and .04 for females).[2] The curve fitting results show the same mathematical function, with virtually identical parameters, to fit the two curves that Farrington claims are substantially different. Thus, Farrington's analysis shows the age distribution of male and female crime in England to be

[2]This equation has the form $y = ax^b e^{-cx}$.

both variant (in terms of the distribution statistics) and invariant (in terms of the curve fitting results). Farrington's conclusion of variance in the age distribution of crime by gender therefore contradicts some of his evidence, implying that Farrington's results cannot be taken as evidence that either confirms or rejects the invariance hypothesis.

Shavit and Rattner's (1988) analysis of survey data on Jewish Israeli men shows the shape of the age-crime curve to be relatively similar for these men across a variety of "social characteristics" (e.g., marital status and religious orthodoxy). There is some variation in older individuals's offending rates in their sample, compared to individuals the same age in the U.S. and England. However, given the age distribution of offending in this sample, statistical controls for other social factors fail to alter the age distribution of offending, suggesting that the age distribution of crime among this sample of Jewish Israeli men is invariant.

Steffensmeier et al. (1989) look at the age distribution of crime in the U.S. in 1940, 1960, and 1980 in a more systematic test of the invariance hypothesis. Relying on the Index of Dissimilarity[3] and χ^2 values, they compare age distributions of crime across offense and time. In regard to the 1980 offense specific age distributions, they find many of these distributions to be statistically different from the burglary distribution. Steffensmeier et al. argue that these results question the application of

[3] The Index of Dissimilarity (D_j) for each offense was computed as

$$D_j = \frac{1}{2}\sum_{i=15}^{49} |b_i - o_{ij}|,$$

where b_i is the percentage of burglary arrests in age group i and o_{ij} is the percentage of other crimes, j, in age group i. The same type of equation was used to compute the Index for the over time age distribution comparisons.

the invariance hypothesis to offense specific data; that each crime type represents a unique set of causes, and as a result implies the offense specific age distributions of crime are not invariant when considered cross-sectionally. Steffensmeier et al.'s results comparing age distributions longitudinally also question the invariance hypothesis. The offense specific age distributions for 1960 and 1980 showed few differences, but there was substantial variation when the offense specific age distributions for 1960 and 1980 were compared with those for 1940. These results suggest that offense specific age distributions of crime are also variable over time, further questioning the validity of the invariance hypothesis.

There are two potential problems with the Steffensmeier et al. (1989) analysis that may cast doubt on the accuracy and strength of their conclusions, however. First, the computation of the Index of Dissimilarity and χ^2 values to determine which distributions are similar or different is problematic. The age distribution of burglary arrests is used as the base category against which to compare all other offenses (see the equation in footnote 2). The use of burglary arrests by Steffensmeier et al. is arbitrary, and the skewed nature of the burglary distribution clearly biases their results in favor of finding variance. Had any other offense specific distribution been used as the base category instead of burglary's, Steffensmeier et al. would have obtained a substantially different pattern of results – some likely supportive of variance and some likely supportive of invariance. Thus, Steffensmeier et al.'s conclusion of variance across offenses cannot be generally valid without further testing, and holds only in the context of comparing other offense specific distributions to the age distribution for burglary.

Second, prior to 1952, the FBI used fingerprint cards to construct the age-specific arrest tables. Since 1952, the FBI has used arrest reports to construct the same tables. This change in measurement is a much more serious problem than Steffensmeier et al. note, however. In the 1953 edition of the *Uniform Crime Reports*, the following comment was made:

> ...[age-specific arrest] statistics since 1952 cannot be compared with similar data published prior to that year. Before 1952 the only local arrest information available for analysis as to personal characteristics was that shown in fingerprint arrest cards received by the FBI from local police agencies. Not all persons arrested are fingerprinted (*particularly young persons*) so that source fell far short of completeness...(1953, p.108, emphasis added).

In other words, there was systematic underreporting of young persons's arrest activity. This systematic reporting bias poses a serious threat to Steffensmeier et al.'s conclusions, since the use of the 1940 *UCR* data again biases their longitudinal analysis toward finding variance in the distributions. Further, the use of the 1940 age-specific arrest data, given this systematic bias, appears to provide an invalid comparison. As a result, Steffensmeier et al.'s conclusion of longitudinal variation in the age distribution of crime may also be of questionable validity.

A different approach to testing Hirschi and Gottfredson's invariance proposition uses age-period-cohort analyses of official U.S. crime statistics (Greenberg and Larkin 1985; Steffensmeier, Streifel, and Harer 1987). Age-period-cohort models can test the invariance hypothesis by showing whether age-specific involvement in crime changes by period or cohort (i.e., testing for direct period and cohort effects). If age-specific involvement does change by period or cohort, the implication is that the age distribution of crime is not invariant, since the different social conditions assumed to be present in different periods and cohorts has led to different age distributions of crime.

Greenberg and Larkin (1985) use official data from seven U.S. cities for 1970, 1975, and 1980, and demonstrate that crime uniformly decreases with increased age, controlling for period and cohort effects. The period effect is not statistically significant, controlling for age and cohort effects.[4] They find weak evidence for cohort effects, as some of the younger cohorts had persistently higher rates of offending than the older cohorts. However, the parameter estimates in their model are not stable, and varied substantially with the specific model parameterization (1985, p. 236). In conclusion, Greenberg and Larkin noted that period and cohort effects cannot explain the effect of age on crime, implying support for the invariance hypothesis. Moreover, "Consistency across social conditions tells us that there are some age effects that are common to a wide range of social conditions" (1985, p. 239).

Steffensmeier et al.'s (1987) age-period-cohort analysis attempts to sort out the effects of relative cohort size on the national crime rate. In contrast to Greenberg and Larkin (1985), Steffensmeier et al. find no cohort effect, but do find a strong period effect. Steffensmeier et al. (1987) then claim the age-period model to be a better overall model, explaining 97.75% of the variance with 40 parameters and 320 data points, than either the age-cohort (95.5% of the variance and 49 parameters) or age-period-cohort models (99.21% of the variance and 80

[4]Cohen and Land's (1987) paper predicting homicide and motor vehicle theft rates in the U.S. also failed to find a period effect, and successfully modeled these crime rates without including a period effect.

parameters). The Greenberg and Larkin (1985) and Steffensmeier et al. (1987) studies unfortunately demonstrate how the parameterization of age-period-cohort models can provide potentially unreliable and inconsistent results, which has long been a basis for criticizing these models (Mason and Fineberg 1985). Since these papers conflict on whether periods or cohorts can alter age-specific offending, it is unclear whether they provide evidence for or against the invariance hypothesis.

The recent research on age and crime tends to agree on the importance of age when looking at the level of crime in a society. However, differences remain regarding what factors, if any, explain the shape and/or stability of the age-crime curve. Although some researchers have attempt to statistically differentiate age-crime distributions by gender (Farrington 1986), offense (Steffensmeier et al. 1989), and time (Steffensmeier et al. 1989), the results have yet to convincingly demonstrate that the age distribution of crime is either variant or invariant. The confusion over the variance-invariance of the age distribution of crime is further increased in the case of Steffensmeier et al. (1989) when they invalidly compare two different types of data to reach their conclusion of variance over time. Additionally, those researchers testing for period and cohort effects (Greenberg and Larkin 1985; Steffensmeier et al. 1987) present evidence that questions, more than supports, the importance of such effects. The argument has been that period and cohort effects lead to different levels of criminality from one generation to the next, meaning the age distribution of crime cannot be invariant. The results presented above are model dependent and inconsistent, however, providing no clear evidence for or against the invariance hypothesis. The research on age and crime suffers many problems – some logical (e.g., Farrington's (1986) curve fitting exercise that showed invariance while he concluded variance), some methodological (e.g., Steffensmeier et al.'s (1989) possibly inappropriate comparison of arrest data), some statistical (e.g., Greenberg and Larkin's (1985) and Steffensmeier et al.'s (1987) model parameterization) – and has failed to resolve whether the age distribution of crime is stable over time.

Two additional methodological problems inhibiting advancement in this research, not yet discussed, concern the misunderstanding of the dependent variable and failure to use data from other than official sources. First, with the exception of Farrington's (1986) Appendix and Steffensmeier et al.'s (1989) analysis, every other paper uses arrest *rates*. Clearly, arrest rates vary from one year to the next – not just by age group, but for the entire population. More importantly, the problem with using age-specific arrest rates is that rates miss the emphasis on the *distribution* of arrests, which is really the key notion behind the invariance hypothesis. Age-specific arrest rates, alone, cannot provide the answer to whether the age distribution of crime is the same or different, although this has been the most common means of testing the invariance hypothesis. Conversely, using a simple proportion of total arrests for each age group as a measure of the age distribution of crime will also be inadequate, since larger population groups will invariably account for larger proportions of total arrests without having offended at a higher rate.

Second, all the recent research claiming to test Hirschi and Gottfredson's invariance hypothesis has used official statistics. No study has used self-report data as another source to either validate or reject Hirschi and Gottfredson's claim of a stable age distribution of crime. If the invariance argument is valid, then it should hold for self-report as well as official data. The following analysis thus attempts to correct for these problems, bringing some standardization to the research on age and crime, and advancing our understanding of the stability or variability involved in this relationship.

THE CURRENT STUDY

Of primary concern in this analysis are three specific hypotheses derived from Hirschi and Gottfredson's (1983) general invariance proposition. First, does the age distribution of crime have the same shape over time and across data set? If the distributions are virtually the same, then support for invariance hypothesis would be implied, since different social and cultural conditions did not affect the age distribution of crime. Second, given a specific age group, is there any substantial variation in that age group's criminal activity over time? If age groups do not account for similar levels of crime over time, there is evidence against the invariance hypothesis since each age group's level of offending is not constant. Third, given birth cohort, does each cohort follow a similar pattern of offending? If different birth cohorts follow similar patterns of age-specific offending, invariance is suggested, since other social factors have not altered the general shape of the age distribution of crime for individuals born in different years.

Samples

The *Uniform Crime Reports* (*UCR*) data are limited to those years where the FBI used arrest reports to construct the age-specific arrest distributions. The period, 1952 to 1987, represents the longest possible range for a valid longitudinal comparison of age-specific arrests. Since the

FBI's use of fingerprint cards prior to 1952 resulted in systematic underreporting of juvenile arrests, any comparison of pre- and post-1952 age-specific arrest data is likely to be misleading (cf. Steffensmeier et al., 1989).

The data from the Bail Decisionmaking Study (BDS) provide another source of official crime information on the relationship between age and crime. This study, conducted by Goldkamp and Gottfredson in Philadelphia (see Chapter 2 for details), was restricted to 4,792 individuals aged 18 and older.[5]

The relationship between age and crime can be tested in three ways with the BDS. First, by simply looking at the age distribution of offenders in the sample. Because the sample was selected on the bases of charge severity and judge, the ages of the offenders in the sample should be representative of the general court population in Philadelphia at the time this data set was collected. Second, given that the offender was released from jail prior to any subsequent court appearances (n=4,307), we can examine the age distribution of Failure-to-Appear (FTA). In other words, the focus of this second analysis is on an additional violation committed by the offender following arrest and becoming part of the BDS sample. Namely, did the offender fail to show up for at least one required court appearance? A conventional 120-day follow-up period after arrest is used here, since offenders who are likely to FTA will do so in this time (Gottfredson and Gottfredson, 1988). Third, and similar to FTA, is a focus on whether the individual was rearrested for a new crime (not

[5]In the originial sample of 4,800 offenders, there were only 7 persons younger than age 18, which would provide a base far too small for subsequent analysis. Therefore, these 7 cases were removed from the sample. Additionally, there was one other case where the age of the individual was missing.

associated with an FTA) in the 120 days following the initial arrest.

The National Youth Survey (NYS) and Seattle Youth Study (SYS) contain a variety of self-report delinquency items. In an attempt to make a general delinquency measure comparable across these two data sets, in addition to being compatible across all four waves of the NYS, a list of 15 self-report delinquency items provides the source of information for the analyses below. Unfortunately, of the 37 original delinquency items in the NYS, 12 were omitted from nearly one-half of the questionnaires administered for Wave 2. Thus, any longitudinal comparison of a general delinquency scale is by necessity limited to the remaining 25 items. This list was then further reduced when it was compared to the items in the SYS. Thirteen items were found to have virtually the same wording, and two other items were the same except for the value of the dollar amount that was stolen.[6] One major difference in the wording of the NYS and SYS questions concerned whether individuals had committed the act in the last year (as asked in the NYS) or whether individuals had ever committed the act (as asked in the SYS). As seen below, this difference has a substantial effect on the shape of the age-crime curve.

Measures

Given the problems with arrest rates and simple proportions noted above, the *PAI* (Percent Age Involvement) suggested by Steffensmeier et al. (1989) is used here. The *PAI* represents the proportion of total arrests accounted for by each age group (i.e., a simple proportion),

[6]These 15 items are: Theft of an item worth $2 or less (SYS) or $5 or less (NYS), Theft of an item valued between $2 and $50 (SYS) or $5 and $50 (NYS), Theft of an item worth more than $50, Fighting, Purchasing stolen property, Runaway, Carried a hidden weapon, Hit a teacher, Hit a parent, Sold drugs, Joyriding, Sexual assault, Used physical force on others to get what you want, Stolen school property, Break in.

standardized for the proportion of the total population in that age group, and is scaled to range from 0% to 100%. An identical measure was used by Thompson, Bell, Long, and Miller (1989) to compare age distributions of fertility.[7] Thus, following the work of Steffensmeier et al. (1989) and Thompson et al. (1989), the *PAI* for arrests is directly related to age-specific arrest rates,[8] and calculated as

$$PAI_{ij} = \frac{r_{ij}}{\sum_{i=15}^{49} r_{ij}} * 100,$$

where r_{ij} is the age-specific arrest rate, and PAI_{ij} is the Percent Age Involvement for age group i in year j.[9]

For ease of interpretation, these results are presented in both tabular and graphical form. The emphasis on graphs, rather than a more sophisticated statistical analysis, is based on the dubious quality of many prior age and crime analyses that have been statistically oriented.[10] The following analyses are an attempt to present a more fundamental description of the relationship between age and crime.

[7]Rapoport (1983, pages 37-38) also derived a measure similar to the *PAI* to compare age-specific fertility distributions, rather than age-specific fertility rates.

[8]To compute the age-specific arrest rates, the number of arrests for all crimes for each age group was divided by the estimated resident population for that age group, as published by the Census Bureau (1965, 1974, 1981, 1987). Following the work of Steffensmeier and Harer (1986), the age-specific arrest rates were calculated as:

$$r_{ij} = \frac{A_{ij}}{P_{ij}} * 100,000,$$

where A_{ij} represents the number of arrests in age group i (15,16,...,23,24,25-29,30-34,...,45-49) and year j (1952,1953,...,1987), P_{ij} represents the estimated population in age group i and year j, and r_{ij} represents the age-specific arrest rate per 100,000 people for age group i in year j. Additionally, all five-year age groups are represented by the midpoint for the range of ages.

[9]Appendix A presents a derivation of the *PAI* equation to show how it is, in fact, a standardized proportion.

[10]According to Long and Fox (1989/90), this is unfortunately a widespread problem.

FINDINGS

Cross-Sectional Age-Crime Curves

Uniform Crime Reports. Table 3.1 presents the *PAI* values for each age group for the years 1952 to 1987. Figure 3.1 shows the age distribution of total crime for the years 1952, 1963, and 1987, using the *PAI*. These three years are used for both clarity of presentation and to illustrate the change in the shape of the age-crime curve. Plots of the *PAI* for each year from 1952 to 1987 showed a shift in the shape of the age distribution of crime from being nearly equally distributed among older persons (age 20 and older) to being concentrated among youths. From 1952 to 1962, the peak age of offending was either 21 or 24-years-old (except in 1961 when the peak was 18-years-old), and the rate of decline in age-specific offending following the peak was slight – the curve for 1952 is representative of the 1952 to 1962 time period. After 1962, the peak age of offending was between 16 and 18-years-old, without exception, and the rate of decline following the peak age was also quite comparable, although not identical. Interestingly, from 1965 to 1973, the peak age was 16-years-old, while the peak was 18-years-old for the 1974 to 1987 time period. The plot for the 1963 age distribution of crime in Figure 3.1 represents the transition in the age distribution of crime to being youth dominated, and the plot for 1987 is representative of the age-crime curves between 1963 and 1987.

What the results in Figure 3.1 mean, is that an apparently substantial shift in the age distribution of crime occurred between 1952 and 1963, but has remained quite stable since 1963 by having nearly the same peak age of offending, and a similar rate of decline following the peak in every year. While these results do not clearly confirm or refute the invariance hypothesis, there was considerable stability in the shape of the age distribution of total crime from 1963 to 1987, suggesting more substantive support for a stable age distribution of crime. Additionally, it is unclear at this point whether the observed change in the shape of the age-crime curve between 1952 and 1963 is a result of social changes or improvements in the FBI's data collection procedures. (This issue is discussed below.)

Bail Decisionmaking Study. Table 3.2 presents the proportion of the sample in each age group, in addition to the PAI values for FTA and Rearrest. Figures 3.2 through 3.4 are based on Table 3.2.

Figure 3.2 displays the proportion of offenders in each age group in the BDS sample. Interestingly, the peak age represented in the sample is 18-years-old, which is the same peak age in the *UCR* from 1974 to 1987. Again, given that age was not a criteria used in the selection of the sample, it is striking how similar the shape of the curve in Figure 3.2 is to the 1987 *UCR* curve in Figure 3.1. This suggests that the pattern of age and crime found in the *UCR* is then not simply an artifact of the FBI's aggregation of national crime statistics, as some have argued (see, for example, Blumstein et al., 1988a). Further, the BDS sample was found by Goldkamp and Gottfredson to have been charged with slightly more serious offenses, compared to the entire population of offenders in the Philadelphia court system, meaning that the severity of initial charge has not altered the proportional age involvement in crime in the BDS.

Figure 3.3 displays the PAI values for FTA. From ages 18 to 57, there is an overall decline in the PAI, although in some cases, there is substantial variation from one age group to the next. Between ages 57 and 68, there is wild variation in the PAI, where the values range from

0.0 to slightly under 2.5% at 67-years-old. Then, for age groups over 67, the PAI has a value of 0.0%. This graph suggests that it is older individuals who are more likely to be high risks for FTA. This conflicts with other knowledge about FTA, and the other age distributions of crime presented thus far. However, as discussed below, a possible reason for the apparently high level of age-specific FTA among older individuals may still be due to relatively small numbers of these individuals.

Figure 3.4 displays the PAI values for Rearrest. Overall, the same pattern found in Figure 3.3 is observed here, although there is less variation in the PAI from one age group to the next, except for 69-year-olds. Thus, again, the pattern of age-specific illegal activity does not conform exactly to expectations of a continual decline across the older age groups.

If the extreme PAI value changes in Figures 3.3 and 3.4 are simply a function of small group sizes, then grouping the data for older age groups should smooth out the variation seen in Figures 3.3 and 3.4. Table 3.3 presents the PAI values for the grouped data. To keep these results comparable to those for the UCR, the same age categories are used through age 49, followed by an age group that includes all offenders 50-years-old and above.

Figure 3.5 shows the plot of the PAI values for FTA using the grouped data. While the plot is not identical to the UCR and first BDS age-crime curves, there is clearly a steady trend toward decreasing FTA activity as individuals age that is comparable across graphs. The PAI values for Rearrest are shown in Figure 3.6, and demonstrate an even more pronounced decline in the level of rearrest for older age groups. Thus, much of the variation seen in Figures 3.3 and 3.4 was indeed removed by grouping the data in a way consistent with the *UCR* categories, which make the results appear more similar to previous plots than was apparent when the data were not grouped for older age groups.

National Youth Survey and Seattle Youth Study. Table 3.4 displays the proportion of each age group reporting at least one delinquent act along with the *PAI* values for both the NYS and SYS. The values in Table 3.4 are plotted in Figure 3.7. All four of the NYS curves show a peak at either 15- or 16-years-old. Clearly, the *PAI* values are not identical across waves of the NYS. However, there is remarkable consistency in the shape of the age distributions of crime and delinquency. Thus, while the peak age of offending in the NYS is different from that found in the *UCR*, there remains a great deal of similarity in the overall shape of the curves.

The SYS age-crime curve is flat and does not follow the same pattern as presented in the other data sets. The reason for this, as suggested above, may be found in the wording of the questions. The NYS delinquency items ask whether the act has been committed in the last year, whereas the SYS items ask whether the act has *ever* been committed. Initially, this distinction did not seem to be important to assessing the relationship between age and crime, but the SYS age distribution of delinquency curve in Figure 3.7 suggests otherwise. In Table 3.4, the percentage reporting that they had ever committed a delinquent act was either 90% or 92%, meaning that by the age of 15, nearly everyone who was going to commit a delinquent act of some type, had already done so. One implication raised by this SYS finding is that questions worded as "ever" will not give age-specific distributions that are comparable to those found in other studies. A theoretical implication of the SYS results, discussed in more detail below, concerns researchers who are searching for the onset of crime and delinquency. If the samples used in such studies do not include very young individuals, onset will likely have already occurred.

Age Group and Cohort Offending Patterns

Uniform Crime Reports. Figures 3.8 and 3.9 display the *PAI* values for ages 15 to 19 and 20 to 24, respectively, for the years 1952 to 1987. Among the 15 to 19-year-olds, there is some variation across the 1952 to 1987 time period. With the exception of 19-year-olds, each age group's low *PAI* value occurred in the early 1950s, and increased gradually throughout the 1960s, peaked in the early 1970s, and has either gradually declined or remain relatively constant since then. Nineteen-year-olds followed the same pattern of age-specific offending through the early 1970s, but their proportional involvement has continued to slightly increase, rather than decline. Restricting the time period to 1963 to 1987, based on the stability of the annual distributions, reveals a somewhat stable pattern. There are differences in the yearly *PAI* values, but the magnitudes of these variations are relatively small (most less than 1%).

Offending among 20 to 24-year-olds fails to reveal any pattern. Throughout the 1950s and 1960s, the *PAI* values increased and decreased in no consistent way. Since 1970, there has been a small increase (again less than 1%) in the *PAI* values for all five age groups. Overall, then, from 1952 to 1987, the level of age-specific offending for individuals aged 20 to 24 was quite stable.

Given the apparent stability in age-specific offending among 20 to 24-year-olds, and the slight increase among 15 to 19-year-olds, there must have been a decline in older individuals's offending in recent years – since a distribution must sum to 100%. Figures 3.8 and 3.9 also reconfirm the pattern discussed in Figure 3.1 – that there was an apparently substantial change in the level of age-specific offending among individuals less than 20-years-old and over 24-years-old between 1952 and 1963. At the same time, Figures 3.8 and 3.9 also show considerable stability in the level of age-specific offending between 1963 and 1987.

Figure 3.10 presents the plot of the *PAI* values for four different birth cohorts for the ages 15 to 24. These four cohorts cover the thirty-six year period from 1952 to 1987. Cohort 1 consists of individuals aged 15 in 1952, Cohort 2 consists of individuals aged 15 in 1961, Cohort 3 consists of individuals aged 15 in 1970, and Cohort 4 consists of individuals aged 15 in 1978. The rationale for limiting the analysis to this age range (15 to 24 years) is twofold. First, each age group is made up of persons exactly the same age (i.e., same birth cohort), rather than a mix of persons with different ages from different birth cohorts (e.g., persons aged 25 to 29). Second, the argument in favor of cohort effects suggests that each cohort may follow a different pattern of criminal activity. If this is the case, the shape of the curves should be substantially different for these four cohorts.

The curves in Figure 3.10 demonstrate that cohort does have some effect on the magnitude of age-specific offending. Three patterns are especially noteworthy in Figure 3.10. First, Cohort 1 does not peak in its age-specific offending until it is 21-years-old. This is different from the other three cohorts, which show a peak at either 16 (Cohort 3) or 18-years-old (Cohorts 2 and 4). The fact that Cohort 1's peak age of offending occurred at a later age than in the other three cohorts is again consistent with the apparent shift in the age distribution of crime to younger offenders between 1952 and 1963.

Second, while there appear to be rather large differences in the PAI values for the 15 to 20-year-old age groups, the differences in PAI values for 21 to 24-year-olds is near 1% for each age group. For 21-year-olds, the range between minimum and maximum PAI values is 1.1%. Similarly, the ranges are 0.9%, 0.8%, and 1.0% for 22 to 24-year-olds, respectively. Again, this suggests that age-specific offending for individuals in their 20s has remained fairly stable, which is also consistent with the results presented in Figure 3.9.

Third, with the exception of Cohort 1, the other cohorts follow essentially the same pattern of age-specific offending. The PAI values are obviously different (although by no more than 0.5% for Cohorts 3 and 4), but the shape of the curves describing the pattern of age-specific offending for Cohorts 2 through 4 are approximately the same. The differences in the magnitudes of the PAI values mean that age-specific offending has changed some over time, but the shapes of the curves in Figure 3.10 also reveal that similar peak ages of offending and rates of decline following the peak occur for cohorts with different PAI values. The increasing similarity in the pattern of offending for more recent cohorts also suggests a trend toward stability in the age distribution of crime. It should also be noted that if other cohorts's PAI values were plotted, there would be a clear tendency toward more recent cohorts showing a similar pattern of offending – see any set of diagonal values in Table 3.1.

National Youth Survey. Figures 3.11 and 3.12 display the age group and cohort plots for the NYS, following the same logic of presentation as in Figures 3.7 through 3.9.[11] The age group plots in Figure

[11]Two data points were omitted from Figure 3.11, because they occurred only once.

3.11 show the level of age-specific delinquency to be quite similar over the four years of NYS data. The values are not identical, but there are no wild fluctuations from year to year that would suggest the values are not stable, overall. Interestingly, the stability of age-group offending in the NYS corresponds well with the pattern of offending displayed in the *UCR*.

Figure 3.12 shows the seven cohort plots. Remarkably, the pattern of offending exhibited by each of the cohorts is quite similar. The cohorts aged 16-years-old and younger in Wave 1 all have a peak age of offending at either age 15 or 16, followed by a similar decline in age-specific offending over the four year period covered by the NYS.

SUMMARY AND CONCLUSIONS

These analyses have tested the invariance proposition in three ways. First, cross-sectional plots of the age distribution of crime were examined to see whether the curves had the same shape in every year from 1952 to 1987 in the *UCR*, and in the other three data sets. Although the shapes of the curves were not identical, the findings above indicate that the age distribution of crime in the U.S. has been stable since 1963, but shifted between 1952 and 1963 from being approximately equally distributed among older offenders (age 25+) in 1952 to being concentrated among younger offenders since 1963. The age-crime curves found in the other three data sets provided supporting evidence for the stability observed in the *UCR* data. The curves, in nearly every case, approximated the shape of the *UCR* results, implying that the age distribution of crime is stable over time and type of data used.

These are 11-year-olds in Wave 1 and 20-year-olds in Wave 4.

Second, the *PAI* values for age groups 15 to 24-years-old were examined for the 1952 to 1987 time period in the *UCR* and age groups 12 to 19-years-old in the four waves of the NYS data. The *UCR* graphs confirmed the finding of a shift to younger offenders in the cross-sectional age distributions of crime between 1952 and the mid-1960s. Additionally, while the *PAI* values for 15 to 19-year-olds showed an overall increase between 1952 and 1987, there was virtually no change among 20 to 24-year-olds, and a slight decrease among individuals over age 24. The NYS data contained a more limited range of years to compare age-specific offending, and found these to be quite stable over the four year period.

Third, in the *UCR*, the *PAI* values for four birth cohorts covering the 1952 to 1987 time period revealed that more recent cohorts have tended to similar patterns of offending. Specifically, there were considerably different *PAI* values for cohorts in the teen years, but by age 21, there was less than a 1% difference. Further, the cohort results again demonstrated the stability in offending among individuals aged 21 to 24. In the NYS, no such discrepancy was found when cohort age-specific offending was analyzed, even though the cohorts were compared across ages 12 through 19-years-old, which showed the most variation in the *UCR* results. Interestingly, then, the NYS data show more recent cohorts to have quite similar patterns of offending, validating the similarity observed for Cohorts 3 and 4 in Figure 3.9.

Overall, the findings in this chapter are supportive of the invariance hypothesis. The U.S. age distribution of crime was stable since 1963, following a period of considerable change between 1952 and 1963. While the U.S. age distribution of crime from 1952 to 1987 fails to clearly confirm or reject the invariance hypothesis, the distribution was stable for a much longer period (1963 to 1987) than it was variable (1952 to 1963). However, age-crime curves from the other three data sets also revealed an age-specific pattern of offending comparable to that found in the *UCR*. Taken together, Figures 1 through 12 provide substantial support for a claim that the age distribution of crime is invariant.

Furthermore, a question raised by the *UCR* findings concerns the validity of the data published by the FBI. It is interesting to note how in more recent years, when the FBI's data collection procedures have improved, that more stability in the age distribution of crime has been observed. If the more recent FBI data are indeed more accurate, and not systematically biased in some way (as it was prior to 1952), then there is considerably more support for the invariance proposition, since stability has been observed in the more valid data on the age distribution of crime.

Two methodological findings also emerge from the analyses in this chapter. First, the age relationship with crime does not vary by type of data used. As noted above, the age-specific patterns of offending are quite consistent across data sets. The *UCR*, BDS, and NYS all show basically the same age pattern of offending.[12] Some could argue that since the curves are not precisely the same, it implies that the curves are variable. However, such a position misses the great deal of similarity underlying each of the curves presented in this chapter.

Second, the use of the *PAI* in this analysis has corrected for the common mistake of using arrest rates to test the invariance hypothesis. If

[12]The analyses above also showed the wording of the self-report delinquency questions in the SYS to make those results non-comparable with the other data sets. The lesson learned here is that by the time individuals are 15-years-old, nearly all have committed some kind of delinquent act, making any discussion on the age distribution of crime very difficult.

the emphasis of the invariance hypothesis is on the age distribution of crime, then rates are entirely inappropriate. A distribution is standardized to sum to 1 (or 100%), which is not possible with age-specific arrest rates. Future research on age and crime must then make an important distinction in the measurement of the dependent variable: Is the focus on age-specific arrest rates or the age distribution of crime? Without a clear understanding of the dependent variable, future research will not advance our understanding of the relationship between age and crime.

Table 3.1: *PAI* Values by Age Group and Year.

	Year											
Age	52	53	54	55	56	57	58	59	60	61	62	63
15	4.0	4.0	4.9	5.2	5.5	5.4	4.9	5.0	5.4	4.8	5.4	6.2
16	5.3	5.3	6.1	6.5	6.8	7.2	6.7	6.3	7.2	5.6	7.4	7.3
17	6.0	6.5	6.4	6.3	6.6	7.3	7.2	7.0	7.0	8.2	7.6	8.2
18	6.4	7.0	6.8	6.4	6.8	7.1	7.6	7.5	7.6	8.2	7.5	7.9
19	6.4	7.1	6.8	6.5	6.7	6.8	7.2	7.4	7.8	7.5	7.2	7.7
20	5.6	6.0	6.3	6.3	6.3	6.6	6.8	6.9	7.4	6.4	7.1	6.8
21	7.0	7.1	7.2	7.7	7.5	7.4	7.6	7.6	7.9	7.7	7.7	7.5
22	7.4	7.3	7.4	7.8	7.7	7.2	7.4	7.5	7.4	7.2	7.6	7.2
23	7.4	7.7	7.2	7.5	7.5	7.2	6.9	6.9	7.0	7.3	7.0	7.1
24	7.9	8.0	7.8	7.5	7.4	7.5	7.4	7.3	7.2	7.2	6.9	6.8
27	7.4	7.1	7.0	6.8	6.5	6.3	6.4	6.5	6.1	6.6	6.2	6.0
32	7.2	6.8	6.7	6.6	6.4	6.3	6.3	6.3	5.9	6.5	5.9	5.7
37	7.4	6.9	6.6	6.5	6.4	6.1	6.2	6.3	5.8	6.2	5.8	5.6
42	7.5	6.8	6.7	6.4	6.2	5.9	5.8	5.9	5.4	5.5	5.5	5.4
47	7.1	6.3	6.1	5.9	5.7	5.5	5.5	5.6	5.0	5.1	4.9	4.7

Table 3.1 (Continued)

	Year											
Age	64	65	66	67	68	69	70	71	72	73	74	75
15	7.1	7.7	7.9	8.1	8.4	8.3	8.1	8.5	8.4	8.4	8.5	8.4
16	8.6	8.9	9.5	9.7	9.9	9.7	9.6	9.8	9.8	10.2	9.9	9.8
17	7.5	8.3	8.9	9.5	9.8	9.5	9.5	9.4	9.0	9.5	9.8	9.7
18	8.7	7.5	8.7	9.0	9.5	9.5	9.3	9.2	8.9	9.3	10.0	9.8
19	7.9	8.2	7.1	8.0	8.2	8.4	8.5	8.3	8.1	8.2	8.7	8.9
20	7.2	7.1	7.2	6.3	6.9	7.0	7.6	7.7	7.5	7.6	7.9	8.1
21	7.0	7.3	7.2	7.6	6.6	7.3	7.6	8.0	7.8	7.5	7.5	7.7
22	7.0	6.5	6.8	6.9	7.2	6.4	7.1	7.1	7.6	7.3	7.1	7.1
23	6.8	6.6	6.1	6.5	6.5	7.2	6.0	6.6	6.7	7.0	6.7	6.6
24	6.8	6.5	6.2	5.7	5.8	6.1	6.5	5.4	6.1	6.0	6.3	6.2
27	5.6	5.5	5.3	5.1	4.8	4.8	4.8	4.9	4.8	4.7	4.7	4.7
32	5.3	5.2	5.0	4.7	4.4	4.3	4.2	4.2	4.3	4.0	3.7	3.8
37	5.2	5.2	4.9	4.6	4.2	4.1	4.1	4.0	4.0	3.8	3.4	3.5
42	4.9	4.9	4.7	4.4	4.0	3.9	3.8	3.7	3.7	3.4	3.1	3.1
47	4.3	4.4	4.2	3.9	3.5	3.4	3.3	3.2	3.1	3.0	2.6	2.6

Table 3.1 (Continued)

	Year											
Age	76	77	78	79	80	81	82	83	84	85	86	87
15	8.1	7.8	7.5	7.3	6.9	6.9	6.2	6.1	6.3	6.4	6.1	6.2
16	9.7	9.3	9.3	9.1	8.6	8.4	8.1	7.7	7.9	7.8	7.8	7.5
17	9.4	9.5	9.7	9.7	9.5	9.3	9.1	8.7	8.7	8.8	8.8	8.7
18	9.9	9.7	10.1	10.3	10.2	10.0	9.8	9.4	9.5	9.5	9.8	9.5
19	8.8	8.9	9.0	9.3	9.4	9.3	9.3	9.2	9.1	9.1	9.2	9.3
20	8.2	8.2	8.3	8.6	8.9	8.8	8.9	8.9	8.8	8.8	8.9	8.7
21	7.8	8.1	8.0	8.1	8.4	8.6	8.6	8.6	8.7	8.6	8.6	8.7
22	7.2	7.4	7.5	7.5	7.6	7.7	8.2	8.2	8.0	8.1	8.1	8.2
23	6.8	6.9	6.9	7.0	7.1	7.2	7.4	7.9	7.7	7.7	7.7	7.8
24	6.3	6.3	6.4	6.4	6.6	6.7	7.0	7.1	7.3	7.3	7.2	7.4
27	4.8	5.0	5.0	5.0	5.2	5.4	5.6	5.9	5.8	5.9	6.0	6.1
32	3.8	3.7	3.7	3.6	3.7	3.8	4.1	4.3	4.3	4.3	4.4	4.5
37	3.5	3.4	3.3	3.1	3.0	3.1	3.1	3.2	3.2	3.2	3.2	3.3
42	3.1	3.1	2.9	2.7	2.6	2.6	2.6	2.6	2.6	2.5	2.4	2.3
47	2.6	2.5	2.3	2.2	2.1	2.1	2.0	2.1	2.0	1.9	1.8	1.7

Table 3.2: Bail Decisionmaking Study Proportions by Age and *PAI* Values for FTA and Rearrest.

Age	Proportion of Sample	*PAI* for FTA	*PAI* for Rearrest	Age	Proportion of Sample	*PAI* for FTA	*PAI* for Rearrest
18	7.92	1.09	1.48	51	0.70	0.57	0.65
19	7.77	1.17	1.09	52	0.62	0.30	0.93
20	7.10	1.11	1.11	53	0.60	0.61	0.70
21	6.76	0.84	1.17	54	0.63	0.00	1.29
22	5.78	0.95	0.98	55	0.55	0.38	0.87
23	5.27	1.58	1.17	56	0.44	0.00	0.99
24	4.64	1.02	1.03	57	0.39	0.00	0.77
25	4.86	1.32	1.12	58	0.41	0.96	1.10
26	4.15	1.07	0.99	59	0.22	1.83	0.00
27	3.76	1.01	0.73	60	0.33	0.00	0.00
28	3.39	1.12	1.02	61	0.23	0.00	0.70
29	3.05	1.34	0.74	62	0.23	0.91	1.39
30	2.93	1.30	1.28	63	0.16	0.00	0.87
31	3.09	0.87	0.95	64	0.19	1.14	0.00
32	2.38	0.72	0.67	65	0.19	0.00	0.00
33	1.86	1.21	0.84	66	0.21	1.02	1.55
34	1.84	0.96	0.73	67	0.09	2.29	0.00
35	1.88	0.51	0.62	68	0.09	0.00	0.00
36	1.03	1.12	0.71	69	0.14	0.00	4.64
37	1.35	0.74	1.01	70	0.09	0.00	1.74
38	1.10	0.90	0.82	71	0.05	0.00	0.00
39	1.32	1.03	0.67	72	0.05	0.00	0.00
40	1.14	0.83	0.63	73	0.05	0.00	0.00
41	1.13	0.90	1.09	74	0.02	0.00	0.00
42	1.03	1.68	0.85	75	0.07	0.00	0.00
43	0.94	0.61	0.77	77	0.05	0.00	0.00
44	1.32	0.60	0.68	81	0.02	0.00	0.00
45	0.71	0.52	0.40	87	0.02	0.00	0.00
46	1.12	0.33	0.63				
47	0.74	0.54	0.82				
48	0.95	0.41	0.79				
49	0.84	0.47	0.71				
50	0.53	0.73	0.83				

Table 3.3: Bail Decisionmaking Study Grouped Data – *PAI* Values.

Age Group	*PAI* for FTA	*PAI* for Rearrest
18	1.09	1.48
19	1.17	1.09
20	1.11	1.11
21	0.84	1.17
22	0.95	0.98
23	1.58	1.17
24	1.02	1.03
25-29	1.20	0.96
30-34	1.02	0.94
35-39	0.82	0.75
40-44	0.86	0.76
45-49	0.42	0.64
50-87	0.40	0.77

Table 3.4: *PAI* Values for the National Youth Survey and Seattle Youth Study.

Age	NYS Wave 1	NYS Wave 2	NYS Wave 3	NYS Wave 4	SYS
11	0.123				
12	0.141	0.131			
13	0.149	0.132	0.139		
14	0.156	0.144	0.149	0.155	
15	0.156	0.170	0.150	0.159	0.241
16	0.135	0.166	0.167	0.166	0.248
17	0.139	0.133	0.155	0.160	0.264
18		0.124	0.135	0.131	0.247
19			0.105	0.127	
20				0.101	

Figure 3.1: The U.S. Age Distribution of Crime, 1952, 1963, and 1987.

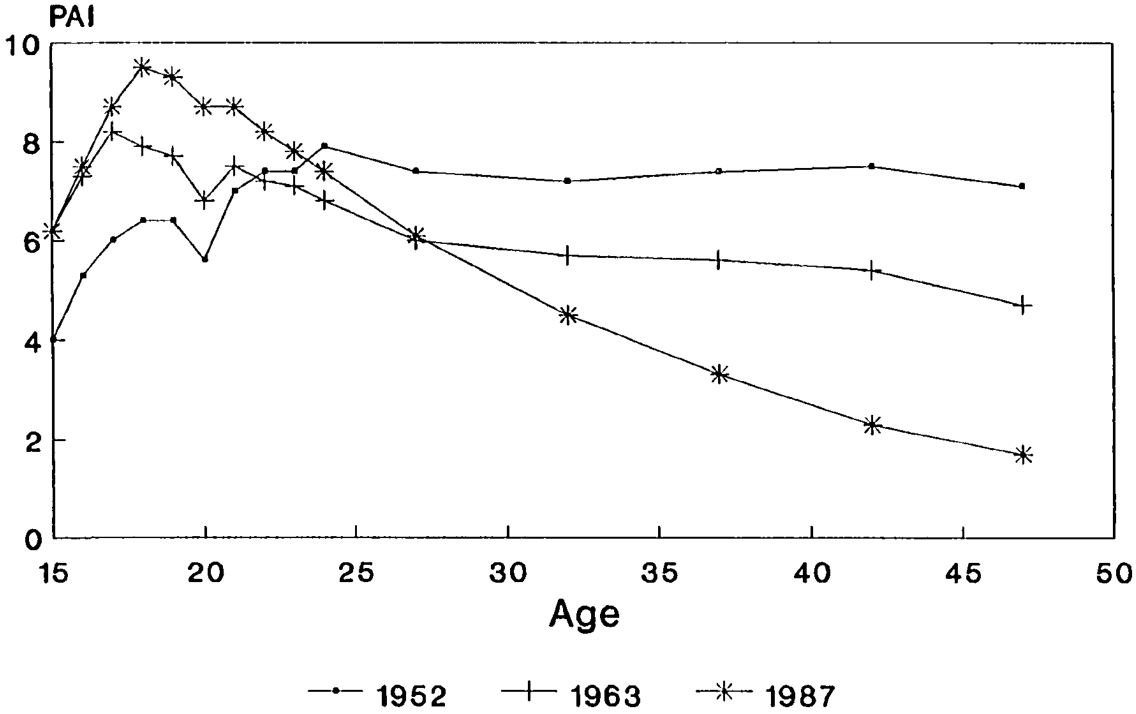


Figure 3.2: BDS Age Group Proportions.

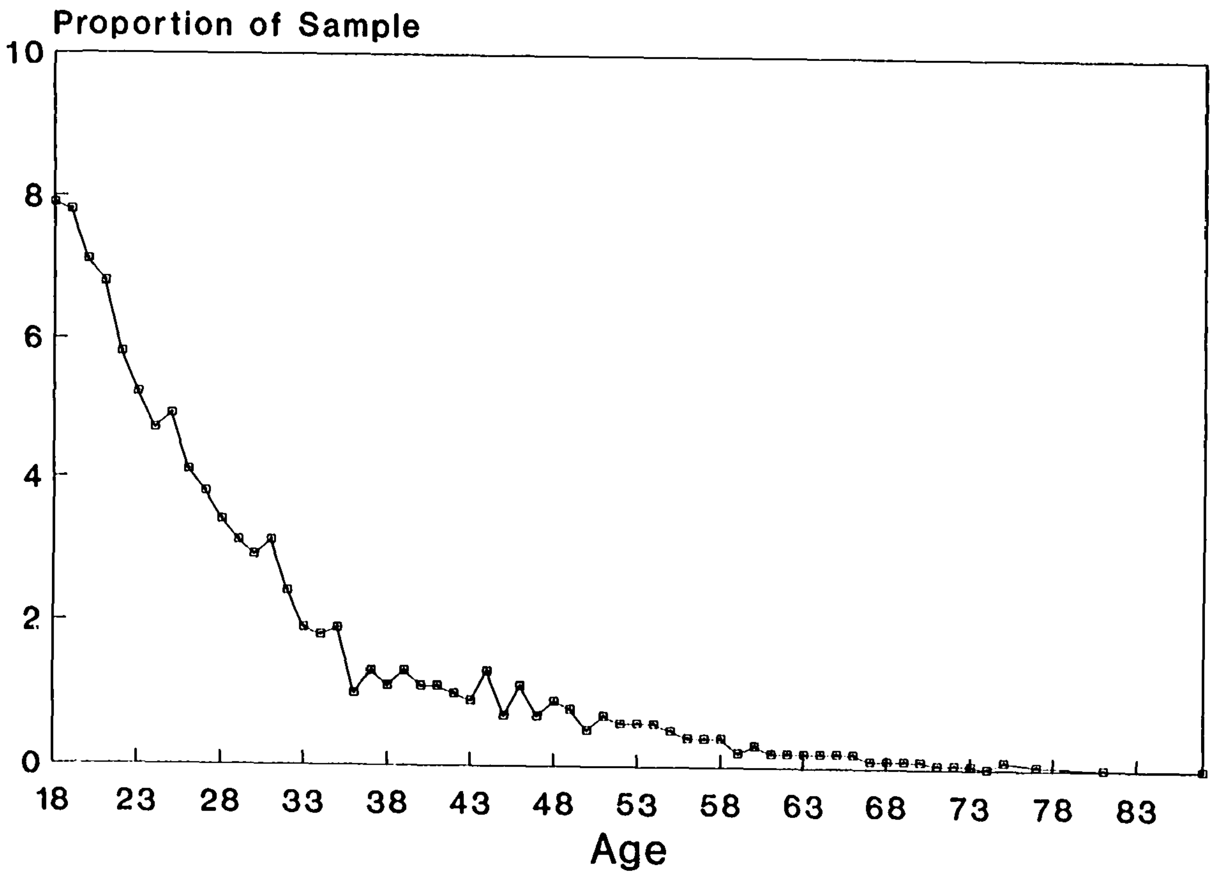


Figure 3.3: BDS PAI Values for FTA.

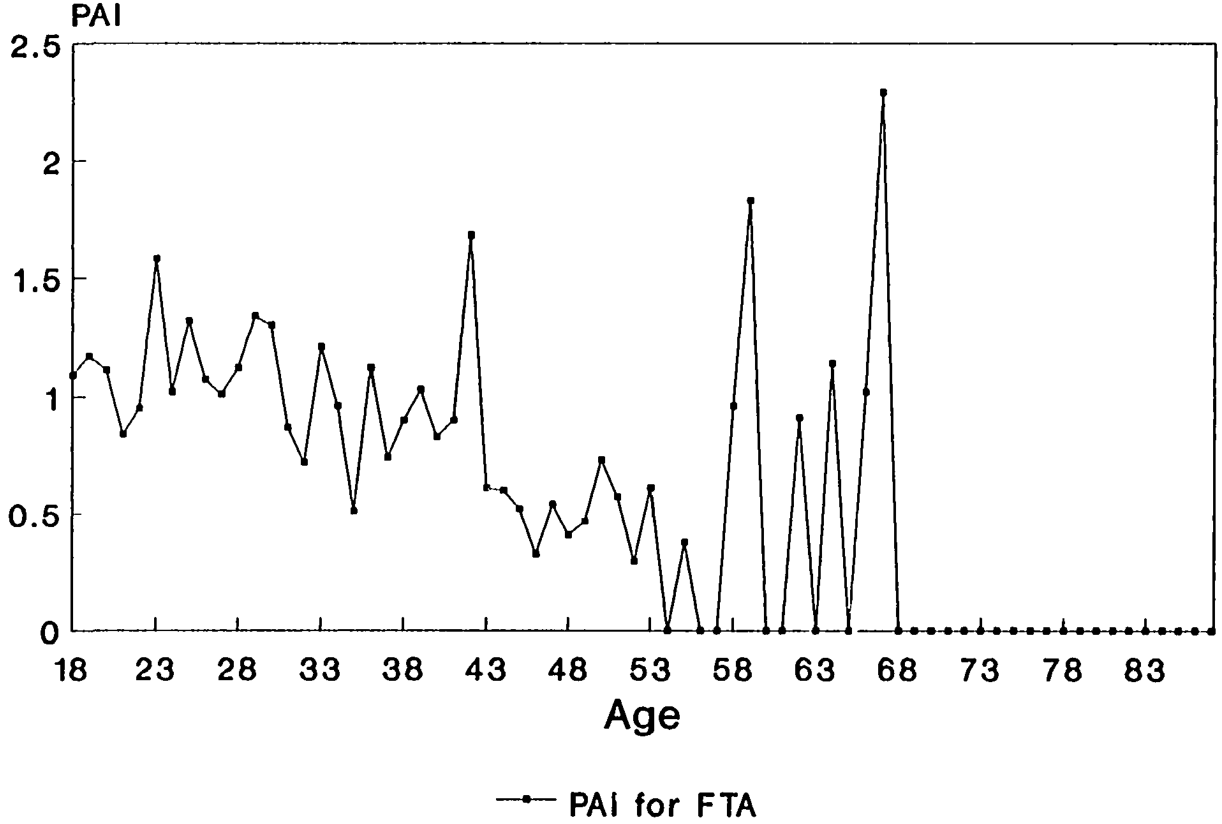


Figure 3.4: BDS PAI Values for Rearrest.

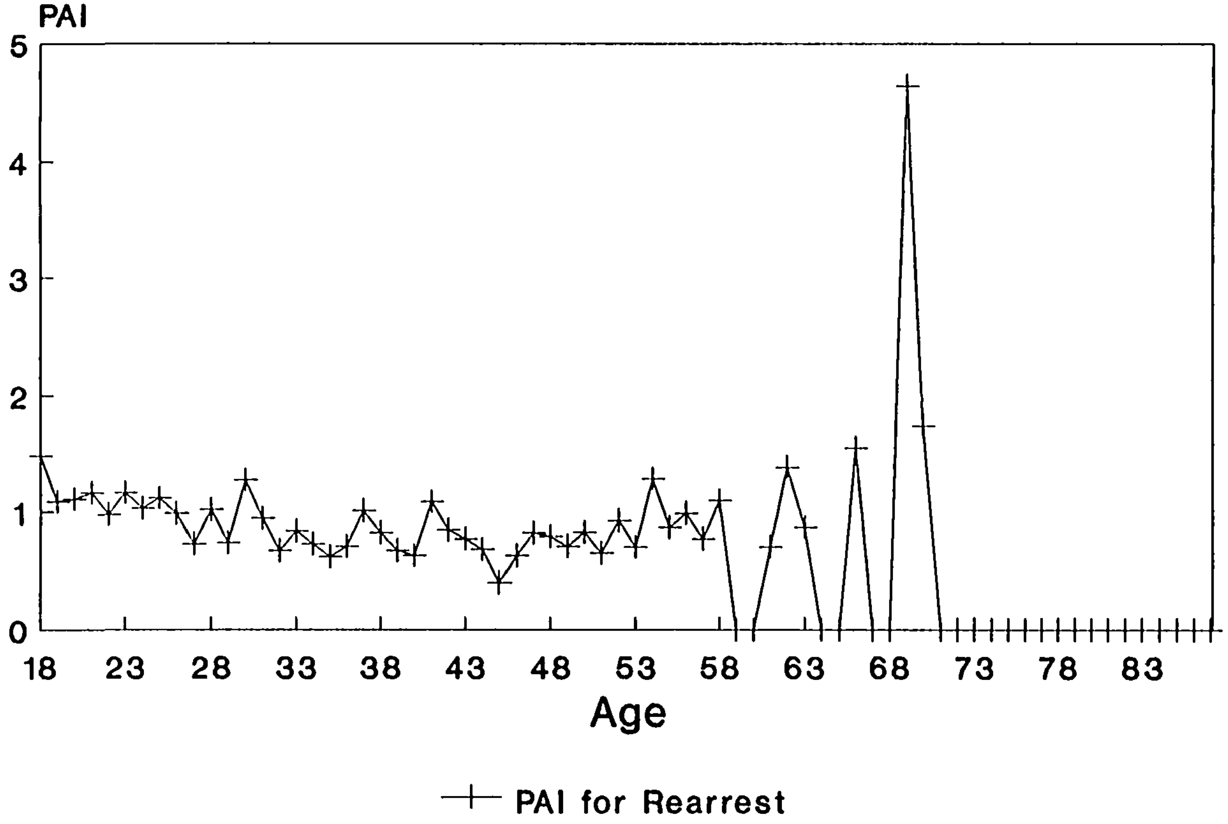


Figure 3.5: BDS PAI Values for FTA,
Grouped Data.

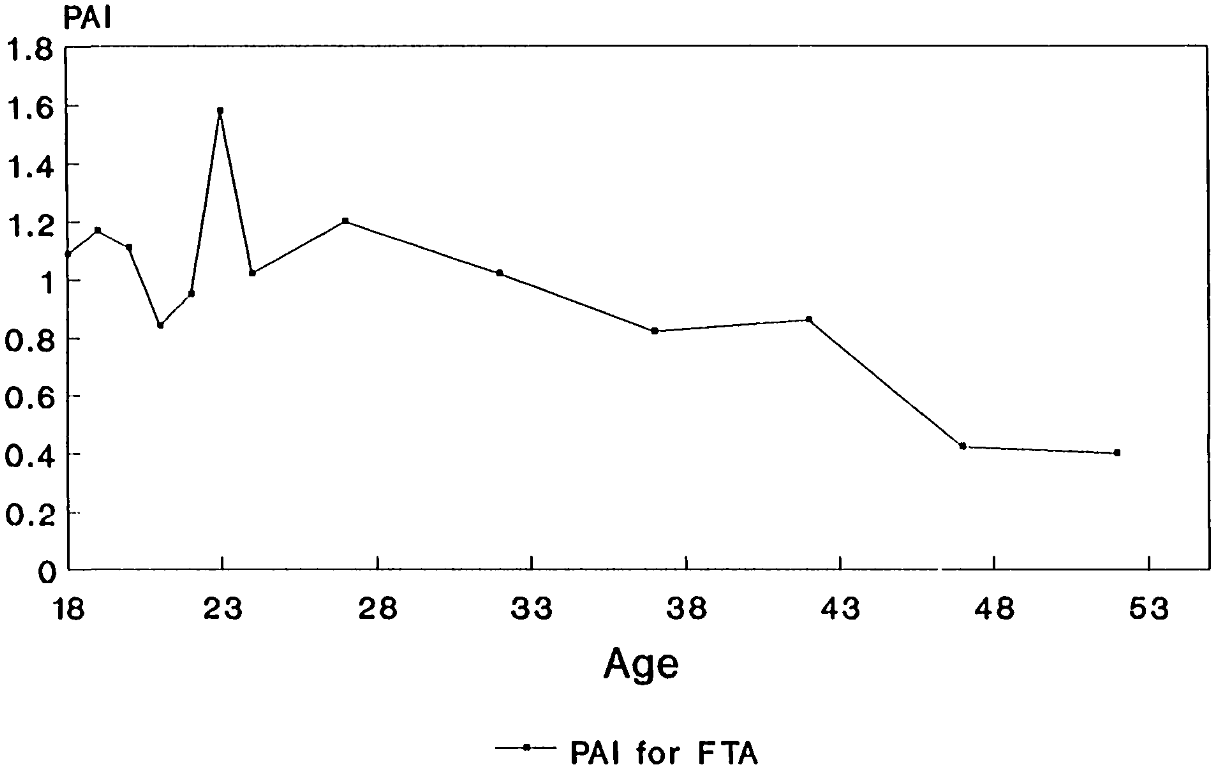


Figure 3.6: BDS PAI Values for Rearrest,
Grouped Data.

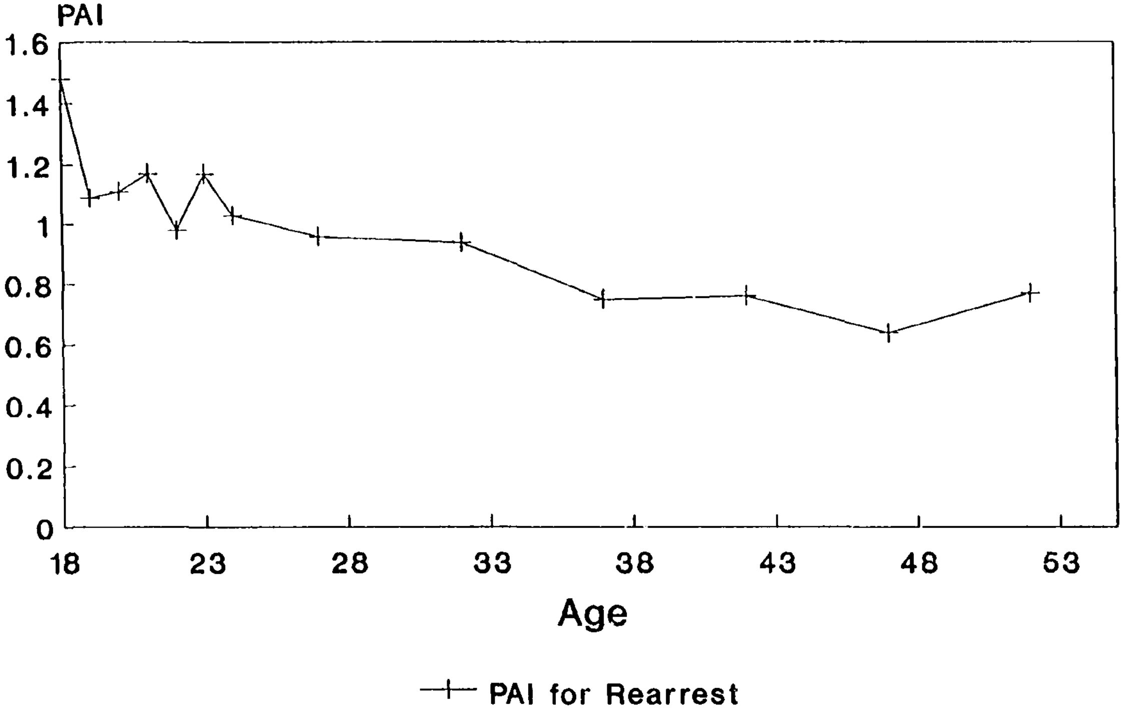


Figure 3.7: NYS and SYS Self-Report PAI Values.

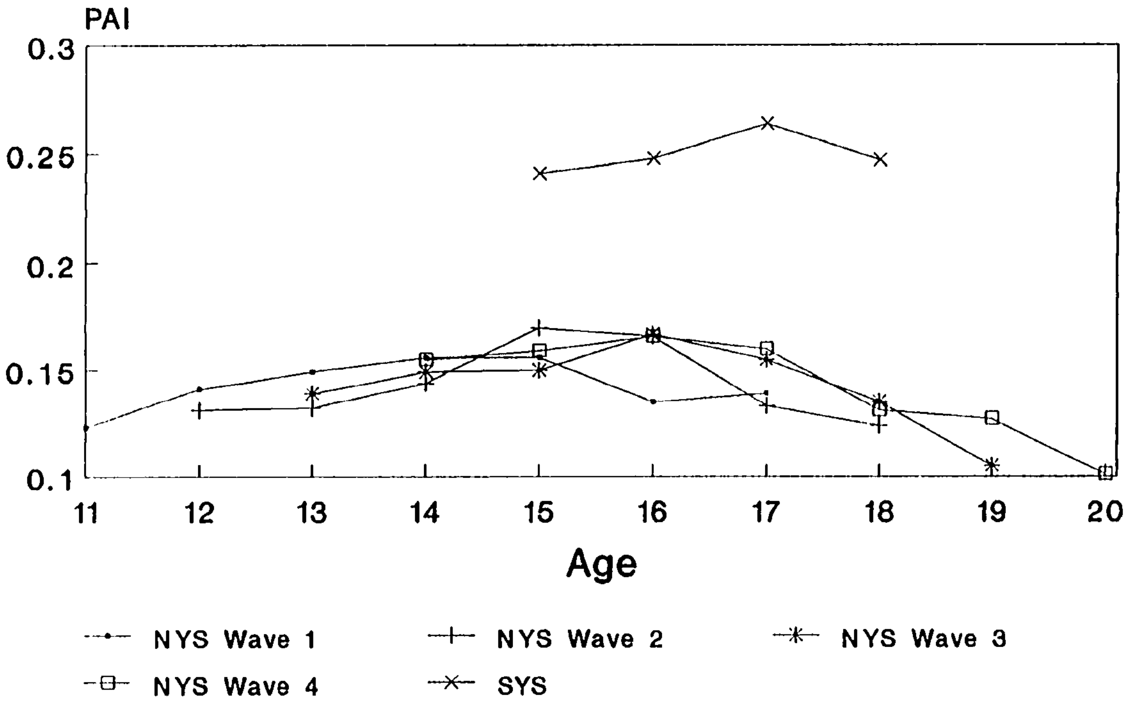


Figure 3.8: PAI Values for 15 to 19-year-olds, by Year.

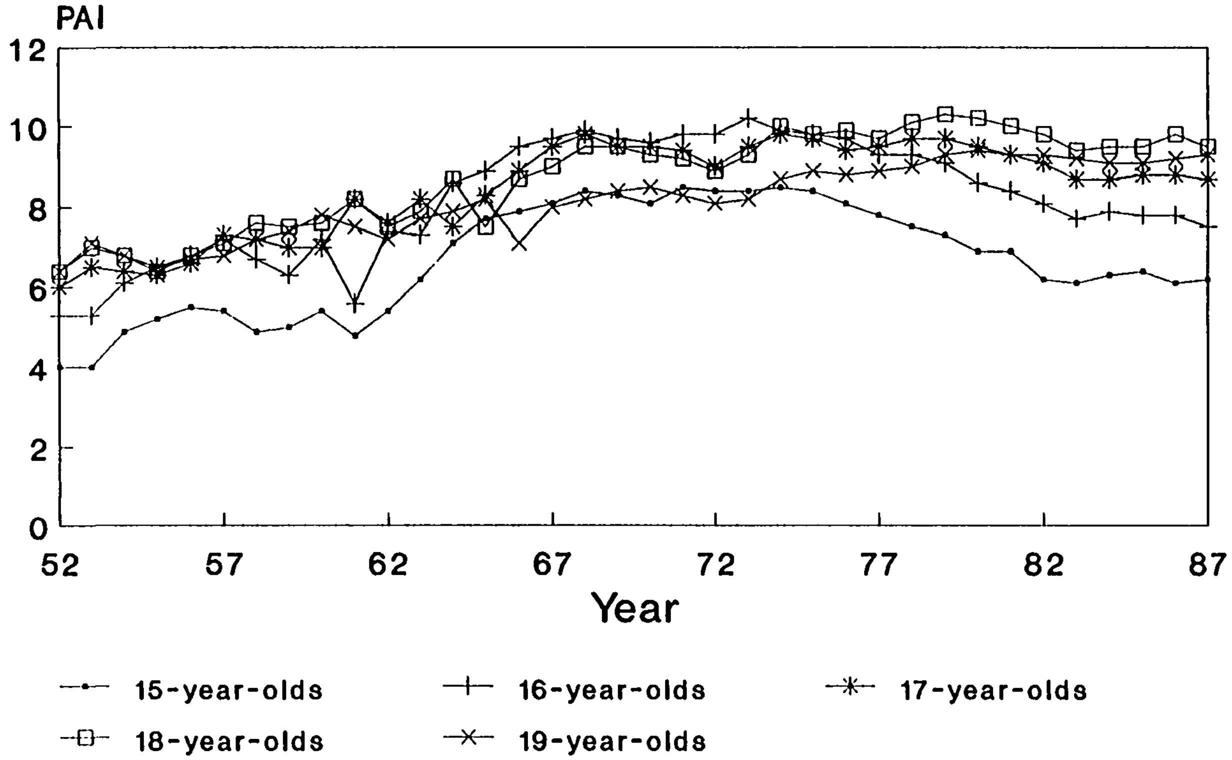


Figure 3.9: PAI Values for 20 to 24-year-olds, by Year.

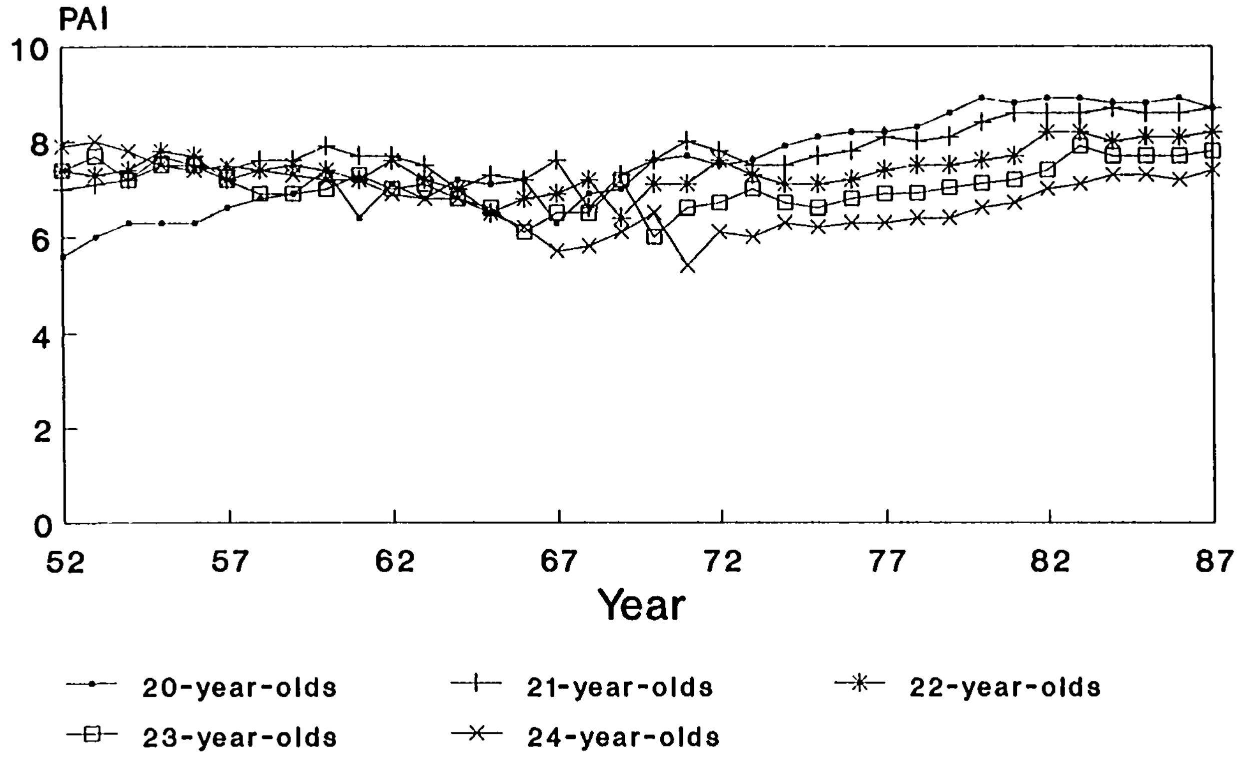


Figure 3.10: UCR Cohort PAI Values.

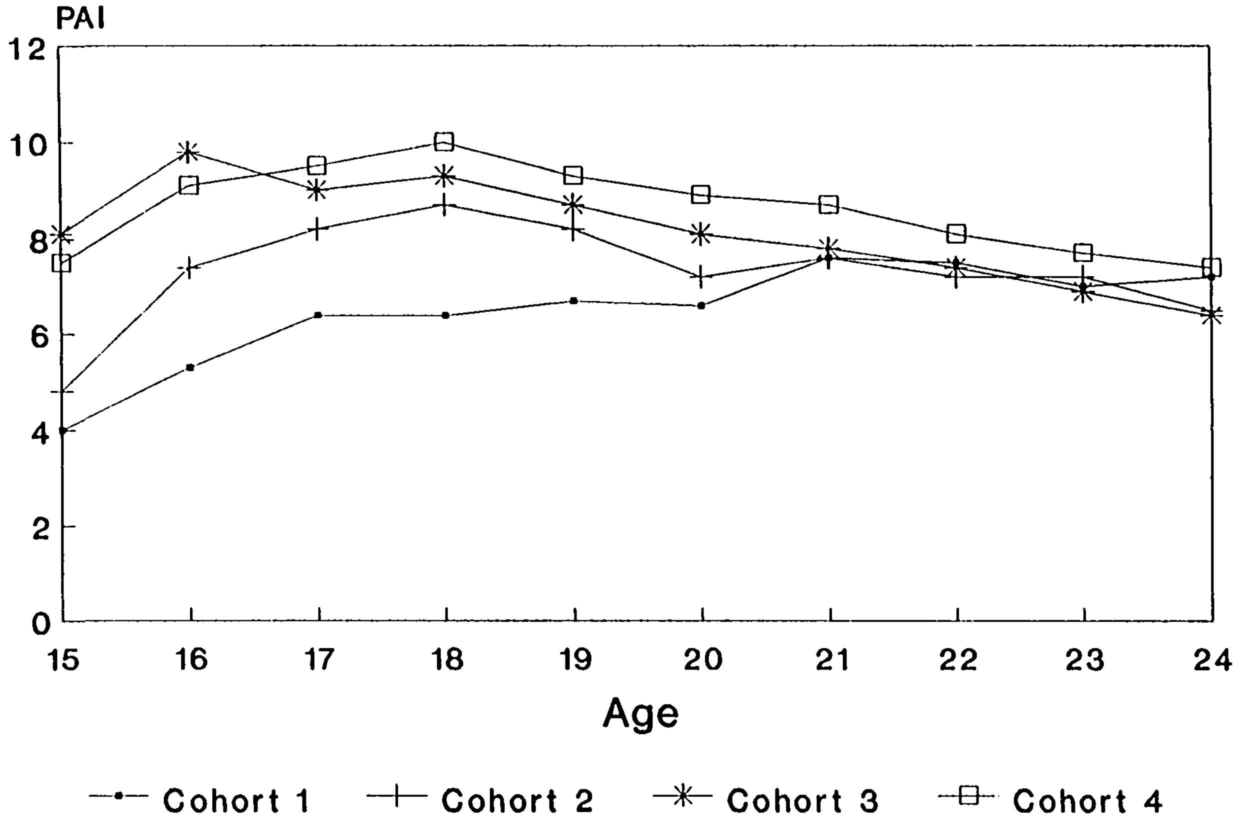


Figure 3.11: NYS Age Group PAI Values.

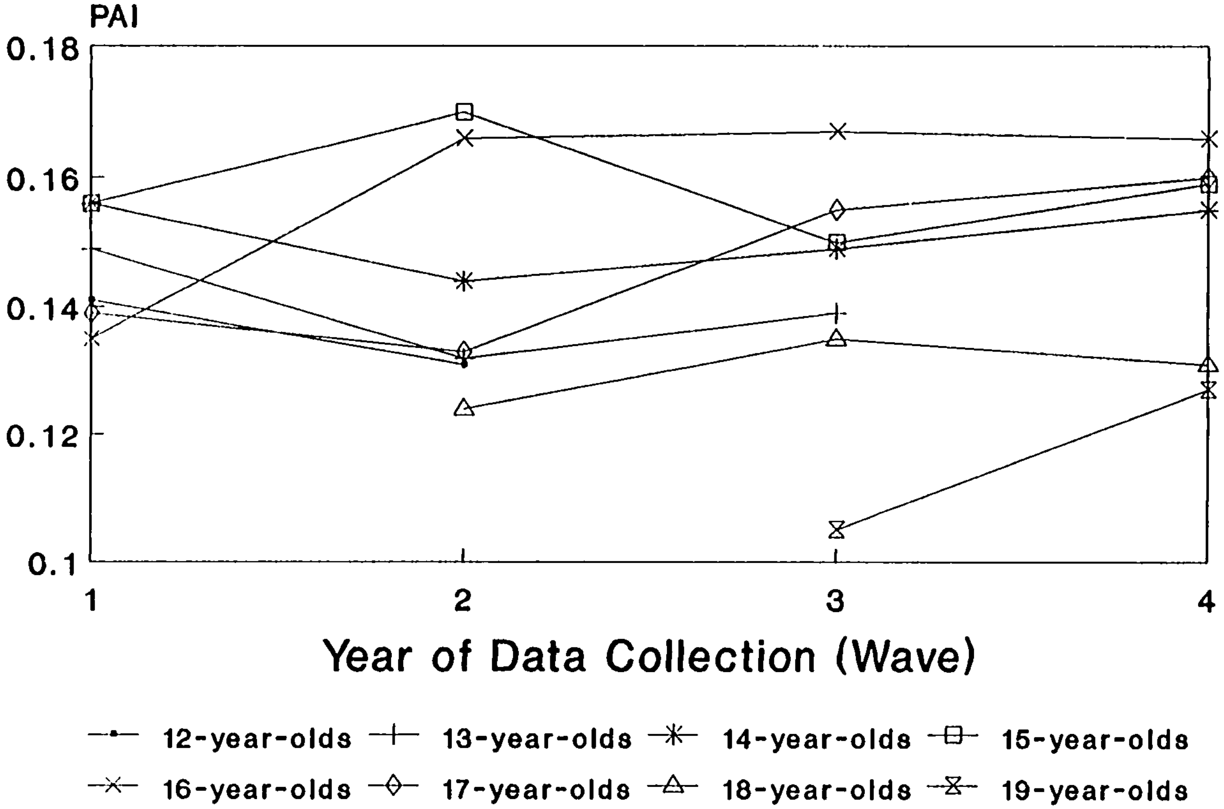
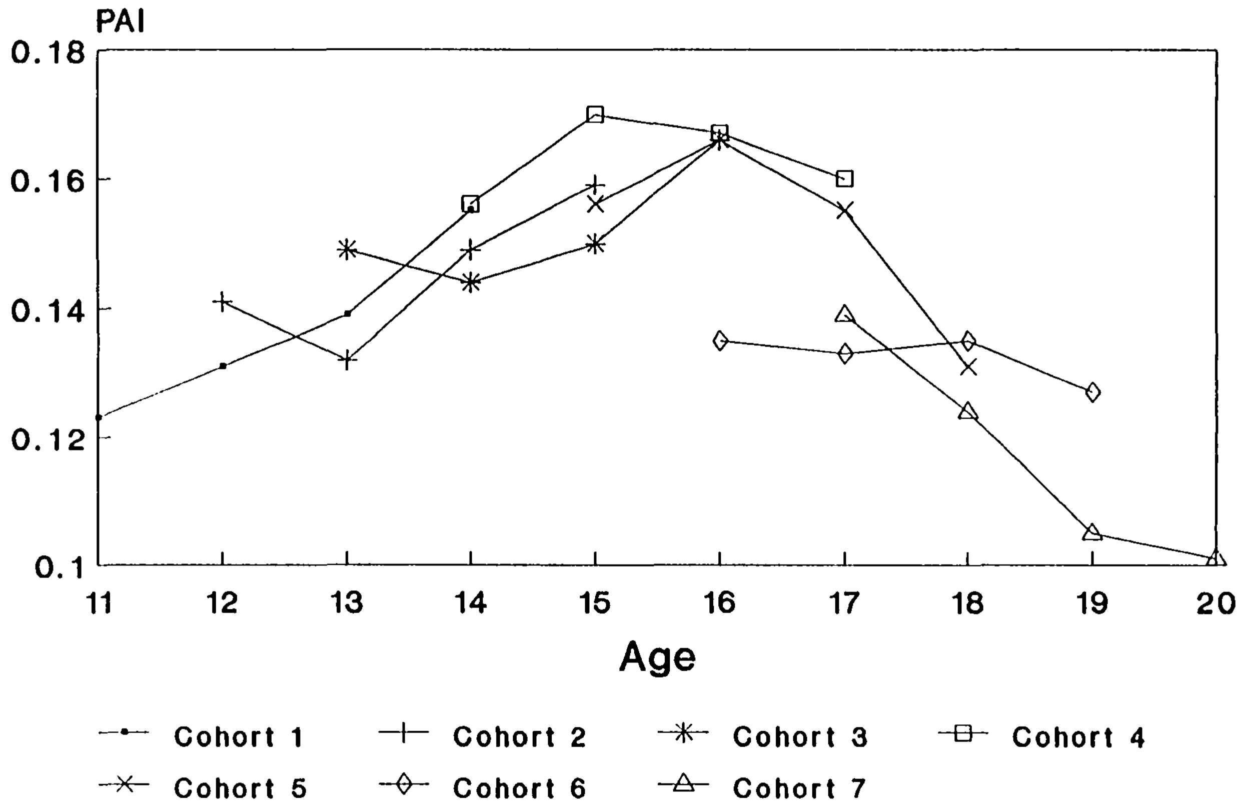


Figure 3.12: NYS Cohort PAI Values.



CHAPTER 4

VERSATILITY IN OFFENDING

INTRODUCTION

A key element of the criminal career paradigm is the notion of specialization in offending, which Blumstein et al. define as the "tendency to repeat the same offense type on successive arrests" (1986:81). Thus, over the course of an individual's criminal career, any single arrest should be predictable on the basis on the most recent prior arrest. However, in partial recognition of the narrowness of this definition, Blumstein, Cohen, Das, and Moitra (1988) revised the definition of specialization to say that offenders will tend to *cluster* the type of their offenses, and that the nature of these offense clusters will change over time.[1] For example, rather than require offenders arrested for burglary at Time 1 to be subsequently charged with burglary to demonstrate specialization, the offense cluster could be called theft, meaning that *any* subsequent property crime would be indicative of specialization in theft offenses. In the longitudinal sequence of offenses defining a criminal career, according to Blumstein et al. (1986, 1988), individuals should commit a variety of offenses at the start of their criminal careers (i.e., as adolescents), but as they age and become more successful and proficient at some crimes, they should tend to repeat those types of crimes where they have been more successful. In other words, the criminal career view claims that specialization in criminal

[1] At the same time this is a definition of specialization, it is also called the "specialization hypothesis."

activity is more likely over time. The reason being that specialization is cost-effective. Individuals who have had some experience committing particular crimes in the past will recognize that they are more skillful at those crimes. In addition, increased levels of criminal expertise may lower the chances of being caught when the crime is committed again, and the person should know how to retrieve a greater reward from the criminal act (see Pyle, 1983, Chapter 2).[2] At a minimum, then, this view of offending assumes that successful execution of profitable crimes requires relatively high skill levels (see Cohen, 1986; Blumstein et al., 1988). Thus, as individuals gain experience committing crimes, they should tend to concentrate (or cluster) their activities into more profitable crimes.

In contrast, control theories see crime as a general phenomenon that provides some measure of pleasure to the individual committing the offense. The specific form of this pleasure could be as diverse as mood enhancement or monetary gain. The key is that crimes are seen as providing short-term gains that are more attractive to individuals with lower levels of self-control, because it is those individuals who will be least likely to consider the long-term consequences of their acts, and more likely to act impulsively. In short, control theory sees criminal offending as versatile, in stark contrast to the criminal career view that claims offenders specialize in offending due to more long-term concerns with a successful criminal career. Thus, where the criminal career view sees rational, long-term oriented offenders, control theories see pleasure-seeking, short-term oriented individuals. On the basis on time

[2]Recall that the criminal career view does not explicitly claim offenders are rational actors. However, as discussed in Chapter 1, the criminal career paradigm is derived from microeconomic perspectives that do rely heavily on the assumption of rational criminals (see Blumstein and Nagin, 1978).

orientation alone, then, the criminal career view expects offenders to specialize, while the control view expects offenders to commit a variety of crimes to satisfy immediate desires.

This chapter focuses on empirically testing the specialization hypothesis, using three of the four data sources described above.[3] Prior to presenting the results from these analyses, however, the recent research purporting to test the specialization hypothesis is reviewed and critiqued, once again (unfortunately) revealing logical and methodological shortcomings in this research.

RECENT RESEARCH

Cohen (1986) has reviewed and critiqued the research on specialization appearing prior to 1986, and readers are referred to that paper for a more detailed discussion of the early specialization research. Briefly, in her review of five studies on specialization, she notes that Wolfgang, Figlio, and Sellin (1972) and Rojek and Erickson (1982) found very little evidence of specialization in offending among juveniles, Bursik (1980) found weak evidence in support of specialization among juveniles, while Blumstein, Cohen, and Das (1985) and Moitra (1981) found more substantial support for offense specialization among adult offenders. Cohen then reanalyzes the data published in the Wolfgang et al., Rojek and Erickson, and Bursik studies to statistically compare their results with those of Blumstein et al. (1985) and Moitra (1981). She concludes, based on these new findings, that all five studies show some minimal support for a general notion of offense specialization. More specifically, Cohen summarizes the specialization research by saying

[3]The National Youth Survey is not analyzed in this chapter for reasons explained below.

> ...there are differences in the level of specialization by juvenile and adult offenders. Specialization is evident and strong in all offense types among adult offenders, but it is more sporadic and somewhat weaker among juvenile offenders. Among adults, specialization is strongest for drugs, fraud, and auto theft – all offenses that play a role in organized illicit markets. It is weakest, although still significant, for the more impulsive, violent crimes of murder, rape, and weapons offenses (1986:395).

Since Cohen's review, there have been five additional attempts to test for specialization in offending. These studies all claim to demonstrate support for offense specialization. For example, Kempf (1987) analyzes a sample of males born in Philadelphia in 1958 who had 5 or more records of police contact (n=982). She split this group of offenders by race (white, non-white) and by police contacts before or after the individual's eighteenth birthday (adult offender, adult non-offender). This partitioning created four subsamples: white adult offenders (n=125), non-white adult offenders (n=458), white adult non-offenders (n=84), and non-white adult non-offenders (n=315). Kempf uses transition matrices, similar to the studies reviewed by Cohen, to test for specialization. She finds few offenders tending to repeat immediate past crimes. This finding held regardless of the subsample used and the crime type considered. Kempf also looked at the proportion of offenses an individual committed that were in the same general crime type. Many of the values were between 10 and 20 percent, with the highest value being 32 percent for property crime among white adult offenders. In other words, among white adult offenders with five or more police contacts, 32% had been charged with property crimes more than once. Although Kempf concludes that her analysis clearly demonstrates support for the specialization hypothesis – since there was not perfect versatility among offenders – she appears to be mistaken. Her results show offending not to be entirely independent from one offense to the next offense, but there was much unpredictability in offending, especially since a person's next offense could not be predicted very well knowing only the immediate past offense.

Wolfgang, Thornberry, and Figlio (1987), use the same data set as Kempf and conclude that adult offenders were as versatile in their offending as were juveniles. Specifically, Wolfgang et al. (1987) find that offenders were most likely to commit a non-index offense and/or stop committing crimes as they aged, similar to the pattern observed when the sample was younger (Wolfgang, Figlio, and Sellin, 1972). Thus, not only were offenders found to be versatile in their criminal activity, but these same individuals committed less serious crimes or quit offending as they aged. These findings are at odds with the claim that specialization becomes more likely as individuals age and gain more experience committing crime.

Farrington, Snyder, and Finnegan's (1988) analysis is similar to both Kempf's and Wolfgang et al.'s, but uses information on 69,271 juveniles in Utah (n=34,134) and Maricopa County, Arizona (n=35,137). To test for specialization in offending, they focus on individuals with 2 or more referrals (n=28,201) and 10 or more referrals (n=1,979), and compare these individuals across 21 different offenses. For the individuals with 2 or more referrals, the highest "Forward Specialization Coefficient" (FSC)[4] is

[4]An FSC value of 0 represents complete versatility, while an FSC value of 1 represents perfect specialization, and is based on Haberman's Adjusted Standardized Residuals (ASR). In the Farrington et al. paper, as well as the other studies using the FSC, the

0.292 for runaway, and the lowest is 0.026 for trespassing, with the overall average across the 21 offenses being 0.107. The same pattern holds for the individuals with 10 or more referrals. Runaway again has the highest FSC value at 0.301, trespassing the lowest at 0.012, and the overall average is 0.098. Interestingly, the overall average FSC shows the level of specialization to *decrease* as the number of referrals increased. In short, again contrary to the specialization hypothesis, individuals with more offenses (referrals in this case), demonstrate less offense specialization. Farrington et al. thus err when they conclude

> Specialization tended to increase with successive referrals, however, especially for the persistent offenders with 10 or more referrals, and especially for liquor, drug, and robbery offenses (1988:483).

It is unclear what results Farrington et al.'s conclusion refer to, because liquor, drug, and robbery offenses also showed decreases in the level of specialization. Liquor's FSC declined from .218 to .175, Drug's FSC from .129 to .120, and Robbery's FSC from .116 to .052 (1987:476, Table 4). Further, every table in their paper contradicts their conclusion about offense specialization. Nearly every offense shows a decrease in the value of the FSC when the sample is restricted to those individuals with 10 or more referrals. This finding is contrary to the prediction of increased offense specialization among individuals who commit more crimes. In the end, although not apparently their intention, Farrington et al. (1988) show juvenile offenders to become more versatile, and not specialized, in their criminal behavior as they commit more crimes.

independence model is used as the baseline against which to compute the ASR and the FSC.

A fourth transition matrix analysis to test for specialization was published by Blumstein et al. (1988). They use a sample of 32,197 adults (aged 17 or older) arrested in the period 1974 to 1977 for any of the six most serious index offenses[5] in the Detroit SMSA (n=18,635) or in the remaining Southern Michigan region (n=13,562). Blumstein et al. then focus on two groups of offenders – those with 1 or more prior arrests and those with 4 or more prior arrests. Again, the idea is to test for an effect of increasing specialization given increased levels of prior offending. Based on FSC values, Blumstein et al. (1988) reach two apparently contradictory conclusions. First, they claim there is no trend in specialization (1988:326). Yet, they also note that "...some specialization was found in all crime types for adult offenders" (1988:341). How can this be possible? Unfortunately, Blumstein et al. (1988) use the same faulty logic Kempf (1987) and Farrington et al. (1987) exhibited by concluding specialization in offending when no FSC value is found to be zero. In short, a double standard is used, where specialization is imputed when offenders are not shown to be completely versatile in their offending, yet the reverse is not held to be true. Namely, that lack of complete specialization is indicative of versatility. For example, an FSC value of 0.10 would be taken as evidence of specialization, since offenders are said to be 10% specialized. At the same time, however, offenders are not seen as being 90% versatile. In general, this approach makes little sense. The implication of this work is that researchers looking for specialization will always find it, since FSC values will likely always be greater than zero, which does not seem to be the most appropriate way of testing any kind of an explanation.

[5]These are criminal homicide, forcible rape, robbery, aggravated assault, burglary, and motor vehicle theft.

Brennan, Mednick, and John (1989) take a slightly different approach to assessing specialization, by not using transition matrices, in analyzing a sample of 28,884 Danish men to see if violent offenders are more likely to specialize than other offenders. Of the 28,884 men in the initial sample, a subsample of 735 had arrest records for at least one violent offense, and 147 had arrest records indicating 2 or more violent offenses. The analysis by Brennan et al. is restricted to the 147 individuals with 2 or more prior violent offense arrests. Brennan et al. claim to find specialization in violence among this subsample by using a Bernoulli probability model, and comparing the predicted number of offenders under this model (assuming independence) to the observed number of offenders. It is unclear, however, just how many individuals are indeed specialists in violence. Brennan et al. fail to give any further sample size information once they focus on the 147 two-time offenders out of initial 28,884 individuals. However, computations based on several bar graphs in the paper suggest that Brennan et al. have found approximately 20 specialists in violence. And while these individuals may in fact be specialists in violence, a substantive question raised by this finding concerns whether 20 specialists in violence, out of a sample of 28,884 Danish men, provide a meaningful group on which to validate theories of crime or base public policies?

In sum, the research on specialization in offending has emphasized the use of transition matrices, and generally reached similar conclusions, although many times at odds with the results presented in the corresponding tables (e.g., Kempf, 1987; Farrington et al., 1987). Specialization is found to the extent that a small number of offenders commit the same general type of crime on two consecutive occassions.

Otherwise, offenders show a great deal of versatility, by committing different crimes for subsequent offenses. There are four serious problems with this research on specialization, however, that lead to questions about the validity of the conclusions in these five papers.

First, the use of transition matrices has focused only on the most serious charge that an individual receives when they come into contact with the criminal justice system. Additional information about the other offenses the individual has either concurrently been charged with or been charged with in the past are lost, which may bias the potential results. For example, consider an offender who at Time 1 was charged with rape and burglary, and at Time 2 was charged with aggravated assault, arson, and auto theft. The two most serious offenses at each time are rape and aggravated assault (by the criteria in Wolfgang et al., 1985). Thus, if the offense categories in a specialization analysis are theft, personal, drug, and non-index offenses, this individual would give the appearance of being a "violent" offender. This categorization would be quite misleading, since the same individual also committed three property crimes (burglary, arson, and auto theft). On the basis of some other criteria than the most serious offense (e.g., number of property as opposed to personal offenses), this same person could be a property offender. This example, while contrived, shows how the research claiming to find specialists in violent or property crime may be based on faulty measurement of criminal activity. If specialization research uses only part of an offender's criminal activity to reach conclusions, the corresponding measurement errors call into question the validity of the findings.

Second, the specialization hypothesis as recently stated – that as offenders age and commit more crimes they are more likely to commit the same types of crime – implies an interaction effect between age and criminal offending. Nowhere in the specialization research currently in print is this interaction effect explicitly tested. Kempf (1987) and Wolfgang et al. (1987) indirectly test for this interaction when the transition matrices they construct are split by age (under 18-years-old and 18-years-old and above). However, without statistical tests to show whether these two tables are different, these authors may err when they conclude that there is an increased likelihood of specialization as individuals age.

Third, the criminal career paradigm emphasizes the offender's *career* in crime – that it is inappropriate to look at only a cross-section of an individual's illegal activity, and that a more extended period of time needs to be examined. However, with the exception of the Brennan et al. (1989) paper, every other specialization paper considers crimes at only two points in time (i.e., a simple Markov model), rather than evaluate all this information simultaneously. Thus, even if it was granted that using only the most serious offense in transition matrices was somehow appropriate, latent class markov models (e.g., Poulsen, 1982) could be used to simultaneously test every transition matrix in a study to evaluate whether individuals really were clustering their offending in certain areas over time. The findings from such an analysis would provide a much more convincing test of increased specialization in offending as offenders aged and commited more crimes.

Fourth, Kempf (1987), Farrington et al. (1987), and Blumstein et al. (1988) all use the FSC to measure the degree of offense specialization in a sample. This is problematic for specialization research, however, in that the FSC is computed assuming a model of independence in a transition matrix. There are no alternative models suggested by the researchers claiming to have found specialization. Thus, while they can claim that an offense at Time 1 is not entirely independent of the offense committed at Time 2, this research has really missed an opportunity to specify the nature of the relationship between prior offense and current offense. More importantly, this research has failed to establish offense specialization as the statistical alternative to independence in offending. Without that specification, this research has failed to produce clear evidence that specialization in offending exists.

The following analyses do not use transition matrices to test for specialization among offenders. Rather, they use a variety of approaches – graphical, logistic regression, and latent class models – that may enlighten discussion on whether offenders specialize in their illegal activity.

THE CURRENT STUDY

Uniform Crime Reports

Since the *UCR* does not contain individual level data, it is slightly more difficult to assess whether criminal offenders tend to commit the same types of offenses as they age and continue to offend. However, an indirect test, which still provides substantial information, looks at the age distribution of arrest for each offense. The idea here is that if offenders tend to commit some crimes more than others as they age, which has been argued in recent specialization research (i.e., Cohen, 1986; Blumstein et al., 1988), the distribution of arrests for these crimes should be substantially different from the age distribution of total crime. In other words, the specialization hypothesis suggests that older offenders will tend to commit some types of crime more often than others. If the specialization hypothesis holds, this trend should manifest itself in different age distributions for specific forms of crime.

Similar to the analyses of the age distribution of total crime in Chapter 3, the percent age involvement (PAI) values are calculated for each specific offense and for total crimes. The UCR values for 1980 are used in the following analysis. To help interpret the offense specific PAI values, Figures 4.1 to 4.13 display the age distribution for total arrests and two specific offense. The two offense specific distributions were chosen by alternating top and bottom of the list of crimes contained in the UCR data. Thus, some figures contain very serious crimes, such as rape, along with less serious crimes, such as suspicion, in the same graph.

Additionally, the rationale for choosing the 1980 UCR is to correct for a mistake in Steffensmeier et al.'s (1989) analysis of the same data. Specifically, their error was in using the age distribution of burglary arrests as the baseline distribution against which to compare all other offense-specific distributions. Their use of burglary arrests was arbitrary, and the use of any one of the other possible 26 offense distributions (including total arrests) would likely have provided substantially different results. The choice of total arrests as the baseline distribution provides a more meaningful comparison in that it can demonstrate how a single offense distribution is indeed different from all other types of crime.[6]

Findings. Figures 4.1 through 4.13 show that only one offense – gambling – has an age distribution that is substantially different from that for the total age distribution of crime in 1980. Gambling offenses peak in the early 20's, not unlike many other offenses, and also begins a

[6] A way to think about this comparison is analogous to testing whether a single observation (an offense-specific age distribution of crime) is different from the mean (the total age distribution of crime).

rather sharp decline. But, instead of continuing to decline, the *PAI* values for gambling offenses again increase, peaking a second time in the late forties. With the exception of this single offense, however, all other crimes follow a pattern very similar to that for total crimes.[7]

Clearly, the offense specific distributions are not identical. The values of the means, modes, and medians vary from one distribution to the next. However, as demonstrated in Chapter 3, variation in these values should not detract from the underlying similarity among the curves. Thus, Figures 4.1 through 4.13 all show that most crimes do not become more attractive to older individuals, with the exception of gambling. Further, these figures also reconfirm the finding in Chapter 3 of a stable age distribution of crime across offense type, in addition to the time and data set similarities.

Summary. The use of *UCR* offense specific arrest data can only indirectly test for specialization. The way that test was constructed here compared each offense specific age distribution with the age distribution for total arrests. For the specialization hypothesis to be correct, the age distributions for some specific offenses should have been quite different, as those crimes became more or less attractive to aging individuals who had committed many previous crimes. The results presented here do not support the specialization hypothesis, except for gambling offenses, which did show a pattern of age-specific offending quite different from that for all other crimes.

[7]While gambling offenses appear to imply specialization for gamblers, it is worthwhile to keep in mind that gambling offenses accounted for 0.38% of all crimes in 1980. Thus, while granting apparent specialization for this one offense implies support for the criminal career paradigm, among the other 99.62% of all crimes, there was no obvious difference in the age distribution of arrests for each offense and total crimes.

Bail Decisionmaking Study

The BDS data provide information on 3104 offenders with one or more prior arrests (of the initial 4800 offenders in the sample). The BDS data are particularly useful for testing specialization among offenders, because they contain substantial information on the arrest histories of the offenders in the sample, and permit a direct test of the interaction effect of age and prior criminal activity.

The dependent variable in the following analyses is current charge,[8] which has four categories–drug, property, personal, and other offense. To test for specialization, a model was constructed to use an offender's age and prior criminal activity to predict current charge. If specialization in offending exists, the type of offense involved in the current charge should be predictable from prior offenses and age.

The independent variables specified in the following analyses were age, proportion of prior arrests that were serious property offenses, proportion of prior arrests that were serious personal offenses, and proportion of prior arrests that were drug offenses. Interactions between age and each of the prior record variables were also included to specifically test the claim that increased age, along with increased offending, results in a greater tendency to specialization among offenders. This model – with direct and interaction effects – is displayed in Figure 4.14.

Due to the categorical nature of the dependent variable, logistic regression was used to test the model displayed in Figure 4.14. Additionally, the subsample of offenders with one or more prior arrests was further restricted in subsequent analyses to offenders with five or

[8]Only the first charge – the most serious – is used in these analyses, in order to make the results compatible with the research discussed above.

more prior arrests, and ten or more prior arrests. The additional partitioning of the sample by prior record focus the analyses on individuals who have been more "active" criminals. Then, given these three subsamples of increasing prior criminal activity, analyses of Figure 4.14 were performed on the total subsample and race and gender groups within specific prior record groups when the sample size was large enough to permit a meaningful test.

Again, the justification for the approach discussed here lies in the notion that people who have committed more of a particular type of offense in the past, and who are older, should be more likely to commit that same type of offense in the future. Support for offense specialization will be found if the odds that offenders tend to commit the type of crime they have currently been charged with increase as the proportion of prior offending in that type of crime increases and the age of the offender simultaneously increases. Otherwise, the data will support the claim that offenders are versatile in the types of crimes they commit.

Univariate Results. Table 4.1 lists each variable, as described above, and its possible values for the entire BDS sample. Tables 4.2, 4.3, and 4.4 present the means and standard deviations for each of these variables for the three prior record subsamples (one or more prior arrests, five or more prior arrests, and ten or more prior arrests, respectively). Each column in Tables 4.2 through 4.4 then represents a further partitioning of the subsample by gender and race, where appropriate sample sizes are left for further logistic analyses.

The values displayed in Tables 4.2 through 4.4 for the total subsamples show the only substantial difference from one subsample to the next is increased mean age. This is hardly surprising, however, as individuals will need to age in order to accumulate further arrests. The means of the prior record variables are all quite stable across the three subsamples, as are the interaction effect variables.

Within each prior record subsample, there are other, more significant differences. The subsample of female offenders with one or more prior arrests show considerably less prior involvement in property and drug offenses compared to male offenders. Additionally, white males have much more prior involvement in drug related offenses, while non-white males have much more prior involvement in personal offenses. Further, there is also a substantial age difference between white and non-white males,with non-white males tending to be slightly older, on average.

Within the subsample of offenders with five or more prior arrests, the same patterns for white and non-white males exists, although the magnitude of the differences in age and prior drug and personal offending decreases. Similarly, for offenders with ten or more prior arrests, there is even less discrepancy in the values of the independent variables. This implies that as offenders accumulate more arrests and convictions, they become increasingly similar as a group, and are less easily differentiated on the basis of common demographic characteristics such as age, race and gender.

Multivariate Results. Tables 4.5 through 4.10 present the parameter estimates with their standard errors for the model displayed in Figure 4.13.[9]

[9] Each independent variable is represented by three parameter estimates in Tables 4.5 through 4.10. The first estimate refers to the log of the odds of being charged with a drug offense as opposed to some other offense, while the second estimate compares property offenses to other offenses, and the third estimate compares personal offenses to other offenses.

Tables 4.5 and 4.6 present the results for the test of offense specialization in the subsample of offenders with one or more prior arrests. Table 4.5 displays the parameter estimates, while Table 4.6 displays the parameter estimates for the interaction effects. Clearly shown in Table 4.5 is that most of the individual parameter estimates are not statistically significant. Table 4.6 then adds to the interpretability of the initial estimates by summing the appropriate parameter values and computing the standard errors for the interaction effects.

In the total subsample, only two of the interaction effects are statistically significant, but they provide some interesting results. First, for a given age, an increase in the proportion of prior arrests for personal offenses increases the chances that the offender was currently charged with a personal offense as opposed to any other offense (drug, property, or other). Second, for a given age, an increase in the proportion of prior offenses that were drug related decreases the chances that the offender has currently been charged with a property offense as opposed to any other offense (drug, person, or other).

When this subsample is split by gender, the pattern is basically the same. For males of a given age, as the proportion of prior offending in drug related offenses increases, the chances that they have currently been charged with a property offense decrease compared to all other offenses. For females with a given level of prior property offense activity, as age increases, they become much less likely to be charged with a drug related offense compared to all other offenses.

When males are then split by race, no interaction effect is statistically significant for white males, indicating that age and prior offending activity have very little predictive value on future criminal activity. For non-white males, the same pattern holds. Namely, that for a given age, as the proportion of prior offending in drug related offenses increases, individuals become less likely to be charged with a property offense.

Tables 4.7 and 4.8 display the parameter estimates and interaction effects, respectively, for the multivariate analysis of the subsample of offenders with five or more prior arrests. The pattern of statistically significant effects found in Table 4.7 is virtually the same as that found in Table 4.5. Table 4.8 shows that for the total subsample of offenders, no interaction effect is statistically significant. When only males are used in the analysis, the statistically significant finding is that for a given level of prior drug offending, as age increases, individuals become less likely to be charged with a drug offense compared to all other offenses (personal, property, and other). And when males are split by race, no effect is statistically significant.

Tables 4.9 and 4.10 display the parameter estimates and interaction effects, respectively, for the multivariate analysis of the subsample of offenders with ten or more prior arrests. The pattern of statistically significant effects in Table 4.9 is again quite similar to those in Tables 4.5 and 4.7. Table 4.10 shows that for the total subsample of offenders, the models again fit, but few parameters are statistically significant. In fact, the only statistically significant finding is the same as for males with five or more prior arrests, but even greater magnitude. To reiterate, for a given level of prior offense activity that is drug related, as age increases, individuals become much less likely to have currently been charged with a drug offense, compared to all other offenses.

Summary. The test for specialization in the BDS data suggests that very few offenders commit crimes in a predictable manner, based on their prior offending, and not their most serious prior offenses. Recall that the operationalization of the specialization hypothesis suggested that an offender's current charge type (drug, personal, property, or other) should have been predictable based on the proportion of all prior arrests that fell within given offense types. Further, all this was evaluated through an interaction effect of age and offending, that as offenders aged and committed increasingly more crime in a particular offense category, their current charge should have been more predictable.

Considering the findings in Table 4.5 through 4.10, only the total subsample of offenders with one or more prior arrests showed any evidence of specialization. Specifically, this finding says that for a given age, as an offender's prior offense activity in personal offenses increased, that offenders was more likely to have currently been charged with a personal offense. However, when the group of offenders is broken down by race and gender, this effect disappeared. Overall, then, the support for offense specialization is very weak in the BDS data; and given that the effect was statistically significant in only one instance, there is an even greater likelihood that the finding is due to chance.

There are two other findings worth reiterating. First, the chances of a drug related charge decrease for older offenders, given some level of previous drug related offending, which actually indicates a type of "despecialization." Second, the chances of a property charge decrease as the level of prior drug offending increases, controlling for age of the offender. This suggests that offenders with more prior offenses are somewhat less likely to be charged with property offenses, as opposed to all other offenses. This is consistent with the *UCR* offense specific age distributions of crime that showed property crimes to be committed more often by adolescents, and other crimes to be committed more often by older individuals.

Again, there were no clearly consistent patterns of offense specialization in the BDS data. Although a few isolated effects are statistically significant, the total volume of paramter estimates suggests that too much emphasis on these effects may be misleading. In addition, it should be noted that race and gender made little difference to the pattern of results, meaning that all offenders in the BDS data show a high degree of unpredictability, regardless of age, race, gender, and prior record.

Seattle Youth Survey

The SYS data provide a considerably different source of information on which to evaluate individuals and their specialization in offending. The approach taken in analyzing the SYS is to test whether individuals fall into different latent classes of offenders - personal, property, or non-delinquents.

Four delinquency items are used in the following analyses - theft of an item worth $2 or less (RIP2), theft of an item worth between $2 and $50 (RIP250), hit a teacher (HITTEACH), and fought with someone other than a sibling (FIGHT).[10] RIP2 and RIP250 represent property crime, while HITTEACH and FIGHT represent personal offenses. Each item was coded as 0-1, where a 1 indicated that the individual had ever committed the act, while the 0 indicated that the individual had never committed the act. Due to sample size limitations, only males are used in

[10]The National Youth Survey data do not produce any four-way cross-tabulations (coded as 0-1) where there are fewer than three zero-cells. When there are only sixteen cells in a table, the estimation of a statistical model becomes difficult when there are so many empty cells. Thus, rather than produce results that have dubious accuracy, the National Youth Survey was not used to test for specialization.

the following analyses.[11] Tables 4.11 through 4.13 display these four-way cross-tabulations for all males in the SYS data, white males, and black males, respectively. These three tables are used in the following latent class analyses.

The test for specialization involves searching for distinct classes of offenders. If the specialization hypothesis is to hold in this self-report data, there should be individuals who are non-delinquents, along with individuals who have concentrated their offending efforts in either personal or property offenses. Thus, the specific statistical test below examines whether there are three distinct classes of individuals in the SYS data and compares this to a model where there are only two classes of individuals – delinquents and non-delinquents. If the two-class model fits well, it implies that crime commission is general – that individuals do not concentrate their activity in one area, but commit a variety of offenses to satisfy some pleasure-seeking desire.

Findings. Tables 4.14 through 4.16 present the overall model fits for the independence, unrestricted two-class and three-class, and restricted three-class[12] models for all males, white males, and black males, respectively.

In all three tables, the only model to clearly not fit was the independence model, which implies there is only one latent class of individuals. The other three models provide good fits to the data in Tables 4.11 through 4.13. Given that these three models fit well, some other criterion needs to be used to decide which of these models would be

[11] This does not imply that female offense specialization may not be interesting to examine. It does mean there were to few females to provide a table with no empty cells.

[12] The restriction introduced into this model is that individuals who have hit a teacher are assigned, with a probability of 1.0, to the personal offender latent class.

the best overall description. Using parsimony as that criterion results in the two-class model being more attractive for all three groups. Males in the SYS, then, show offending to be a fairly general phenomenon, where individuals committing the simple theft activities are also committing some personal crimes. And while the three-class models have a lower Index of Dissimilarity and Likelihood-Ratio χ^2, it is not convincing to argue that the slight improvement in overall model fit justifies the increased complication in the model structure by having three latent classes as opposed to two.

Summary. Similar to much of the previous research that has tested for specialization among juveniles (Bursik, 1980; Kempf, 1987; Wolfgang et al., 1972, 1987; Farrington et al., 1987; Rojek and Erickson, 1982), the SYS results show how there is again little evidence in support of juvenile offense specialization. Tests of four latent class models demonstrated the two-class model to be the most parsimonious model that best fit the data, where the two classes were delinquents and non-delinquents. The primary implication of these findings is that offense specialization is unnecessary to describe the pattern of offending among the male juveniles in the SYS data.

The SYS data have also supported the BDS findings that showed no difference in offense specialization by race. Prior research on incarcerated offenders (e.g., Blumstein et al., 1988) using only transition matrices claimed there were significant differences between whites and blacks in their tendency to specialize. Neither the BDS nor the SYS data was able to replicate this claim.

SUMMARY AND CONCLUSIONS

The specialization hypothesis claims that as individual offenders age and continue to commit crimes, they become more likely to commit the same crime type on successive offenses. The analyses in this chapter have examined this hypothesis in three different ways with three different data sets. Overall, the findings were not supportive of the notion that older, more experienced offenders tend to commit the same type of crime.

Offense specific data from the *Uniform Crime Reports* showed the age distribution of gambling offenses to be the only curve not comparable to the age distribution for total crimes. The logic of this test was that some crimes should be more attractive to older offenders because they are potentially more profitable and may require more skill to be successful (Cohen, 1986; Blumstein et al., 1988). Figures 4.1 through 4.13 show this not to be the case, that most crimes exhibit virtually the same age-specific pattern of offending.

The Bail Decisionmaking Study data also failed to show offenders specializing in their illegal activity. Using logistic regression, a model that included age, prior record information (crime type), and interaction effects between age and prior offending to predict current charge was tested on multiple subsamples distinguished by the number of prior arrests (1 or more, 5 or more, and 10 or more), race (white, non-white), and gender. Overwhelmingly, the results showed the independent variables to not have an effect on predicting current charge. Thus, the specialization hypothesis was again not supported in a test of its predictive validity.

The Seattle Youth Survey, similar to the *UCR* and BDS data, again failed to support the specialization hypothesis. Latent class models testing whether adolescent males fell into two distinct classes of offenders (i.e., non-delinquent, personal, and property classes) showed the distinction between personal and property crimes not to be particularly helpful in explaining the distribution of individuals across the four-way cross-tabulation. The model that had the best overall fit was a two-class model of delinquents and non-delinquents, meaning that the individuals involved in the property crimes were also likely to be involved in the personal offenses. In addition, the BDS results of no differences between black and white males were also confirmed.

The findings in this chapter thus pose serious problems for the specialization hypothesis. There were virtually no findings here that support the specialization in offending notion, regardless of how specialization was operationalized or tested.

In part, the differences in findings from those previously published in studies of specialization are due to different methods used to test for specialization. However, the analyses conducted in this chapter – especially the logistic regression and latent class analyses – are far more comprehensive than any of the transition matrix approaches. The logistic regression analysis of the BDS data explicitly tested for an age and prior offense interaction effect implied in prior research, but never tested. The latent class analysis, while not incorporating age, tried to assess whether individuals committing illegal acts tended to commit those acts to the exclusion of other acts.

The results in this chapter suggest that the methods used to test for specialization may need modification. Interestingly, in the analyses here, where no transition matrix is used, no specialization is found. Yet, in virtually every study using these matrices, specialization is found. Prior to general refutation of the specialization hypothesis, a variety of additional analyses on previously published data needs to be undertaken to determine the extent to which the method of analysis produced findings of specialization. The validity of the specialization hypothesis must be held in doubt until these additional analyses are completed.

In addition to this methodological implication, the findings in this chapter also cast doubt on the accuracy of the criminal career view. While this view makes specialization in offending a key characteristic of offenders, the results here fail to find a minimal level of specialization. Conversely, control theory claims that criminal offending is a general phenomena, that all crimes, regardless of specific type, will appeal to individuals committing crimes. The results reported here clearly support the control theory view of criminal offending.

There will no doubt continue to be substantial research assessing the level of specialization or versatility in offending. The question that will need to be addressed in all these studies is: Does the analysis demonstrate actual offense specialization or that offenses are not entirely independent? The argument, and analyses, in this chapter claim that research needs to demonstrate that specialization occurs, not merely that subsequent offenses are not independent.

Table 4.1: List of Variables and Possible Values.

Variable	Possible Values
Current Charge	0 = Other Offense 1 = Drug Offense 2 = Theft Offense 3 = Violent Offense
Age of Offender	14 to 87
Proportion of Prior Arrests that are Serious Property	0 to 1
Proportion of Prior Arrests that are Serious Personal	0 to 1
Proportion of Prior Arrests that are Drug	0 to 1
Age * Proportion Property Arrests	
Age * Proportion Personal Arrests	
Age * Proportion Drug Arrests	

Table 4.2: Means and Standard Deviations by Race and Gender for Offenders with One or More Prior Arrests.

Variable	Total Subsample Mean (s.d.)	Males Mean (s.d.)	Females Mean (s.d.)	White Males Mean (s.d.) x	Non-white Males Mean (s.d.)
Age	30.347 (11.281)	30.364 (11.375)	30.197 (10.406)	28.265 (10.689)	30.083 (11.516)
Proportion Property	0.109 (0.213)	0.117 (0.219)	0.031 (0.127)	0.113 (0.227)	0.119 (0.216)
Proportion Personal	0.181 (0.274)	0.187 (0.274)	0.121 (0.262)	0.094 (0.200)	0.219 (0.289)
Proportion Drug	0.142 (0.268)	0.148 (0.271)	0.092 (0.239)	0.203 (0.311)	0.129 (0.253)
N	3104	2795	309	713	2082

Table 4.3: Means and Standard Deviations by Race and Gender for Offenders with Five or More Prior Arrests.

Variable	Total Subsample Mean (s.d.)	Males Mean (s.d.)	White Males Mean (s.d.)	Non-white Males Mean (s.d.)
Age	33.315 (11.448)	33.429 (11.513)	31.064 (11.257)	34.045 (11.505)
Proportion Property	0.124 (0.164)	0.130 (0.165)	0.127 (0.161)	0.130 (0.167)
Proportion Personal	0.164 (0.184)	0.171 (0.186)	0.091 (0.112)	0.191 (0.196)
Proportion Drug	0.129 (0.187)	0.133 (0.189)	0.190 (0.217)	0.118 (0.179)
N	1309	1216	251	965

Table 4.4: Means and Standard Deviations by Race and Gender for Offenders with 10 or More Prior Arrests.

Variable	Total Subsample Mean (s.d.)	Males Mean (s.d.)	Non-white Males Mean (s.d.)
Age	36.230 (11.476)	36.491 (11.548)	37.258 (11.346)
Proportion Property	0.131 (0.155)	0.139 (0.158)	0.138 (0.159)
Proportion Personal	0.126 (0.135)	0.133 (0.137)	0.144 (0.143)
Proportion Drug	0.123 (0.168)	0.130 (0.171)	0.119 (0.161)
N	543	493	395

Table 4.5: Logistic Regression Results by Race and Gender for Offenders with One or More Prior Arrests.

Parameter	Total Subsample Estimate (s.e.)	Males Estimate (s.e.)	Females Estimate (s.e.)	White Males Estimate (s.e.)	Non-white Males Estimate (s.e.)
Intercept	1.016 (0.205)	1.104 (0.221)	0.459 (0.577)	0.263 (0.416)	1.595 (0.270)
	0.951 (0.342)	0.983 (0.367)	0.763 (0.988)	0.254 (0.642)	1.452 (0.455)
	-1.001 (0.221)	-0.975 (0.241)	-1.102 (0.580)	-0.764 (0.453)	-1.073 (0.291)
Age	-0.044 (0.006)	-0.047 (0.006)	-0.028 (0.017)	-0.035 (0.013)	-0.056 (0.007)
	0.013 (0.011)	0.013 (0.011)	0.018 (0.032)	0.020 (0.022)	0.005 (0.014)
	0.028 (0.007)	0.030 (0.008)	0.019 (0.019)	0.014 (0.015)	0.037 (0.009)
Proportion Property	0.838 (0.766)	1.289 (0.814)	-20.777 (10.182)	2.799 (1.631)	0.571 (0.955)
	1.157 (1.033)	1.163 (1.084)	-5.592 (12.483)	2.385 (1.725)	0.545 (1.419)
	0.122 (0.677)	0.251 (0.712)	-14.139 (9.420)	0.898 (1.388)	-0.006 (0.850)
Proportion Personal	0.244 (0.554)	0.069 (0.588)	0.848 (1.832)	1.691 (1.859)	-0.509 (0.642)
	0.365 (0.865)	0.596 (0.923)	-2.120 (2.713)	1.919 (2.854)	0.013 (1.001)
	0.707 (0.627)	0.823 (0.663)	-0.167 (2.139)	0.731 (1.805)	1.096 (0.736)
Proportion Drug	-0.831 (0.784)	-0.852 (0.815)	-2.066 (3.591)	1.748 (1.734)	-1.754 (0.957)
	0.081 (0.834)	-0.002 (0.861)	-0.107 (3.894)	-0.481 (1.821)	-0.020 (1.022)
	1.467 (0.822)	1.245 (0.851)	3.301 (3.796)	1.221 (1.750)	1.433 (1.011)
Age * Proportion Property	0.008 (0.026)	-0.005 (0.028)	0.555 (0.277)	-0.032 (0.059)	0.007 (0.032)
	-0.037 (0.037)	-0.039 (0.040)	0.119 (0.282)	-0.081 (0.065)	-0.016 (0.052)
	-0.012 (0.026)	-0.021 (0.028)	0.339 (0.231)	-0.028 (0.056)	-0.018 (0.033)
Age * Proportion Personal	0.047 (0.019)	0.052 (0.020)	0.026 (0.056)	0.010 (0.069)	0.063 (0.021)
	0.012 (0.032)	0.006 (0.034)	0.084 (0.104)	-0.014 (0.111)	0.014 (0.036)
	0.030 (0.024)	0.022 (0.026)	0.075 (0.079)	0.021 (0.072)	0.011 (0.028)
Age * Proportion Drug	0.028 (0.030)	0.031 (0.031)	0.030 (0.136)	-0.053 (0.071)	0.057 (0.036)
	-0.086 (0.031)	-0.082 (0.033)	0.107 (0.146)	-0.038 (0.076)	-0.090 (0.038)
	-0.055 (0.032)	-0.048 (0.034)	0.132 (0.140)	-0.043 (0.073)	-0.056 (0.039)

Table 4.6: Interaction Effects by Race and Gender for Offenders with One or More Prior Arrests.

Parameter	Total Subsample Estimate (s.e.)	Males Estimate (s.e.)	Females Estimate (s.e.)	White Males Estimate (s.e.)	Non-white Males Estimate (s.e.)
Age +	-0.036 (0.026)	-0.052 (0.028)	0.527 (0.277)	-0.107 (0.060)	-0.049 (0.033)
Age *	-0.024 (0.036)	-0.026 (0.041)	0.137 (0.283)	-0.114 (0.089)	-0.011 (0.053)
Proportion	0.016 (0.083)	0.009 (0.030)	0.358 (0.231)	0.012 (0.060)	0.019 (0.035)
Property					
Age +	0.003 (0.019)	0.005 (0.020)	-0.002 (0.058)	0.084 (0.047)	0.007 (0.024)
Age *	0.025 (0.034)	0.019 (0.035)	0.102 (0.109)	0.078 (0.075)	0.019 (0.039)
Proportion	0.058 (0.025)	0.052 (0.028)	0.094 (0.081)	0.031 (0.055)	0.048 (0.030)
Personal					
Age +	-0.016 (0.031)	-0.016 (0.032)	0.002 (0.137)	0.082 (0.056)	0.001 (0.037)
Age *	-0.130 (0.034)	-0.069 (0.035)	-0.089 (0.149)	-0.015 (0.061)	-0.085 (0.040)
Proportion	-0.026 (0.033)	-0.018 (0.035)	-0.113 (0.141)	-0.006 (0.057)	-0.019 (0.040)
Drug					
Proportion	0.846 (0.766)	1.284 (0.815)	-20.222 (10.185)	3.149 (1.892)	0.578 (0.956)
Property +	1.120 (1.034)	1.124 (1.091)	-5.473 (12.487)	3.864 (2.726)	0.529 (1.420)
Age *	0.110 (0.678)	0.230 (0.713)	-13.800 (9.422)	-0.513 (1.725)	-0.024 (0.850)
Proportion					
Property					
Proportion	0.291 (0.554)	0.121 (0.589)	0.874 (1.841)	-1.439 (1.440)	-0.446 (0.643)
Personal +	0.377 (1.034)	0.602 (0.924)	-2.036 (2.715)	-1.312 (2.140)	0.027 (1.001)
Age *	0.737 (0.678)	0.845 (0.664)	-0.092 (2.141)	2.246 (1.598)	1.107 (0.736)
Proportion					
Personal					
Proportion	-0.803 (0.785)	-0.821 (0.815)	-2.036 (3.594)	- 3.554 (1.701)	-1.697 (0.958)
Drug +	-0.005 (0.835)	-0.080 (0.861)	-0.214 (3.897)	-2.537 (1.873)	-0.110 (1.023)
Age *	1.412 (0.822)	1.197 (0.852)	3.169 (3.798)	1.036 (1.735)	1.377 (1.011)
Proportion					
Drug					

Table 4.7: Logistic Regression Parameter Estimates by Race and Gender for Offenders with Five or More Prior Arrests.

Parameter	Total Subsample Estimate (s.e.)	Males Estimate (s.e.)	White Males Estimate (s.e.)	Non-white Males Estimate (s.e.)
Intercept	0.635 (0.391)	1.042 (0.428)	0.560 (1.061)	1.203 (0.482)
	1.482 (0.650)	1.366 (0.692)	-0.354 (1.574)	1.817 (0.780)
	-1.068 (0.425)	-0.896 (0.467)	-0.547 (1.093)	-1.017 (0.531)
Age	-0.038 (0.010)	-0.046 (0.011)	-0.056 (0.029)	-0.046 (0.012)
	-0.002 (0.017)	0.001 (0.019)	0.027 (0.049)	-0.008 (0.021)
	0.022 (0.012)	0.021 (0.013)	-0.005 (0.032)	0.027 (0.015)
Proportion	2.957 (1.815)	3.210 (1.890)	3.651 (4.986)	2.522 (2.064)
Property	4.072 (2.611)	3.979 (2.725)	8.071 (6.402)	3.448 (3.109)
	-0.147 (1.661)	-0.504 (1.724)	1.962 (4.159)	-1.157 (1.944)
Proportion	-0.804 (1.404)	-1.569 (1.440)	1.899 (5.885)	-1.712 (1.528)
Personal	-1.717 (2.092)	-1.389 (2.139)	1.055 (10.758)	-2.042 (2.217)
	2.030 (1.548)	2.236 (1.597)	-0.942 (6.061)	2.919 (1.718)
Proportion	-3.028 (1.671)	-3.682 (1.701)	-3.526 (4.034)	-3.693 (2.058)
Drug	-2.675 (1.780)	-2.521 (1.836)	-4.989 (5.204)	-3.318 (2.111)
	1.941 (1.655)	1.063 (1.734)	-1.802 (4.409)	1.222 (2.028)
Age *	-0.051 (0.057)	-0.061 (0.059)	-0.003 (0.170)	-0.054 (0.064)
Proportion	-0.123 (0.083)	-0.115 (0.087)	-0.262 (0.220)	-0.094 (0.097)
Property	-0.014 (0.056)	-0.009 (0.058)	-0.086 (0.147)	0.013 (0.065)
Age *	0.115 (0.045)	0.130 (0.046)	0.070 (0.201)	0.125 (0.048)
Proportion	0.091 (0.071)	0.077 (0.073)	0.198 (0.405)	0.085 (0.075)
Personal	0.026 (0.052)	0.010 (0.053)	0.177 (0.222)	-0.017 (0.056)
Age *	0.115 (0.054)	0.128 (0.055)	0.146 (0.143)	0.128 (0.064)
Proportion	-0.014 (0.056)	-0.015 (0.057)	0.155 (0.191)	-0.008 (0.064)
Drug	-0.056 (0.053)	-0.027 (0.056)	0.110 (0.160)	-0.042 (0.063)

Table 4.8: Interaction Effects by Race and Gender for Offenders with Five or More Prior Arrests.

Parameter	Total Subsample Estimate (s.e.)	Males Estimate (s.e.)	White Males Estimate (s.e.)	Non-white Males Estimate (s.e.)
Age +	-0.089 (0.058)	-0.107 (0.060)	-0.053 (0.172)	-0.100 (0.065)
Age *	-0.125 (0.085)	-0.114 (0.089)	-0.235 (0.226)	-0.102 (0.099)
Proportion Property	0.008 (0.057)	0.012 (0.060)	-0.091 (0.150)	0.040 (0.066)
Age +	0.077 (0.046)	0.084 (0.047)	0.014 (0.203)	0.079 (0.049)
Age *	0.089 (0.073)	0.078 (0.075)	0.225 (0.408)	0.077 (0.077)
Proportion Personal	0.048 (0.053)	0.031 (0.055)	0.172 (0.224)	0.010 (0.058)
Age +	0.077 (0.056)	0.082 (0.056)	0.090 (0.146)	0.082 (0.065)
Age *	-0.016 (0.058)	-0.015 (0.061)	0.182 (0.197)	-0.016 (0.066)
Proportion Drug	-0.034 (0.054)	-0.006 (0.057)	0.105 (0.163)	-0.015 (0.064)
Proportion	2.906 (1.827)	3.149 (1.892)	3.648 (4.989)	2.468 (2.065)
Property +	3.949 (2.624)	3.864 (2.726)	7.809 (6.405)	3.354 (3.110)
Age * Proportion Property	-0.161 (1.671)	-0.513 (1.725)	1.876 (4.162)	-1.444 (1.945)
Proportion	-0.689 (1.411)	-1.439 (1.440)	1.969 (5.888)	-1.587 (1.529)
Personal +	-1.626 (2.104)	-1.312 (2.140)	1.253 (10.766)	-1.957 (2.218)
Age * Proportion Personal	2.056 (1.557)	2.246 (1.598)	-0.765 (6.066)	2.902 (1.719)
Proportion	-2.913 (1.680)	-3.554 (1.701)	-3.380 (4.036)	- 3.565 (2.059)
Drug +	-2.689 (1.789)	-2.537 (1.837)	-4.834 (5.207)	-3.326 (2.111)
Age * Proportion Drug	1.885 (1.664)	1.036 (1.735)	-1.692 (4.412)	1.180 (2.029)

Table 4.9: Logistic Regression Parameter Estimates by Race and Gender for Offenders with Ten or More Prior Arrests.

Parameter	Total Subsample Estimate (s.e.)	Males Estimate (s.e.)	Non-white Males Estimate (s.e.)
Intercept	0.399 (0.694)	1.042 (0.801)	1.124 (0.902)
	0.562 (1.111)	-0.142 (1.267)	-0.294 (1.368)
	-1.180 (0.720)	-0.839 (0.828)	-0.742 (0.908)
Age	-0.033 (0.016)	-0.046 (0.018)	-0.043 (0.021)
	0.012 (0.028)	0.028 (0.032)	0.030 (0.034)
	0.020 (0.184)	0.016 (0.021)	0.015 (0.023)
Proportion	3.673 (3.094)	4.067 (3.278)	3.379 (3.624)
Property	7.432 (4.819)	7.509 (5.135)	6.832 (5.726)
	-0.422 (2.709)	0.951 (2.855)	0.489 (3.312)
Proportion	4.134 (3.315)	2.154 (3.453)	5.443 (3.979)
Personal	7.693 (5.393)	9.581 (5.719)	9.693 (6.186)
	1.762 (3.203)	1.709 (3.363)	0.393 (3.583)
Proportion	-5.466 (2.819)	-6.530 (2.889)	-6.585 (4.041)
Drug	-2.534 (3.321)	-1.069 (3.537)	2.593 (4.971)
	4.776 (2.910)	3.266 (3.019)	5.406 (3.886)
Age *	-0.051 (0.090)	-0.068 (0.094)	-0.077 (0.104)
Proportion	-0.177 (0.134)	-0.169 (0.145)	-0.152 (0.162)
Property	-0.000 (0.085)	0.006 (0.088)	-0.033 (0.102)
Age *	-0.014 (0.093)	0.036 (0.096)	-0.044 (0.107)
Proportion	-0.014 (0.149)	-0.187 (0.157)	-0.191 (0.167)
Personal	0.024 (0.099)	0.016 (0.103)	0.050 (0.110)
Age *	0.168 (0.081)	0.189 (0.082)	0.185 (0.109)
Proportion	0.003 (0.090)	-0.028 (0.095)	-0.117 (0.125)
Drug	-0.122 (0.080)	-0.082 (0.083)	-0.139 (0.103)

Table 4.10: Interaction Effects by Race and Gender for Offenders with Ten or More Prior Arrests.

Parameter	Total Subsample Estimate (s.e.)	Males Estimate (s.e.)	Non-white Males Estimate (s.e.)
Age +	-0.084 (0.082)	-0.114 (0.095)	-0.120 (0.106)
Age *	-0.165 (0.137)	-0.141 (0.148)	-0.122 (0.165)
Proportion	0.020 (0.087)	0.022 (0.091)	-0.018 (0.104)
Property			
Age +	-0.047 (0.094)	-0.010 (0.098)	-0.087 (0.109)
Age *	-0.002 (0.151)	-0.159 (0.160)	-0.161 (0.171)
Proportion	0.044 (0.032)	0.032 (0.105)	0.065 (0.112)
Personal			
Age +	0.134 (0.083)	0.143 (0.084)	0.142 (0.111)
Age *	0.015 (0.094)	0.000 (0.100)	-0.087 (0.130)
Proportion	-0.102 (0.082)	0.066 (0.085)	-0.124 (0.105)
Drug			
Proportion	3.623 (3.096)	3.999 (3.279)	3.302 (3.625)
Property +	7.255 (4.821)	7.340 (5.137)	6.680 (5.729)
Age *	-0.422 (2.711)	-0.945 (2.856)	0.456 (3.313)
Proportion			
Property			
Proportion	4.129 (3.317)	2.190 (3.454)	5.399 (3.981)
Personal +	7.679 (5.395)	9.394 (5.721)	9.502 (6.190)
Age *	1.786 (3.204)	1.725 (3.365)	0.443 (3.585)
Proportion			
Personal			
Proportion	-5.299 (2.820)	-6.341 (2.890)	-6.400 (4.043)
Drug +	-2.531 (3.322)	-1.097 (3.539)	2.476 (4.972)
Age *	4.654 (2.911)	3.184 (3.011)	5.267 (3.887)
Proportion			
Drug			

Table 4.11: Four-way Cross-tabulation for all Males in the Seattle Youth Study.

Fight	Hit Teacher	Theft \$2-\$50	Theft Under \$2	Frequency
0	0	0	0	129
0	0	0	1	185
0	0	1	0	20
0	0	1	1	172
0	1	0	0	10
0	1	0	1	15
0	1	1	0	6
0	1	1	1	23
1	0	0	0	69
1	0	0	1	149
1	0	1	0	11
1	0	1	1	269
1	1	0	0	15
1	1	0	1	26
1	1	1	0	6
1	1	1	1	75

Table 4.12: Four-way Cross-tabulation for White Males in the Seattle Youth Study.

Fight	Hit Teacher	Theft \$2-\$50	Theft Under \$2	Frequency
0	0	0	0	79
0	0	0	1	130
0	0	1	0	6
0	0	1	1	128
0	1	0	0	5
0	1	0	1	13
0	1	1	0	2
0	1	1	1	14
1	0	0	0	43
1	0	0	1	120
1	0	1	0	6
1	0	1	1	207
1	1	0	0	7
1	1	0	1	14
1	1	1	0	4
1	1	1	1	51

Table 4.13: Four-way Cross-tabulation for Non-White Males in the Seattle Youth Study.

Fight	Hit Teacher	Theft \$2-\$50	Theft Under \$2	Frequency
0	0	0	0	50
0	0	0	1	55
0	0	1	0	14
0	0	1	1	44
0	1	0	0	5
0	1	0	1	2
0	1	1	0	4
0	1	1	1	9
1	0	0	0	26
1	0	0	1	29
1	0	1	0	5
1	0	1	1	62
1	1	0	0	8
1	1	0	1	12
1	1	1	0	2
1	1	1	1	24

Table 4.14: Latent-Class Model Fits for all Males in the Seattle Youth Study.

Model	LR-χ^2	χ^2	DF	D
Independence	256.026	266.544	10	0.166
Two-class (unrestricted)	25.772	26.861	6	0.040
Three-class (unrestricted)	7.171	6.837	3	0.021
Three-class (restricted)	6.884	7.527	3	0.014

Table 4.15: Latent-Class Model Fits for White Males in the Seattle Youth Study.

Model	LR-χ^2	χ^2	DF	D
Independence	182.474	190.044	10	0.157
Two-class (unrestricted)	14.084	14.453	6	0.037
Three-class (unrestricted)	2.231	2.207	2	0.011
Three-class (restricted)	2.242	2.226	2	0.010

Table 4.16: Latent-Class Model Fits for Non-white Males in the Seattle Youth Study.

Model	LR-χ^2	χ^2	DF	D
Independence	87.864	87.184	10	0.183
Two-class (unrestricted)	19.230	18.141	6	0.066
Three-class (unrestricted)	6.660	6.528	3	0.034
Three-class (restricted)	6.659	6.526	4	0.034

Figure 4.1: Offense Specific Age Plots,
Total, Murder, and All Other Offenses.

Figure 4.2: Offense Specific Age Plots, Total, Rape, and Suspicion Offenses.

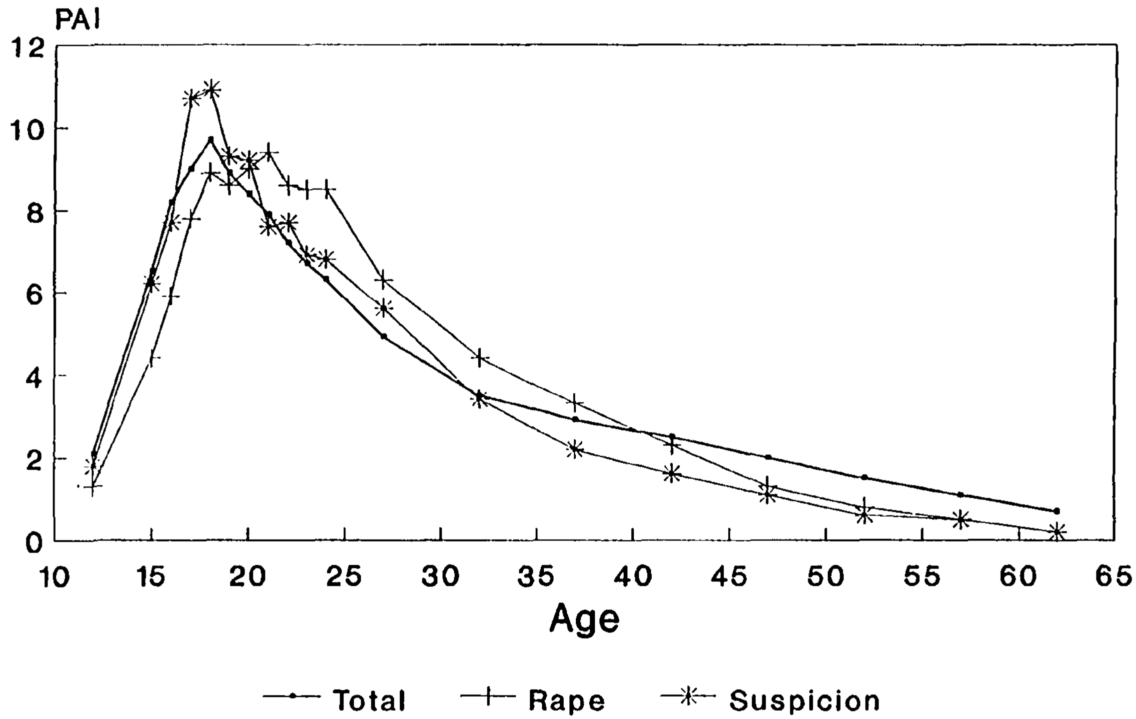


Figure 4.3: Offense Specific Age Plots,
Total, Robbery, and Vagrancy Offenses.

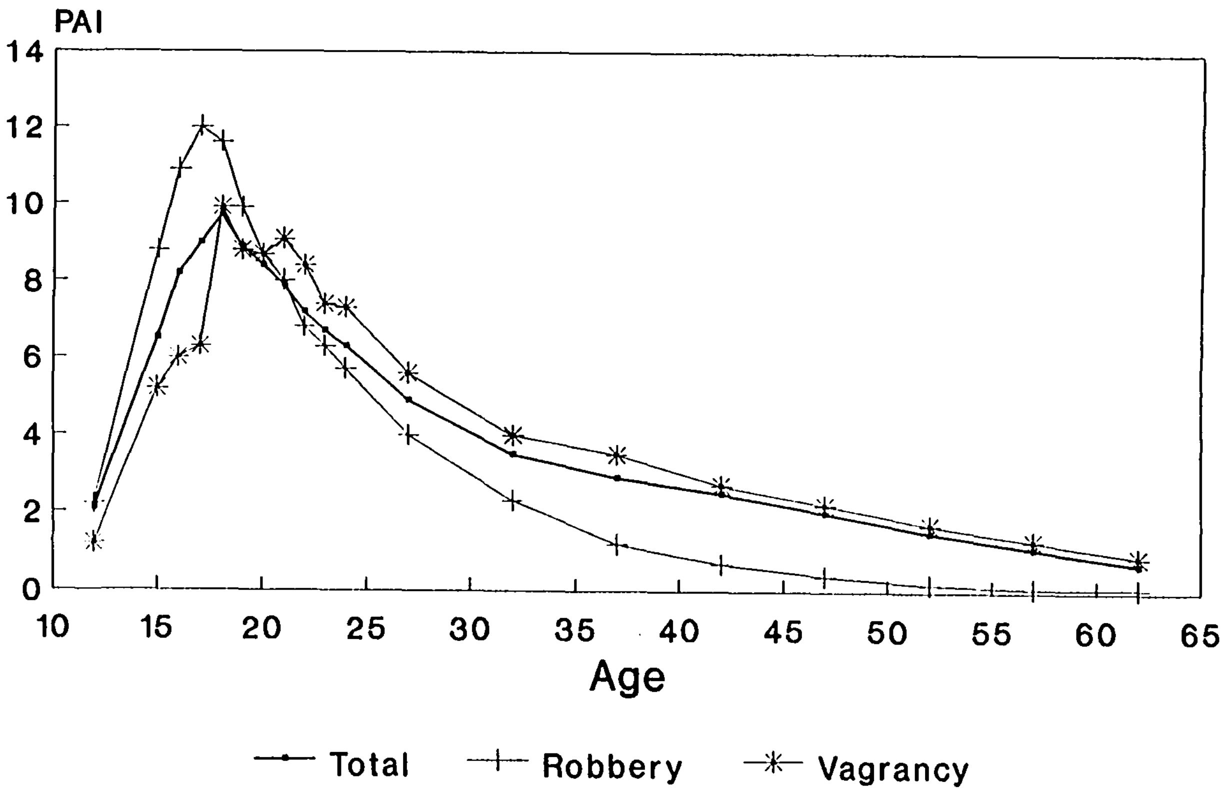


Figure 4.4: Offense Specific Age Plots, Total, Assault, and Conduct Offenses.

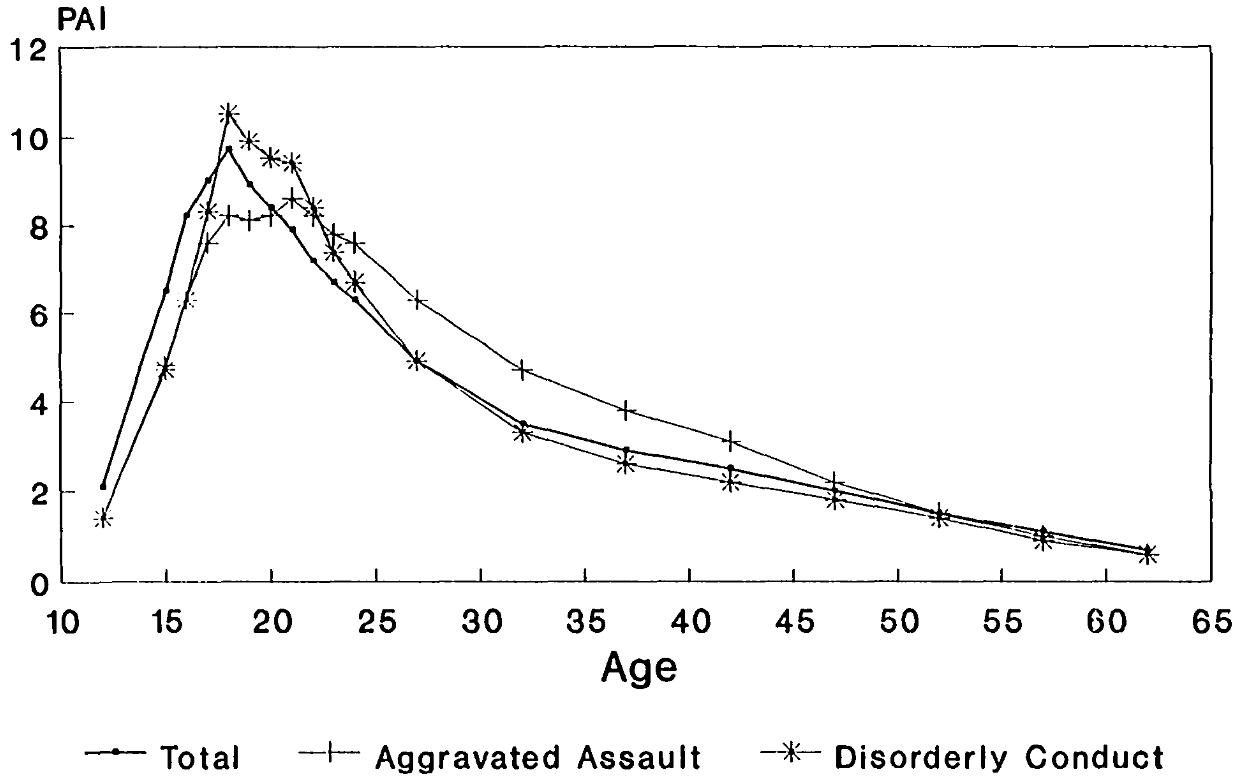


Figure 4.5: Offense Specific Age Plots, Total, Burglary, and Drunkenness Offenses.

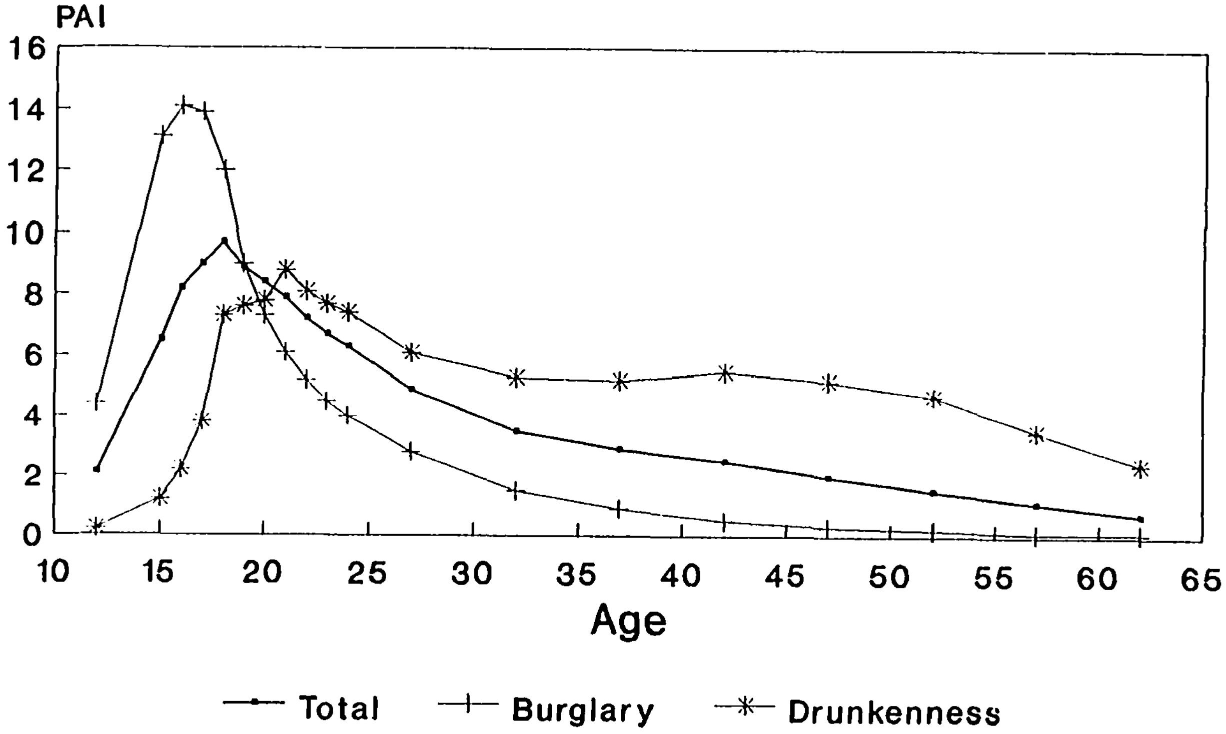


Figure 4.6: Offense Specific Age Plots, Total, Larceny, and Liquor Offenses.

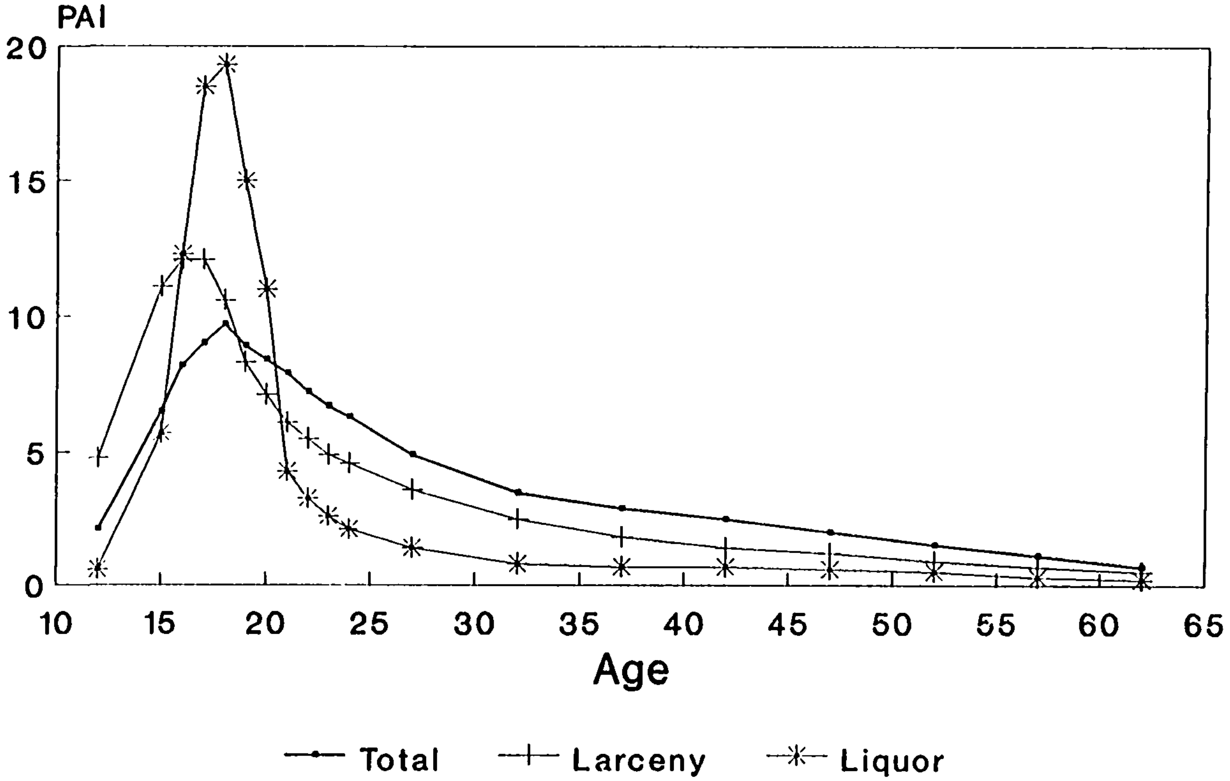


Figure 4.7: Offense Specific Age Plots, Total, Auto Theft, and DUI Offenses.

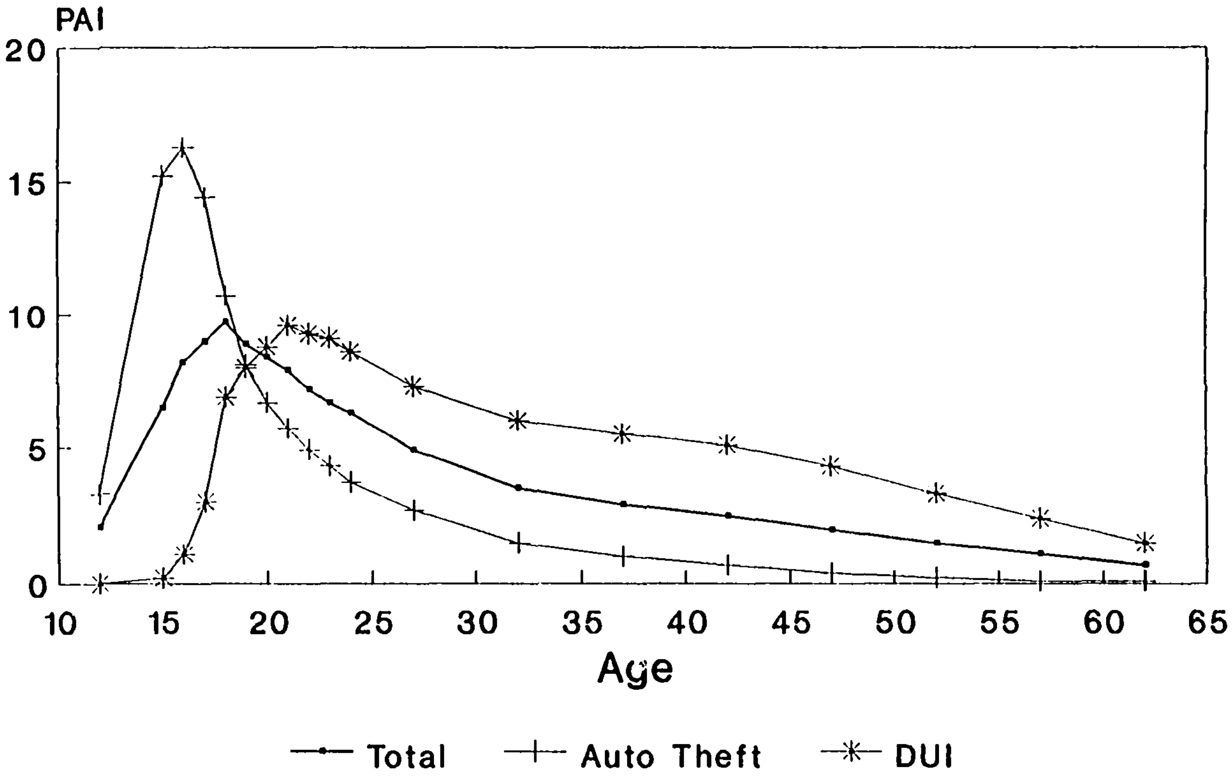


Figure 4.8: Offense Specific Age Plots, Total, Arson, and Family Abuse Offenses.

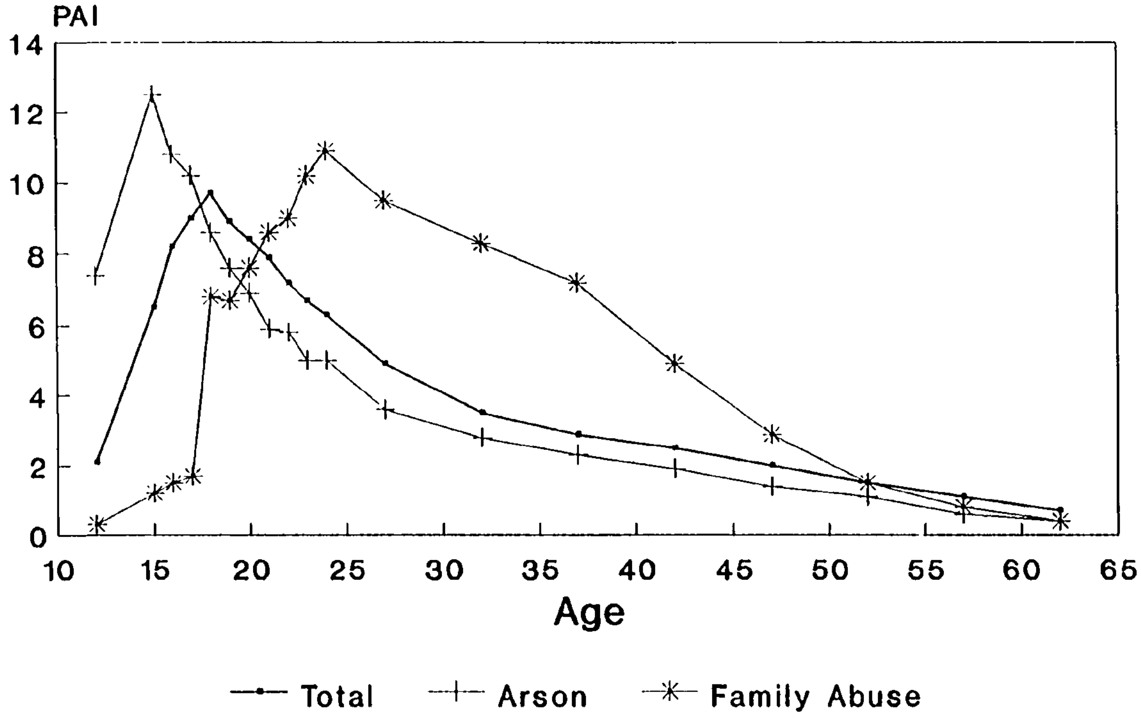


Figure 4.9: Offense Specific Age Plots, Total, Forgery, and Gambling Offenses.

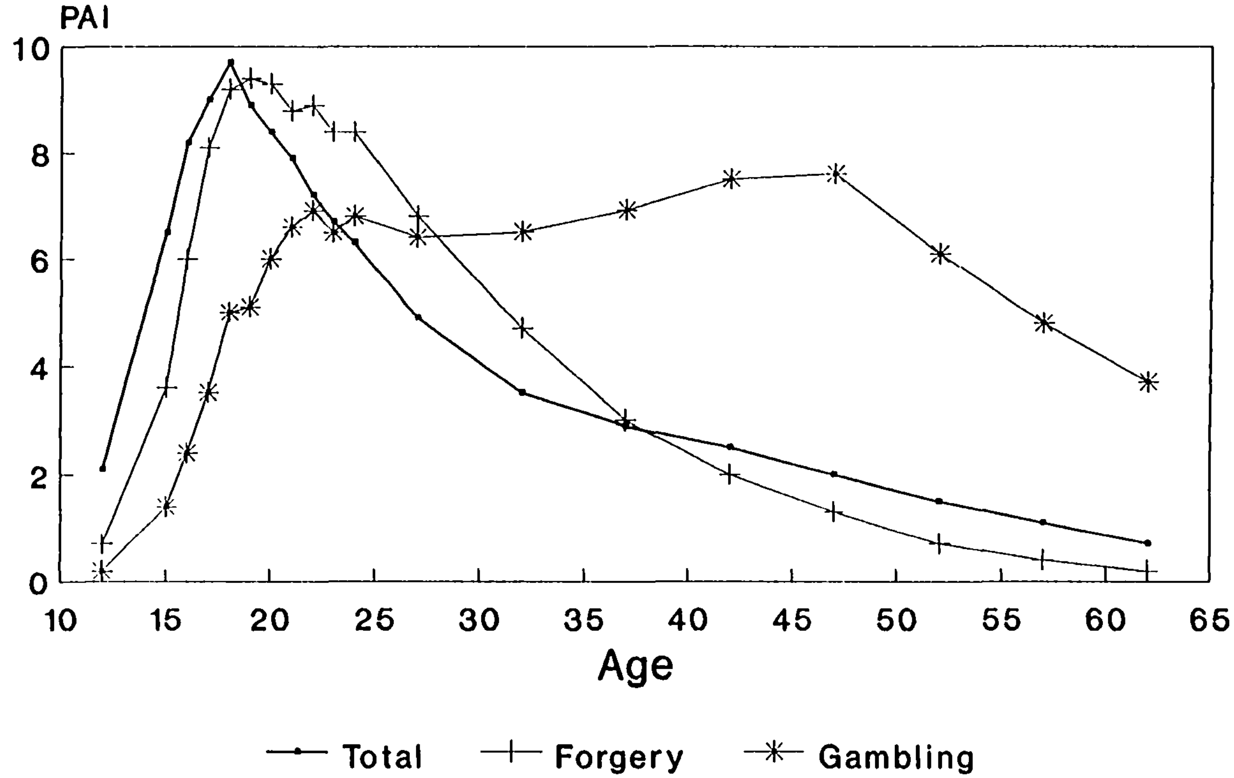


Figure 4.10: Offense Specific Age Plots, Total, Fraud, and Drug Offenses.

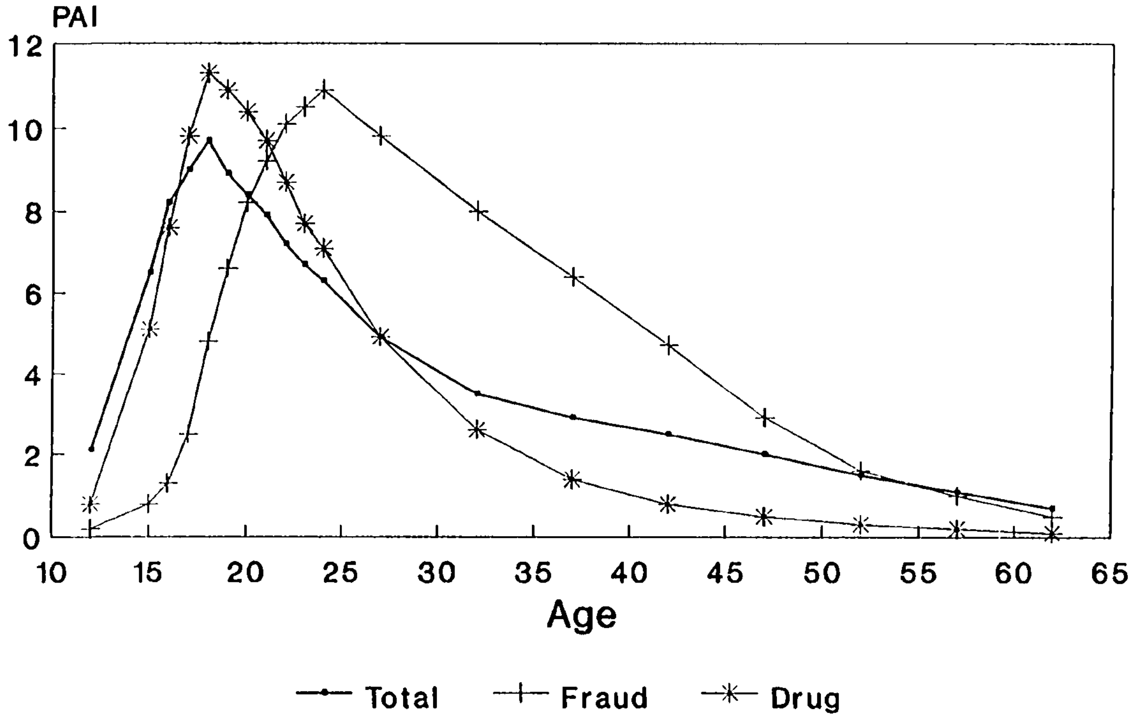


Figure 4.11: Offense Specific Age Plots,
Total, Embezzlement, and Sex Offenses.

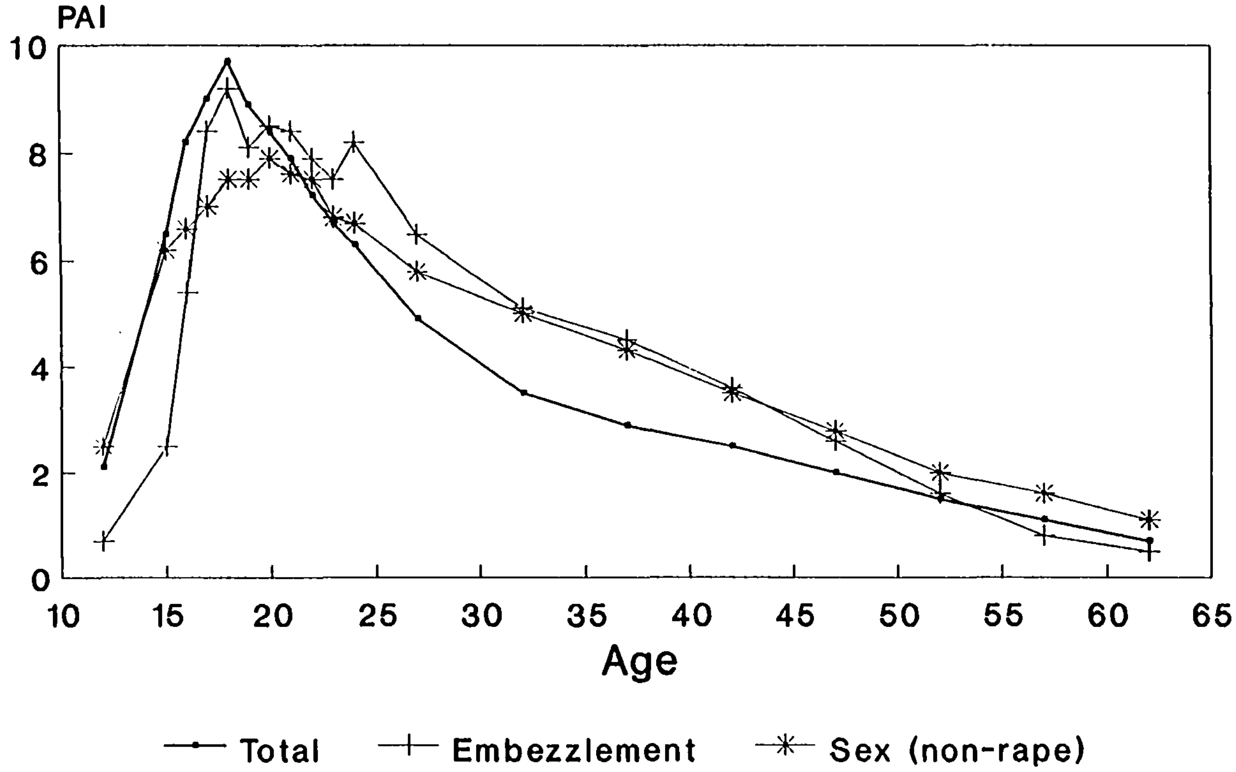


Figure 4.12: Offense Specific Age Plots, Total, Stolen Property, and Prostitution Offenses.

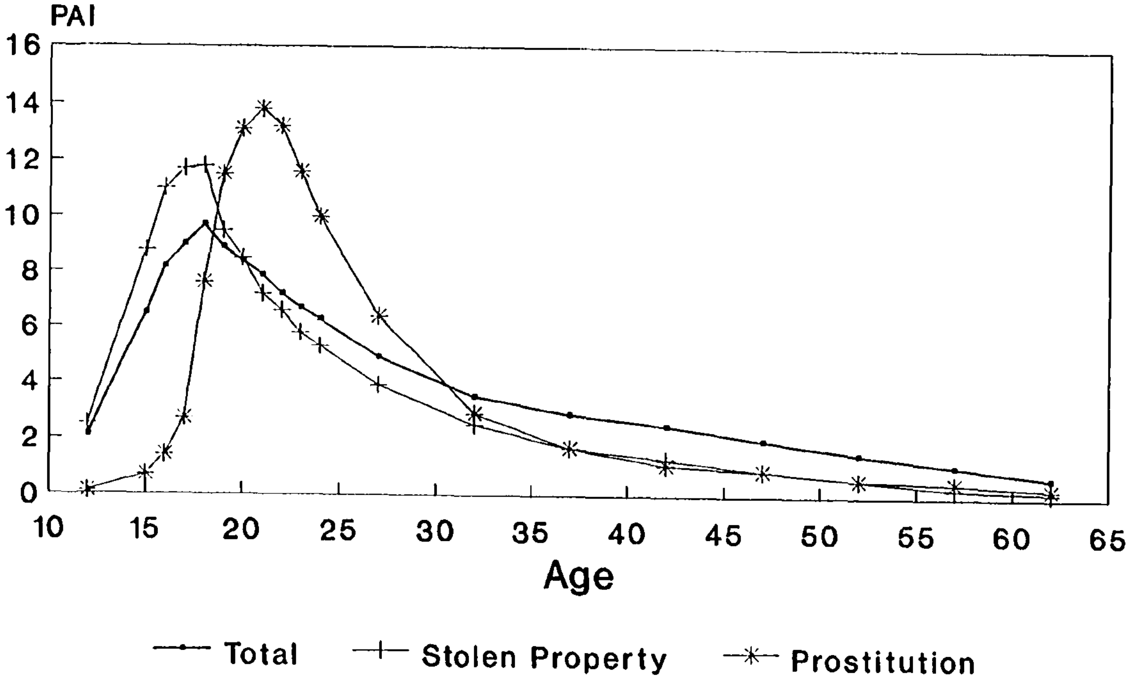


Figure 4.13: Offense Specific Age Plots,
Total, Vandalism, and Weapons Offenses.

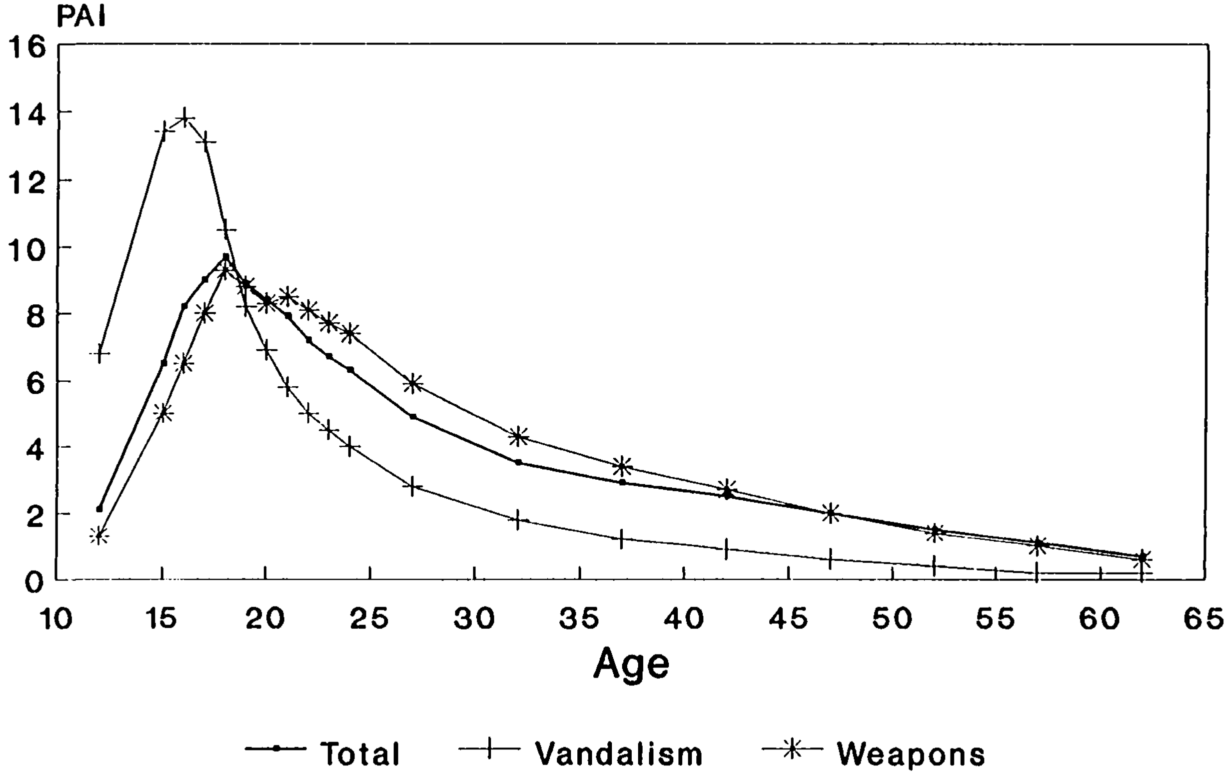
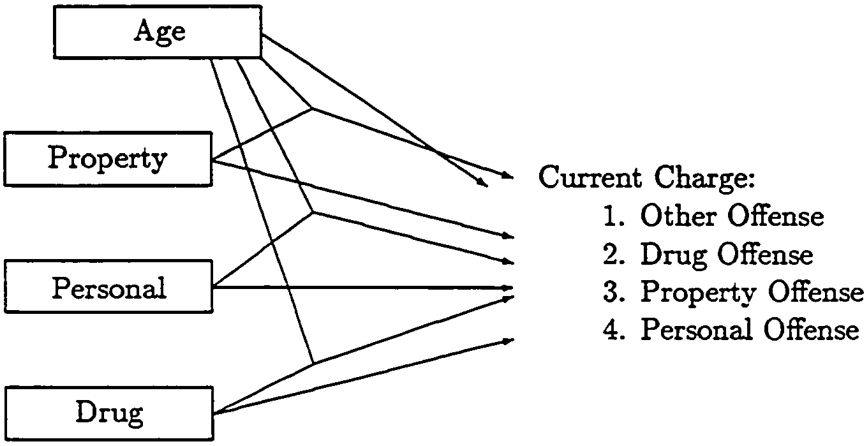


Figure 4.14: Model for Predicting Current Charge.



CHAPTER 5

PARTICIPATION AND FREQUENCY OF OFFENDING

INTRODUCTION

Criminologists have long been concerned with the theoretical importance of the distinction between participation in crime and the frequency with which criminal acts are committed (see Reiss, 1975). At issue has been concern that the causes of initial participation in crime may differ from the causes of continued involvement in criminal activity. Reiss (1975), among others, accurately notes that tests of criminological theory tend to operationalize crime or delinquency as participation (a yes-no dichotomy). While these measures can provide information, the argument goes, they cannot provide the full picture, because individuals committing only one crime *may* differ from individuals committing ten or twenty crimes. For example, Wolfgang et al. (1972) show that the frequency of offending varies substantially by race and SES of the individual. Other studies operationalizing crime as a frequency show patterns of results different from those of studies using a simple dichotomy (Ball, Ross, and Simpson, 1964; Douglas, Ross, Hammond, and Mulligan, 1966; Gordon, 1976; Little, 1965; Monahan, 1960).

Thus, relying on the inconsistency shown by the studies using frequency of crime rather than participation in crime, Blumstein and Grady (1982:255) claim

> ...that one set of factors distinguishes between those persons

> who become involved in crime the first time and those who do not, and that a different set of factors distinguishes those who persist in crime once involved, from those who discontinue criminality at an early stage.

The logic to Blumstein and Grady's claim is consistent with traditional positivistic analyses of crime and delinquency (see Gottfredson and Hirschi, 1990). Specifically, the first concern is to explain why a person commits crime, or, why a person becomes a criminal. This would then represent participation in crime. The second concern is to then try and explain why the person persists in committing crime. However, the world is assumed to be too complicated to fit a single behavioral explanation, and multiple theories must then be used to explain the wide variety of criminal activity. In other words, Blumstein and Grady (1982) assume that the factors causing an individual to commit one crime will be different from the factors causing another individual to commit two crimes, and yet a third individual who commits 5 crimes, and so on (Blumstein et al., 1986, 1988a, 1988b reiterate this claim).

The position of different causes for different frequencies of offending lies in stark contrast to Gottfredson and Hirschi's (1990) claim that the causes of crime are the same, regardless of the frequency at which crime is committed. Recall from Chapter 1 that for Gottfredson and Hirschi (1990), the primary cause of criminal behavior is low self-control. Individuals with low self-control are expected to have higher probabilities of committing crime. The additional factor influencing crime commission is the social situation of the individual, which provides varying degrees of opportunity. In other words, individuals with high levels of self-control would not normally be expected to commit criminal acts, but the social situation may provide opportunities attractive even to them. Conversely, individuals with low self-control may be prevented from committing crimes if they are located in situations where it is very difficult for them to act on their impulses.

Gottfredson and Hirschi's discussion is important for the participation-frequency distinction because they assert that the individual-level causes of crime for the first and subsequent acts are the same (i.e., low self-control). What accounts for the frequency of activity is level of self-control and opportunity, or social situation. In short, the key elements to crime commission are not expected to change as individuals commit more crime. They are always self-control and opportunity. Thus, whether crime is operationalized as a dichotomy to represent participation or a count to represent frequency, Gottfredson and Hirschi (1990) would claim that the correlates of these measures will be the same.

In sum, the hypothesis to be tested in this chapter is the similarity of the causes of participation and frequency of illegal behavior. Proponents of the criminal career view (Blumstein and colleagues, 1982, 1986, 1988a, 1988b) argue that the causes are different for participation and frequency, whereas the control theory relied on in this study (Gottfredson and Hirschi, 1990) argues that the causes are the same.

RECENT RESEARCH

There have been two recent attempts to test for differences in the causes of participation and frequency of crime. Gottfredson and Hirschi (1988), using data from the Richmond Youth Survey, show how several correlates of participation – race, smoking, drinking and dating behavior, grade-point average (GPA), and delinquency of friends – have comparable associations with delinquency operationalized as participation or frequency among active delinquents.[1] Unfortunately, their analysis presents only a series of bivariate correlations, and while the similarity in the patterns of findings is striking, the lack of a multivariate test calls their results into question. It is possible that in a multivariate test of delinquency with these six independent variables, a different pattern of stability (or variability) would be observed.

Paternoster and Triplett's (1988) recent study of participation and frequency of delinquency is the only work that has specifically tested the hypothesis of different causes for these two measures of illegal activity using a multivariate model. They analyzed a sample of 11th grade students in southeastern high schools (n=1,544), using independent variables representing four popular perspectives in criminology – social learning, social control, strain, and deterrence – to model participation and frequency of offending. Four delinquency items – marijuana use, drinking, petty theft, and vandalism – were coded as a dichotomy (0,1) to represent participation and as a count (1,2,3,...) for those individuals who had at least one commission of the act in the previous year to represent frequency.[2] Overall, Paternoster and Triplett found that the same sets of variables tended to explain both participation and frequency in each of the four delinquent acts, and concluded

> ...there was very little difference in the effects of the exogenous variables on the two outcome measures of delinquency (1988:614).

[1] Recall from Chapter 1 that an "active offender" is a person who has committed at least one illegal act in some designated time period (Blumstein et al., 1986).

[2] The participation model was tested with a probit statistical model, while the frequency model was tested with a tobit statistical model.

However, Paternoster and Triplett also argued that the illegal acts they focused on were not serious offenses, and that studies focusing on more serious acts, and using different samples, might reveal a different pattern of results.[3]

Methodological Issues

The Gottfredson and Hirschi (1988) and Paternoster and Triplett (1988) studies thus provide preliminary evidence contradicting the claim of different causes for participation and frequency of offending. However, there are two important methodological issues that have not been satisfactorily resolved. First, does the operationalization of illegal behavior as a dichotomy (to measure participation) or a count of illegal acts among active offenders (to measure frequency) artifactually result in substantially different multivariate statistical models? Limiting the frequency analysis to those individuals with one or more illegal acts introduces censoring, since individuals are excluded from the sample unless the dependent variable (criminal behavior) has a value greater than zero. Censored samples, such as those created in testing multivariate models of frequency of offending among active offenders, can be analyzed with the tobit statistical model (see Judge, Griffiths, Hill, Lutkepohl, and Lee, 1985; Maddala, 1983). The tobit model provides unbiased and consistent regression estimates (where a regression model on the censored sample would not) by introducing controls for the individuals with zero scores on the dependent variable. The tobit model accomplishes this by first computing an individual's chances of having a value on the dependent variable greater than zero (with a probit model). This

[3] In light of the findings in Chapter 4 on the generality of illegal behavior, we can anticipate that specific crimes will have very little effect on whether the causes of participation and frequency are similar or different.

probability then represents a "hazard rate" parameter which is computed for every individual with a non-zero value on the dependent variable, and included as an additional variable in a classic regression analysis on the censored sample.

The parameter estimates produced from a tobit analysis require some care in their interpretation, since they represent both (1) the change in the dependent variable, weighted by the probability of having a non-zero value on the dependent variable and (2) the change in probability of having a non-zero value on the dependent variable, weighted by the expected value of the dependent variable, given that it is non-zero (Judge et al., 1985). For our purposes below, we will be concerned primarily with the sign and statistical significance of each parameter, rather than with a formal interpretation of each parameter's magnitude.

Second, some concern has also been raised in the literature over the "cut-point" to represent participation and frequency of offending (see, especially, Gottfredson and Hirschi, 1986, 1987, and 1988). If the distinction between participation and frequency is made at 0 and 1 to represent active offenders, then researchers using self-report data will likely have some individuals coded as non-offenders (a zero value on the dependent variable) when they have, in fact, committed some other act that was just not recorded or used in the present analysis. In short, the number of illegal acts used to distinguish active offenders from non-offenders is arbitrary. Gottfredson and Hirschi's (1988) and Paternoster and Triplett's (1988) use of one or more offenses is consistent with concerns of the criminal career view that researchers focus on anyone with one or more criminal acts in some time period. However, it would also be reasonable to make a cut at five, ten, or even twenty offenses to try and distinguish the so-called "serious, high-rate" offender from both low-rate and non-offenders (see, for example, Chaiken and Chaiken, 1983; Greenwood, 1983). Fortunately, the tobit model discussed above can be modified to represent a different cut point. Thus, in so far as the data will permit analysis, different cut points will be compared in the analyses below.

THE CURRENT STUDY

To test the hypothesis of different causes for participation and frequency of illegal activity, data from the Bail Decisionmaking Study, Seattle Youth Study, and National Youth Survey are used. The *Uniform Crime Reports* does not provide information on individuals that could be analyzed to shed light on this issue, and is therefore excluded from further consideration in this chapter.

The models to be examined with each data set are essentially multivariate replications of Gottfredson and Hirschi's (1988) effort. A limited number of variables are taken from each data set to represent variables found to be significant predictors of participation in offending in the crime and delinquency literature.[4] The focus of each analysis below is a test of whether predictors of participation also act as predictors of frequency of offending. To further advance our understanding of the frequency distinction, two cut-points (one or more and five or more illegal acts) will also be examined to assess whether different definitions of the

[4]While it would have been nice to test directly Gottfredson and Hirschi's (1990) substantive model of self-control and criminal behavior, none of the data sets was collected with the idea of measuring a concept such as self-control. Thus, rather than produce inaccurate findings about the validity of Gottfredson and Hirschi's (1990) substantive model of crime, simpler models, representing only a few indicators, are used to test for differences in participation and frequency of offending.

active offender substantially alter the pattern of statistically significant predictors in a multivariate model.[5]

Bail Decisionmaking Study

Dependent Variables. To address the question of different causes of participation and frequency, the dependent variables used here are two measures of rearrest while on release status. The measure of participation is simply whether the offender was rearrested in the 120-day period following release. Frequency was measured as the number of times an offender was rearrested, given that there was at least one arrest while on release. This rearrest measure is the same as the variable discussed in Chapter 3, where rearrest represents a new crime committed by the offender following his/her release from jail for the crime that resulted in initial selection to for the BDS sample. Given the time limit on the occurrence of a rearrest in the BDS sample, this measure provides a nice way of evaluating the participation - frequency distinction, since there is an additional control (time) on acceptable values for this measure.[6]

Independent Variables. The literature on the rearrest of released offenders has clearly shown that a combination of legal, community ties, and demographic characteristics provides the best predictors of the likelihood of rearrest (i.e., participation). For the following analysis, gender, age, race, phone service, prior record of arrests, and current charge will be used as the predictors of both the occurrence and the frequency of rearrest. (The reader is referred to Gottfredson and

[5]The BDS data would permit a test of only one cut-point due to the lack of variation on the independent variables, which caused the statistical analysis to fail and not reach a solution.

[6]Of course, it is possible that a released offender may commit one or more crimes and go undetected in this 120 day period. However, the offenders who were rearrested are assumed to be similar to those individuals who committed crimes but were not rearrested.

Gottfredson (1988) for a more detailed discussion of this literature.)

Gender is represented by the variable Female, which is coded as a "1" if the offender is female, and as a "0" for males. Race is represented by the variable White, which is coded as a "1" for white offenders, and as a "0" for non-white offenders (most of whom were black). Prior research suggests that females, whites, and older individuals will have lower chances of rearrest and fewer rearrests if rearrested at least once.

Phone service is coded as a "1" if the offender had phone service at the time of arrest, and "0" otherwise. This variable has a negative relationship with pre-trial misconduct, and though the reason for this is not entirely clear, it has been taken as an indicator of ties to the community, and has been shown to be a reliable predictor of rearrest.

Prior record of arrests is coded as a "0" if there was no record of arrest prior to the offender's being arrested and placed in the BDS sample. Individuals with any number of prior arrests received a value of "1." This item has been shown to have a positive relationship with rearrest, where those individuals arrested in the past stand a higher likelihood of being arrested again.

Current charge is represented by the variable Theft Offense, which is coded as a "1" if the offender's first charge is for a theft offense, and "0" otherwise. Current charge has also been shown to have an effect on the likelihood of rearrest, where those offenders charged with a theft offense stand a greater likelihood of being rearrested during the pre-trial process.

In sum, the demographic variables, as coded for the following analysis are all expected to reduce both the chances of rearrest and the frequency of rearrest among those arrested for a new offense. Phone service is also expected to have the same negative effect. Prior arrest record and theft offense as the first charge are, conversely, expected to increase the chances of rearrest and frequency of rearrest.

Findings. Table 5.1 presents the means, standard deviations, and ranges for the variables included in the following analyses of the released population at risk of committing a new crime and being rearrested (n=4,006).

Table 5.2 presents the probit and tobit estimates for the hypothesized model. The probit analysis tests the participation model. Age, phone service, and prior record have statistically significant effects on rearrest. As expected, individuals with prior records were more likely to be rearrested, while older individuals and people with phone service were less likely to have been rearrested.

The second column of Table 5.2 displays the tobit estimates testing the hypothesized model against frequency of rearrest among all offenders with one or more arrests while on release. The pattern of statistically significant findings in the frequency model is identical to that found in the participation model. Increased age and and having phone service predicted lower odds of being rearrested and fewer rearrests among those offenders who were rearrested. Individuals with prior records had higher chances of rearrest and increased frequencies of rearrest.

To summarize, the BDS sample of released offenders in Philadelphia seriously questions the validity of the criminal career claim that the causes of participation and frequency of offending may be substantially different. Using variables found to have significant effects on the chances of pre-trial misconduct in other criminal justice literature, the results in Table 5.2 show the statistically significant predictors of participation to be the same as the statistically significant predictors of rearrest. This finding is, again, contrary to predictions made by the criminal career view.

Seattle Youth Study and National Youth Survey

Dependent Variables. Relying on the generality of delinquency results presented in Chapter 4, participation and frequency measures of delinquency were constructed using two theft and two violence measures. From the SYS, the four items are

1. Theft of an item worth $2 or less.
2. Theft of an item worth $10 to $50.
3. Hit a teacher.
4. Fought with other students.

The NYS delinquency items are similar:

1. Theft of an item worth less than $5.
2. Theft of an item worth $5 to $50.
3. Hit a teacher.
4. Fought with other students.

The only substantive difference between the two data sets is the value of the stolen items. However, both items represent theft of $50 or less. Participation in delinquency is measured by whether an individual has committed any one of the four delinquent acts and is coded as (0,1). Frequency of delinquency among active delinquents is represented by the total number of times the individual claims to have committed all four acts.

Independent Variables. Similar to the BDS analysis, demographic characteristics – age, race, and gender – are included below to model the different mean levels of delinquency among the different groups. The coding of these variables also follows that in the BDS analysis, where gender is represented by the variable Female and race is represented by the variable White. Again, based on prior research on the demographic correlates of delinquent behavior, females, whites, and older individuals are expected to have both lower chances of participating in delinquency and fewer delinquent acts, if they have committed any delinquent acts.

Three other variables are included in the following analyses, because prior research has shown them to be strongly related to delinquency. First, delinquent friends has a positive relationship with delinquency, where those individuals claiming to have friends involved in delinquent activities are themselves more likely to be involved in delinquency (see, for example, Akers et al., 1979). In the SYS, this item was measured by whether the respondent had any friends (to his or her knowledge) who had been arrested. Those individuals responding "yes" were coded as a "0," while individuals responding "no" were coded as a "1" to represent the variable "No Delinquent Friends." In the NYS, "No Delinquent Friends" is represented by those individuals responding that none of their friends had committed any one of ten delinquent acts.[7] Again, individuals with no delinquent friends received a "1", while individuals with friends involved in any of the ten delinquent acts received a "0." Individuals with no delinquent friends are then expected to be unlikely to participate in delinquency and to have low frequencies as well.

Second, Grade Point Average (GPA) has also been shown to have a

[7] These delinquent acts are cheating on tests, destroying property, using marijuana, stealing something worth less than $5, hitting someone, using alcohol, breaking into a vehicle, selling hard drugs, stealing something worth more than $50, and suggesting one break the law.

negative relationship with delinquent behavior (see, for example, Hirschi, 1969). In both the SYS and NYS, scores of "4" represent an A average, "3" a B average, and "2" a C average. Then, due to differences in the original questions, in the SYS, a "1" represents a D average or lower, while in the NYS, a "1" represents a D average, and a "0" an F average. Based on prior work, it is expected that as GPA increases, the chances and frequency of delinquency will decrease.

Third, dating behavior has a positive relationship with delinquency, where those individuals who regularly date have increased chances of delinquent behavior (see, again, Hirschi, 1969). In both the SYS and NYS, this item is coded as a "1" if the respondent said that s/he regularly dates (at least once a week), and "0" otherwise.

In sum, females, whites, older individuals, those individuals with no delinquent friends, and those persons with higher GPA's are expected to have lower chances of participation in delinquency and lower frequencies of delinquency. In contrast those individuals who regularly date are expected to have higher chances of participation and higher frequencies of delinquent behavior.

Findings. Tables 5.3 and 5.4 display the means, standard deviations, and ranges for the variables included in the SYS and NYS participation and frequency analyses below.

Table 5.5 presents the probit and tobit estimates for the SYS analysis. The probit results show that increased age, having no delinquent friends, and higher GPA all have statistically significant effects that reduce the chances a person has participated in any delinquent behavior, as expected. Dating has a significant positive relationship with participation, also as expected.

The tobit estimates for frequency operationalized as one or more delinquent acts shows the same variables have statistically significant effects as in the participation model. In other words, increased age, having no delinquent friends, and higher GPA reduce the chances of delinquency and reduce the frequency of delinquency if it has occurred. Similarly, dating increases the chances of delinquency and its frequency, too.

To investigate the effects of a different cut-point for frequency of delinquent behavior, frequency was also operationalized as five or more delinquent acts. The number of statistically significant variables is reduced, with age and dating no longer having significant effects on the frequency of delinquent behavior, while having no delinquent friends and higher GPA still reduce the frequency of delinquent behavior. While these results, at first glance, appear to support the criminal career claim of different causes of frequency of illegal behavior, the variation in all the independent variables is reduced considerably when the cut-point is changed from one to five or more delinquent acts. The lack of variation in the independent variables make the statistical estimation more uncertain and difficult, implying that the parameter estimates and their standard errors may be unstable.

Table 5.6 presents the probit estimates for all four waves of data from the NYS. In all four years, females, older individuals, those with no delinquent friends, and those with higher GPA's were less likely to participate in any delinquent activity. In all but the second year, dating significantly increased the chances of participating in delinquency, as expected. The one statistically significant finding that provides an anomaly is that whites were significantly more likely to participate in delinquent activity in the third year. However, given the lack of this variable's statistical significance in all other analyses, this finding may be a chance result.

Table 5.7 shows the tobit estimates for frequency of delinquent behavior operationalized as one or more delinquent acts. The statistically significant parameters in Table 5.7 are identical to those in Table 5.6, with two exceptions. First, white individuals do not have statistically lower frequencies of delinquency in Wave 3, compared to the lower level of participation found in Table 5.6. Second, dating significantly increased the chances of delinquency in Wave 4, but did not increase the frequency of delinquency in the same year.

Table 5.8 provides the tobit estimates for frequency operationalized as five or more delinquent acts. Overall, there is considerable similarity between the pattern of statistically significant parameters in Tables 5.7 and 5.8, since the two tables reveal only four major differences. In Wave 1, age and no delinquent friends had significant negative effects on both participation and frequency defined as one or more delinquent acts, but these items had no effect on frequency when defined as five or more delinquent acts. In Wave 2, age again fails to reduce significantly the frequency of delinquency for the subsample of individuals with five or more delinquent acts. Lastly, in Wave 3, no delinquent friends fails to significantly reduce the frequency of delinquency among the individuals with five or more delinquent acts.

To summarize, there is a great deal of similarity in both the SYS and NYS analyses comparing participation with frequency of delinquency, when the cut-point is operationalized as one or more delinquent acts. When the cut-point for frequency is changed to five or more delinquent acts, the pattern of results is still quite similar to the participation and one or more frequency analyses, although there is some variation. Overall, however, the results in Tables 5.5 through 5.8 imply support for the idea that the causes of participation and frequency of illegal activity are indeed the same, regardless of the operationalization of frequency of illegal activity. Once again, the results call into question the validity of the criminal career view, since the significant predictors of participation also predict frequency of illegal activity, which is contrary to the predictions of this view.

SUMMARY AND CONCLUSIONS

The analyses in this chapter attempt to test the claim that the causes of participation in some form of illegal activity are somehow different from the causes of the frequency of that illegal behavior once it occurs. Using data from the Bail Decisionmaking Study, Seattle Youth Study, and National Youth Survey, multivariate models of participation and frequency of offending were tested with probit and tobit statistical models, respectively, to assess whether the same set of variables that predicted participation also predicted frequency of illegal behavior. Further, in the SYS and NYS analyses, two operationalizations of frequency of delinquency were compared. Specifically, "one or more" and "five or more" delinquent acts were used as two different cut-points to see whether the different operationalizations of delinquency could substantially alter the findings.

Using the Bail Decisionmaking Study, the measure of illegal behavior was operationalized as whether any arrest occurred following an individual's release from jail (participation), and if the offender was rearrested, the number of times (frequency). Testing a model that contained variables representing background characteristics (age, race, and gender), community ties (phone service), and legal characteristics (prior record and current charge), the statistically significant effects predicting participation (analyzed with a probit statistical model) were identical to the statistically significant effects predicting frequency of rearrest (analyzed with a tobit statistical model). Although the use of rearrest as a measure of additional criminal activity among a sample of already arrested individuals could lead to statistical estimation problems due to lack of variation on the independent variables, no such problems were encountered here. But the results do pose a problem for the claim that the causes of initial participation and subsequent frequency of illegal activity are different.

The two self-report data sets revealed a similar pattern of results. In both the Seattle Youth Study and National Youth Survey, the same six items representing demographic (age, race, and gender) and social (delinquent friends, GPA, and dating behavior) characteristics were available to evaluate the proposed hypothesis. In the SYS, there was no difference in the form of the statistically significant model for participation and frequency, when the cut-point for frequency was one or more delinquent acts. When the cut-point was shifted to five or more delinquent acts, there was variation in the set of statistically significant parameters. However, this variation was not sufficient to undermine support for the claim that the causes of participation and frequency of delinquency are the same – because when all results are close to the borderline of statistical significance, apparent differences in outcome are simply much more likely.

In the National Youth Survey, two trivial differences in the pattern of statistically significant effects in the participation and frequency models were observed, when frequency was operationalized as one or more delinquent acts. When the cut-point for the frequency analysis was changed to five or more delinquent acts, there was slight variation in the pattern of statistically significant effects. Again, the overall pattern was one of stability of the causes of participation and frequency of delinquency, regardless of the operationalization of frequency of illegal activity.

To summarize, there is strong support for the idea that the causes of committing one illegal act are the same as the causes of committing many illegal acts. This pattern of similar significant effects held for all three data sets. The findings from the SYS and NYS, using relatively minor theft and violence acts, both confirm and extend the general pattern of results presented by Paternoster and Triplett (1988); namely, that delinquent behavior is predicted equally well, whether operationalized as participation or frequency of illegal activity, or whether frequency was operationalized as one or more or five or more delinquent acts. The results from the BDS extend the generality of the self-report findings by considering a sample of adults who have committed more serious crimes, and show that participation and frequency of rearrest while on release can be explained with the same model.

The claim of Blumstein et al. (1986, 1988a) that the causes of participation and frequency of illegal activity may be different appears to be in error. While the data here have limitations – the SYS and NYS use relatively minor delinquent acts, and only two operationalizations of frequency of offending were analyzed – the three data sets, together, raise serious questions about the claim of different causes. The results in fact suggest that proponents of the claim that participation and frequency require substantively different explanations need to reevaluate this assertion, and propose an alternative that is consistent with the facts.

Table 5.1: Bail Decisionmaking Study Means, Standard Deviations, and Ranges for the Participation and Frequency Analyses (n=4,006).

Variable	Mean	Standard Deviation	Minimum	Maximum
Female	0.140	0.347	0	1
Age	29.270	11.330	14	87
White	0.328	0.470	0	1
Phone Service	0.795	0.404	0	1
Prior Record	0.627	0.484	0	1
Theft Offense	0.268	0.443	0	1
Number of Rearrests	0.246	0.836	0	8
Any Rearrest	0.153	0.360	0	1

Table 5.2: Probit and Tobit Estimates with Standard Errors for the Bail Decisionmaking Study Participation and Frequency Analyses.

Variable	Probit Estimates (s.e.)	Tobit Estimates (s.e.)
Intercept	-0.819 (0.090)	-2.515 (0.309)
Female	-0.105 (0.076)	-0.191 (0.224)
Age	-0.016 (0.002)	-0.051 (0.007)
White	0.017 (0.054)	0.142 (0.159)
Phone Service	-0.154 (0.059)	-0.547 (0.173)
Prior Record	0.581 (0.057)	1.814 (0.177)
Theft Offense	-0.057 (0.056)	-0.142 (0.166)
Sigma		3.064 (0.104)
Likelihood Function	-1635.8	-2538.2
Restricted Likelihood	-1712.5	

Table 5.3: Seattle Youth Study Means, Standard Deviations, and Ranges for the Participation and Frequency Analyses (n=1,471).

Variable	Mean	Standard Deviation	Minimum	Maximum
Female	0.250	0.433	0	1
Age	16.502	0.928	14	18
White	0.703	0.457	0	1
No Delinquent Friends	0.542	0.498	0	1
GPA	2.681	0.744	1	4
Date	1.107	0.310	0	1
Number of Delinquent Acts	1.862	9.031	0	215
Any Delinquency	0.311	0.463	0	1

Table 5.4: National Youth Survey Means, Standard Deviations, and Ranges for the Participation and Frequency Analyses.

Variable	Mean	Standard Deviation	Minimum	Maximum
Wave 1: (n=1,442)				
Female	0.482	0.500	0	1
Age	13.870	1.925	11	17
White	0.806	0.395	0	1
No Delinquent Friends	0.085	0.279	0	1
GPA	2.752	0.818	0	4
Date	0.769	0.422	0	1
Number of Delinquent Acts	7.992	52.940	0	1413
Any Delinquency	0.539	0.499	0	1

Table 5.4 (Continued)

Wave 2: (n=1,440)				
Female	0.478	0.500	0	1
Age	14.850	1.924	12	18
White	0.809	0.393	0	1
No Delinquent Friends	0.076	0.265	0	1
GPA	2.744	0.803	0	4
Date	0.819	0.385	0	1
Number of Delinquent Acts	4.402	18.350	0	400
Any Delinquency	0.478	0.500	0	1

Table 5.4 (Continued)

Wave 3: (n=1,474)				
Female	0.472	0.499	0	1
Age	15.680	1.890	13	19
White	0.807	0.394	0	1
No Delinquent Friends	0.068	0.252	0	1
GPA	2.714	0.822	0	1
Date	0.851	0.356	0	1
Number of Delinquent Acts	3.865	21.650	0	400
Any Delinquency	0.398	0.490	0	1

Table 5.4 (Continued)

Wave 4: (n=1,301)				
Female	0.482	0.500	0	1
Age	16.500	1.833	14	20
White	0.795	0.404	0	1
No Delinquent Friends	0.051	0.221	0	1
GPA	2.699	0.821	0	4
Date	0.893	0.309	0	1
Number of Delinquent Acts	3.402	20.775	0	502
Any Delinquency	0.344	0.475	0	1

Table 5.5: Probit and Tobit Estimates with Standard Errors for the Seattle Youth Study Participation and Frequency Analyses.

Variable	Probit Estimate (s.e.)	Tobit (1+) Estimate (s.e.)	Tobit (5+) Estimate (s.e.)
Intercept	3.265 (0.642)	31.147 (10.993)	10.659 (42.890)
Female	-0.061 (0.086)	-2.198 (1.502)	-4.503 (5.841)
Age	-0.194 (0.039)	-2.023 (0.666)	-1.940 (2.477)
White	-0.100 (0.078)	-0.425 (1.348)	-2.893 (5.144)
No Delinquent Friends	-0.424 (0.073)	-6.225 (1.281)	-16.966 (4.995)
GPA	-0.246 (0.050)	-3.702 (0.878)	-11.628 (3.418)
Date	0.418 (0.127)	-4.192 (2.234)	-4.474 (8.556)
Sigma		18.290 (0.646)	44.207 (3.591)
Likelihood Function	-849.54	-2390.6	-741.02
Restricted Likelihood	-911.49		

Table 5.6: Probit Estimates with Standard Errors for the National Youth Survey Participation Analyses, Waves 1 through 4.

Variable	Wave 1	Wave 2	Wave 3	Wave 4
Intercept	1.762 (0.300)	1.741 (0.310)	2.733 (0.331)	2.821 (0.382)
Female	-0.754 (0.071)	-0.805 (0.071)	-0.740 (0.072)	-0.801 (0.078)
Age	-0.061 (0.019)	-0.054 (0.019)	-0.140 (0.020)	-0.136 (0.022)
White	-0.035 (0.089)	-0.017 (0.088)	0.186 (0.090)	-0.051 (0.093)
No Delinquent Friends	-1.027 (0.146)	-1.014 (0.160)	-1.331 (0.200)	-1.073 (0.225)
GPA	-0.213 (0.043)	-0.242 (0.045)	-0.294 (0.044)	0.325 (0.047)
Date	0.316 (0.087)	0.149 (0.097)	0.276 (0.106)	0.347 (0.131)
Likelihood Function	-872.63	-875.26	-852.78	-717.24
Restricted Likelihood	-995.16	-996.80	-990.54	-837.04

Table 5.7: Tobit Estimates with Standard Errors for the National Youth Survey Frequency Analyses for One or More Delinquent Acts, Waves 1 through 4.

Variable	Wave 1	Wave 2	Wave 3	Wave 4
Intercept	69.105 (20.135)	27.021 (7.560)	45.624 (10.934)	67.289 (13.354)
Female	-39.380 (4.860)	-17.214 (1.804)	-19.014 (2.494)	-19.371 (2.856)
Age	-3.924 (1.290)	-0.875 (0.481)	-3.003 (0.671)	-3.643 (0.787)
White	-1.602 (5.939)	-3.466 (2.132)	4.246 (3.038)	0.241 (3.270)
No Delinquent Friends	-59.889 (11.135)	-23.385 (4.386)	-39.237 (7.463)	-33.319 (8.653)
GPA	-11.982 (2.937)	-5.171 (1.079)	-6.914 (1.436)	-10.890 (1.633)
Date	17.711 (5.964)	2.276 (2.374)	7.789 (3.543)	6.966 (4.627)
Sigma	77.490 (1.992)	27.717 (0.771)	36.642 (1.110)	37.874 (1.318)
Likelihood Function	-4802.8	-3626.4	3313.6	-2584.4

Table 5.8: Tobit Estimates with Standard Errors for the National Youth Survey Frequency Analyses for Five or More Delinquent Acts, Waves 1 through 4.

Variable	Wave 1	Wave 2	Wave 3	Wave 4
Intercept	-13.379 (54.299)	4.302 (22.460)	-15.791 (33.518)	45.461 (38.903)
Female	-94.731 (14.006)	-40.337 (5.933)	-53.695 (8.853)	-45.565 (9.271)
Age	-3.998 (3.510)	-1.453 (1.443)	-3.669 (2.063)	-5.607 (2.341)
White	-3.841 (15.850)	-3.684 (6.246)	7.279 (9.448)	10.648 (9.973)
No Delinquent Friends	-541.942 (1748.360)	-71.550 (23.087)	-268.825 (1049.460)	-69.314 (31.729)
GPA	-31.712 (7.929)	-12.271 (3.158)	-11.508 (4.299)	-20.292 (4.644)
Date	51.047 (17.188)	8.739 (7.176)	25.132 (11.809)	8.457 (13.301)
Sigma	151.719 (7.323)	58.788 (3.280)	79.353 (4.886)	79.279 (5.453)
Likelihood Function	-1859.8	-1386.9	-1206.3	-981.77

CHAPTER 6

SUMMARY AND CONCLUSIONS

INTRODUCTION

Two general questions, one theoretical, one methodological orient this study. The theoretical question focused on whether the criminal career paradigm or control theory provides a better explanation for patterns of criminal activity. The criminal career view is currently popular among criminologists and policy makers, in part because it is apparently simple and atheoretical. However, as demonstrated in Chapter 1, the underpinning to the criminal career view is in fact microeconomic theory, which provides a theory for comparison against control theory. The comparison of the predictions from these two views was provided by three hypotheses. Specifically, the criminal career view and control theory were tested against (1) the stability of the age distribution of crime, (2) the prevalence of versatility in illegal activity, and (3) whether different explanatory models are required for participation in illegal activity compared to the frequency of that illegal activity among so called "active offenders" (i.e., individuals with some minimum number of illegal acts in a specified time period).

The methodological question focused on the pattern of findings provided by four different types of crime data. Specifically, do longitudinal and cross-sectional studies reveal different findings? Do official and self-report data sources give comparable results? Does the pattern of findings change when design (longitudinal or cross-sectional) and source (official or self- report) are simultaneously controlled? In addition to concerns over type of data, alternative methods of testing the three hypotheses were also used to overcome serious limitations in prior research addressing age and crime, versatility in offending, and participation and frequency of offending.

This study has thus been a theoretical and methodological evaluation of two competing views of criminal behavior. The following discussion highlights the major findings presented above, as well as the theoretical and research implications of this work.

SUMMARY OF FINDINGS

Age and Crime

The debate over the age distribution of crime has focused on the stability, or similarity, of the shape of the curve (see, for example, Farrington, 1986; Greenberg, 1985; Hirschi and Gottfredson, 1983, 1985; Steffensmeier, Allan, Harer, and Streifel, 1989). Much of the research on the age distribution of crime has serious logical or methodological problems. The most important of these problems is the measurement of the dependent variable. With the exception of Farrington (1986) and Steffensmeier et al. (1989), researchers have mistakenly assumed that age-specific crime rates could be used to adequately test Hirschi and Gottfredson's invariance proposition. The analyses in Chapter 3, following Farrington's (1986) and Steffensmeier et al.'s (1989) work, uses standardized proportions to represent age-specific offending, and more importantly, test for stability in the age *distribution* of crime.

Using data from the 1952 to 1987 *Uniform Crime Reports*, the Bail Decisionmaking Study, the National Youth Survey, and the Seattle Youth

Study, the age distribution of crime was shown to be stable in three ways. First, cross-sectional plots of the age distribution of crime were examined to see whether the curves had the same shape in every year from 1952 to 1987 in the *UCR*, and in the other three data sets. Although the shapes of the curves were clearly not identical, the findings above suggest that the age distribution of crime in the U.S. has been stable since 1963, but shifted between 1952 and 1963 from being more or less equally distributed among older offenders (age 25+) in 1952 to being concentrated among younger offenders since 1963. The age-crime curves found in the other three data sets provided supporting evidence for the stability observed in the *UCR* data. The curves, with some variation, approximated the shape of the *UCR* results, implying that the age distribution of crime is stable over time and type of data used.

Second, the *PAI* values for age groups 15 to 24-years-old were examined for the 1952 to 1987 time period in the *UCR* and age groups 12 to 19-years-old in the four waves of the NYS data. The *UCR* graphs confirmed the finding of a shift to younger offenders in the cross-sectional age distributions of crime between 1952 and the mid-1960s. Additionally, while the *PAI* values for 15 to 19-year-olds showed an overall increase between 1952 and 1987, there was virtually no change among 20 to 24-year-olds, and a slight decrease among individuals over age 24. The NYS data contained a more limited range of years to compare age-specific offending, and, not surprisingly, found these to be quite stable over the four year period.

Third, in the *UCR*, the *PAI* values for four birth cohorts covering the 1952 to 1987 time period revealed that more recent cohorts have tended to similar patterns of offending. Specifically, there were considerably different *PAI* values for cohorts in the teen years, but by age 21, there was less than a 1% difference. Further, the cohort results again demonstrated the stability in offending among individuals aged 21 to 24. In the NYS, no such discrepancy was found when cohort age-specific offending was analyzed, even though the cohorts were compared across ages 12 through 19-years-old, which showed the most variation in the *UCR* results. Interestingly, then, the NYS data show more recent cohorts to have quite similar patterns of offending, validating the similarity observed for the more recent *UCR* cohorts.

Overall, the findings in Chapter 3 are supportive of the invariance hypothesis. The U.S. age distribution of crime was stable since 1963, following a period of considerable change between 1952 and 1963. While the U.S. age distribution of crime from 1952 to 1987 fails to clearly confirm or reject the invariance hypothesis, the distribution was stable for a much longer period (1963 to 1987) than it was variable (1952 to 1963). However, age-crime curves from the other three data sets also revealed an age-specific pattern of offending comparable to that found in the *UCR*. Taken together, Figures 1 through 12 provide substantial support for a claim that the age distribution of crime is invariant.

Versatility in Offending

In contrast to the research on the age distribution of crime, research on offense specialization has tended to reach similar conclusions; namely, that offenders tend to cluster the types of crimes they commit (Kempf, 1987; Farrington et al., 1988; Blumstein et al., 1988; Brennan et al., 1989). Unfortunately, there are again serious methodological problems with much of this work. Using data from the *UCR*, BDS, and SYS, the specialization hypothesis was examined in three different ways –

graphical, logistic regression, and latent class analyses – to correct for the methodological problems with prior research discussed in Chapter 4. Overall, the findings were not supportive of the notion that older, more experienced offenders tend to commit the same type of crime.

Data from the *Uniform Crime Reports* showed the age distribution of gambling offenses to be the only offense specific age distribution of crime that was not comparable to the age distribution for total crimes. According to specialization researchers (e.g., Cohen, 1986; Blumstein et al., 1988), some crimes should be more attractive to older offenders because they are potentially more profitable and may require more skill to be successful. Figures 4.1 through 4.13 clearly show this not to be the case. Most crimes exhibit virtually the same age-specific pattern of offending as total crimes.

The Bail Decisionmaking Study data also failed to show offenders specializing in illegal activity. A model that included age, prior record information (crime type), and interaction effects between age and prior offending to predict current charge was tested on multiple subsamples distinguished by the number of prior arrests (1 or more, 5 or more, and 10 or more), race (white, non-white), and gender. Overwhelmingly, the results from a battery of logistic regressions showed the independent variables not to have an effect on predicting current charge. Thus, the specialization hypothesis was again not supported in a test of its predictive validity.

The Seattle Youth Survey, similar to the *UCR* and BDS data, also failed to support the specialization hypothesis. Latent class models testing whether adolescent males fell into two distinct classes of offenders (i.e., non-delinquent, personal, and property classes) showed the distinction between personal and property crimes to be not particularly helpful in explaining the distribution of individuals across the four-way cross-tabulation. The model that had the best overall fit was a two-class model of delinquents and non-delinquents, meaning that the individuals involved in the property crimes were also likely involved in the personal offenses. In addition, the BDS finding of no differences between black and white males was confirmed.

Overall, the findings in Chapter 4 pose serious problems for the specialization hypothesis. There were virtually no findings that supported the specialization in offending notion. This pattern held regardless of the operationalization of specialization, how the model was tested, or the type of data used to evaluate the hypothesis.

Participation and Frequency of Offending

The analyses in Chapter 5 attempted to test the claim that the causes of individuals participating in some form of illegal activity are somehow different from the causes of the frequency of that illegal behavior once it occurs. Using data from the Bail Decisionmaking Study, Seattle Youth Study, and National Youth Survey, multivariate models of participation and frequency of offending were tested with probit and tobit statistical models, respectively, to assess whether the same set of variables that predicted participation also predicted frequency of illegal behavior. Further, in the SYS and NYS analyses, two operationalizations of frequency of delinquency were compared. Specifically, "one or more" and "five or more" delinquent acts were used as two different cut-points to see whether the different operationalizations of delinquency could substantially alter the findings.

Using the Bail Decisionmaking Study, the measure of illegal behavior was operationalized as whether any arrest occurred following an individual's release from jail (participation), and if the offender was rearrested, the number of times (frequency). Testing a model that contained variables representing background characteristics (age, race, and gender), community ties (phone service), and legal characteristics (prior record and current charge), the statistically significant effects predicting participation (analyzed with a probit statistical model) were identical to the statistically significant effects predicting frequency of rearrest (analyzed with a tobit statistical model). Although the use of rearrest as a measure of additional criminal activity among a sample of already arrested individuals could lead to statistical estimation problems due to lack of variation on the independent variables, no such problems were encountered here. But the results do pose a problem for the claim that the causes of participation of illegal activity are different.

The two self-report data sets revealed a similar pattern of results. In both the Seattle Youth Study and National Youth Survey, the same six items representing demographic (age, race, and gender) and social (no delinquent friends, GPA, and dating behavior) characteristics were available to evaluate the proposed hypothesis. In the SYS, there was no difference in the form of the statistically significant model for participation and frequency, when the cut-point for frequency was one or more delinquent acts. However, when the cut-point was shifted to five or more delinquent acts, there was some variation in the set of statistically significant parameters, but not enough to lessen support for the claim that the causes of participation and frequency of delinquency are the same.

In the National Youth Survey, there were two trivial differences in the pattern of statistically significant effects in the participation and frequency models, when frequency was operationalized as one or more delinquent acts. When the cut-point for the frequency analysis was changed to five or more delinquent acts, there was slight variation in the pattern of statistically significant effects. However, the overall pattern was one of stability of the causes of participation and frequency of delinquency, regardless of the operationalization of frequency of illegal activity.

To summarize, there was strong support for the idea that the causes of committing one illegal act are the same as the causes of committing many illegal acts. This pattern of similar significant effects held for all three data sets. The findings from the SYS and NYS, using relatively minor theft and violence acts, both confirm and extend the general pattern of results presented by Paternoster and Triplett (1988); namely, that delinquent behavior is predicted equally well, whether operationalized as participation or frequency of illegal activity, or whether frequency was operationalized as one or more or five or more delinquent acts. The results from the BDS extend the generality of the self-report findings by considering a sample of adults who have committed much more serious crimes, and still show that participation and frequency of rearrest while on release can be explained with the same model.

IMPLICATIONS

Theoretical Implications

Much of the work currently published in criminological journals is not directed by a theory of crime. Researchers seem content to document the patterns of offending that some individuals follow over some time period, or to evaluate crime control policies. While neither of these two issues is without merit, the lack of research testing theories of crime suggests that we either know what theory best explains criminal behavior, which is clearly false, or that we have come to accept the idea that no theory of crime can explain illegal behavior with any moderate degree of accuracy, so why bother?

It is hoped that the results presented in this study will provide evidence contrary to the notion that no theory of crime works. Using the age distribution of crime, patterns in offense specialization (or versatility), and the distinction between participation and frequency of offending, a control theory of crime does much to explain the results that were obtained. Gottfredson and Hirschi (1990) claim to have developed a general theory of crime, and the results on age, specialization, and participation would seem to confirm their claim. However, as general as they claim their theory to be, its concepts may be further refined and its predictions more direct.

For instance, one improvement that could be made with Gottfredson and Hirschi's (1990) theory is to specify the functional relationship between self-control and criminal behavior. In Chapter 1, one possibility – an inverse relationship between self-control and crime – was suggested. It would be far too simple to argue that there is a simple negative linear relationship between these two variables. The assumption of an inverse relationship is clearly preliminary, and future efforts could be directed at ascertaining whether the self-control and crime relationship follows this functional form or some other function. The determination of this relationship would do much to advance criminological theory, which has been notoriously naive in its conception of relationships among variables.

Following the specification of the self-control and crime relationship, effort could then be directed at the interaction of the social situation with self-control, and their combined effects on crime. Again, as suggested in Chapter 1, the simplest possibility is that the social situation is additive, meaning that the level of informal social control in any given social situation can have the same relative effect on the chances of crime. Similar to self-control, the assumption of a simple negative linear relationship between informal social control and crime is too naive. There are few real world relationships that can be appropriately described with a straight line.

In sum, a simple trait theory of criminal behavior will be inadequate, as will a theory that relies solely on social factors. If criminological theory is to make advances beyond rehashing strain or cultural deviance theories, efforts must be aimed at describing how individual characteristics interact with social factors to influence the likelihood of crime.

Methodological Implications

Many of the analyses in this study are new to criminology. The analyses used here have attempted to correct for serious methodological flaws in prior research on these same substantive issues. Furthermore, concern for the type of data used to answer these questions about criminal behavior motivated the use of four data sets to lessen the chances of a conclusion being an artifact of the data type.

In Chapters 3 through 5, measurement issues were raised, and answered in generally standard, although sometimes unconventional fashion. In regard to the issue of the invariance of the age distribution of crime, the analysis focused on clarifying exactly what it is that the dependent variable is supposed to be. The invariance claim looks at the *distribution* of crime by age, as opposed to age specific crime rates. Once this issue is more generally resolved in the discipline, we might be able to make some headway in resolving whether the age distribution of crime is indeed stable across varying social and cultural conditions.

The specialization analyses also looked at a measurement issue. Specifically, the question was how to determine whether an individual was specializing in an illegal activity? The standard use of transition matrices, while interesting, and generally straightforward to statistically analyze, provides inadequate and incomplete answers to the specialization question. The three approaches taken here – graphical, logistic regressions, and latent class analyses – come at the problem from a very different perspective. In so doing, they provide more complete tests of the specialization hypothesis. Again, the discipline must learn to adapt to alternative techniques for testing longstanding hypotheses if we expect to answer more fully questions about the nature of crime causation.

The analyses on participation and frequency of offending also extend our methodological understanding. The results in Chapter 5 show that operationalization of crime as a dichotomy (participation) or as a count among so-called "active offenders" (frequency) has little influence on the statistically significant predictors of criminal behavior. The findings in Chapter 5 also show how two different operationalizations of frequency of illegal activity had only minor impact on the pattern of statistically significant predictors. What variation there was in the set of significant predictors could be attributed to the corresponding lack of variation on the independent variables.

The type of data on crime and delinquency that we use has periodically come under scrutiny. There are questions about the adequacy of self-report data (e.g., Hindelang et al., 1981; O'Brien, 1985), official statistics (e.g., McCleary et al, 1982; Hindelang, 1981), and cross-sectional and longitudinal designs (e.g., Gottfredson and Hirschi, 1987; Blumstein et al., 1988a, 1988b). This study used four different types of data in hopes of answering the question: Do different types of data provide substantially different answers? Reviewing the patterns of findings in Chapters 3 through 5, there is little doubt that, overall, the findings are not considerably different when official and self-report data are compared. In addition, and as important, the findings are comparable across the cross-sectional or longitudinal dimension. In short, the four types of data analyzed in this study – official and longitudinal, official and cross-sectional, self-report and longitudinal, and self-report and cross-sectional – reach similar conclusions about criminal behavior.

Unfortunately, it was not possible to use all four data sets in meaningful tests of each of the hypotheses, but there were always at least three data sets used to evaluate a single hypothesis. This should add some credibility to the claim that the type of data we use to test criminological theory is not nearly as important as the quality of that data. In other words, poorly designed and executed studies will produce questionable results, regardless of the nice statistical properties associated with some approaches, and regardless of whether the data are longitudinal or cross-sectional, official or self-report. While properly executed studies will, in the end, likely reach similar conclusions about crime and delinquency, regardless of the data type.

Thus, in our quest for the perfect set of data on illegal behavior, we need to be sensible. Current calls for multiple decade cohort studies may appear, at first glance, to hold promise for answering many questions about criminal behavior. We should be wary, however, of studies claiming to have all the answers, as such studies would seem more prone to problems than the small-scale, or at least focused effort aimed at answering a small number of theoretically interesting questions correctly.

APPENDIX A

Derivation of PAI

The formula for the PAI was given above as

$$PAI = \frac{r_{ij}}{\sum_{i=15}^{49} r_{ij}} * 100.$$

This can be rewritten as

$$\begin{aligned} PAI &= \frac{\frac{A_i}{P_i}}{\frac{A_T}{P_T}} * 100 \\ &= \frac{A_i}{P_i} * \frac{P_T}{A_T} * 100 \\ &= \frac{A_i}{A_T} * \frac{P_T}{P_i} * 100 \\ &= \frac{\frac{A_i}{A_T}}{\frac{P_i}{P_T}} * 100. \end{aligned}$$

The last line is equivalent to the proportion of all arrests (A_i/A_T) in age group i, standardized for the proportion of the total population (P_i/P_T) in age group i.

REFERENCES

Akers, Ronald L. 1985. *Deviant Behavior: A Social Learning Approach*, 3ed. Belmont, CA: Wadsworth.

Akers, Ronald L. 1988. "In the Sutherland Tradition: Progress and Prospects in Social Learnign Theory." Paper presented at the Annual Meetings of the American Society of Criminology, Chicago.

Akers, Ronald L., Marvin D. Krohn, Lonn Lanza-Kaduce, and Marcia Radosevich. 1979. "Social Learning and Deviant Behavior: A Specific Test of a General Theory." *American Sociological Review* 44:636-655.

Allingham, M.G. and A. Sandmo. 1972. "Income Tax Evasion: A Theoretical Analysis." *Journal of Public Economics* 1:323- 338.

Andersen, R.W. 1976. *The Economics of Crime.* London: MacMillan.

Ball, John, Alan Ross, and Alice Simpson. 1964. "Incidence and Estimated Prevalence of Recorded Delinquency in a Metropolitan Area." *American Sociological Review* 29:90-93.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76:169-217.

Berk, Richard A. 1983. "An Introduction to Sample Selection Bias in Sociological Data." *American Sociological Review* 48:386-398.

Blau, Judith R. and Peter M. Blau. 1982. "The Cost of Inequality: Metropolitan Structure and Violent Crime." *American Sociological Review* 47:114-129.

Block, Michael K. and James M. Heineke. 1975. "A Labor Theoretic Analysis of Criminal Choice." *American Economic Review* 65:314-325.

Blumstein, Alfred and Jacqueline Cohen. 1979. "Estimation of Individual Crime Rates from Arrest Records." *Journal of Criminal Law and Criminology* 70:561-585.

Blumstein, Alfred, Jacqueline Cohen, and Soumyo Das. 1985. "Crime-Type Switching in Criminal Careers." Unpublished

Paper. Urban Systems Institute, School of Urban and Public Affairs, Carnegie-Mellon University, Pittsburgh, PA.

Blumstein, Alfred, Jacqueline Cohen, Somnath Das, and Soumyo Moitra. 1988. "Specialization and Seriousness During Adult Criminal Careers." *Journal of Quantitative Criminology* 4:303-345.

Blumstein, Alfred, Jacqueline Cohen, and David Farrington. 1988a. "Criminal Career Research: Its Value for Criminology." *Criminology* 26:1-35.

Blumstein, Alfred, Jacqueline Cohen, and David Farrington. 1988b. "Longitudinal and Criminal Career Research: Further Clarifications." *Criminology* 26:57-74.

Blumstein, Alfred, Jacqueline Cohen, and Daniel Nagin (eds.). 1978. *Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates.* Washington, D.C.: National Academy of Sciences Press.

Blumstein, Alfred, Jacqueline Cohen, Jeffrey Roth, and Christy Visher (eds.). 1986. *Criminal Careers and "Career Criminals," Volume 1.* Report of the Panel on Research on Criminal Careers, National Research Council. Washinton, D.C.: National Academy Press.

Blumstein, Alfred and Elizabeth Grady. 1982. "Prevalence and Recidivism in Index Arrests: A Feedback Model." *Law and Society Review* 16:265-290.

Blumstein, Alfred and Daniel Nagin. 1978. "On the Optimum Use of Incarceration for Crime Control." *Operations Research* 26:381-405.

Brennan, Patricia, Sarnoff Mednick, and Richard John. 1989. "Specialization in Violence: Evidence of a Criminal Subgroup." *Criminology* 27:437-453.

Bursik, Robert. 1980. "Dynamics of Specialization in Juvenile Offenders." *Social Forces* 58:850-864.

Carr-Hill, R.A. and N.H. Stern. 1973. "An Econometric Model of the Supply and Control of Recorded Offences in England and

Wales." *Journal of Public Economics.* 2:289-318.

Carr-Hill, R.A. and N.H. Stern. 1977. "Theory and Estimation in Models of Crime and its Social Control and their Relations to Concepts of Social Output," in M.S. Feldstein and R.P. Inman (eds.), *The Economics of Public Services.* London: MacMillan.

Carr-Hill, R.A. and N.H. Stern. 1979. *Crime, the Police, and Criminal Statistics.* New York: Academic Press.

Carroll, John and Frances Weaver. 1986. "Shoplifters' Perceptions of Crime Opportunities: A Process-Tracing Study," in Derek B. Cornish and Ronald V. Clarke (eds.), *The Reasoning Criminal: Rational Choice Perspectives on Offending*, pages 19-38. New York: Springer-Verlag.

Chaiken, Jan M. and Marcia R. Chaiken. 1983. "Crime Rates and the Active Criminal," in James Q. Wilson (ed.), *Crime and Public Policy*, pages 11-29. San Francisco: ICS Press.

Chambliss, William. 1974. "Toward a Political Economy of Crime." *Theory and Society* 2:149-170.

Chambliss, William. 1988. *Exploring Criminology.* New York: MacMillan.

Chambliss, William and Robert B. Seidman. 1982. *Law, Order and Power*, Rev. ed. Reading, MA: Addison-Wesley.

Cloward, Richard and Lloyd Ohlin. 1960. *Delinquency and Opportunity.* Glencoe, IL: The Free Press.

Cohen, A. 1955. *Delinquent Boys.* New York: The Free Press.

Cohen, Jacqueline. 1986. "Research on Criminal Careers," in A. Blumstein et al. (eds.), *Criminal Careers and "Career Criminals,"* Vol. 1. Washington, D.C.: National Academy Press.

Cohen, Lawrence E. and Kenneth C. Land. 1987. "Age Structure and Crime: Symmetry Versus Asymmetry and the Projection of Crime Rates Through the 1990s." *American Sociological Review* 52(2): 170-183.

Douglas, J.W.B., J.M. Ross, W.A. Hammond, and D.G. Mulligan. 1966. "Delinquency and Social Class." *British Journal of Criminology* 6:294-302.

Durkheim, Emile. 1951. *Suicide.* Glencoe, IL: The Free Press.

Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy* 81:521-564.

Ehrlich, Isaac. 1975. "The Deterrent Effect of Capital Punishment: A Question of Life and Death." *American Economic Review* 65:397-417.

Elliott, Delbert S., David S. Huizinga, and Susan Ageton. 1985. *Explaining Delinquency and Drug Use.* Beverly Hills: Sage.

Farnworth, Margaret and Michael J. Leiber. 1989. "Strain Theory Revisited: Economic Goals, Educational Means, and Delinquency." *American Sociological Review* 54:263-274.

Farrington, David P. 1979. "Longitudinal Research on Crime and Delinquency," in Norval Morris and Michael Tonry (eds.), *Crime and Justice: An Annual Review of Research* 1:289-348.

Farrington, David P. 1986. "Age and Crime," in Michael Tonry and Norval Morris (eds.), *Crime and Justice: An Annual Review of Research* 7:189-250.

Farrington, David P., Howard N. Snyder, and Terrance Finnegan. 1988. "Specialization in Juvenile Court Careers." *Criminology* 26:461-487.

Federal Bureau of Investigation. 1952 through 1987. *Uniform Crime Reports: Crime in the United States.* Washington, D.C.: U.S. Government Printing Office.

Feeney, Floyd. 1986. "Robbers as Decision-Makers," in Derek B. Cornish and Ronald V. Clarke (eds.), *The Reasoning Criminal: Rational Choice Perspectives on Offending*, pages 53-71. New York: Springer-Verlag.

Fox, James A. 1978. *Forecasting Crime Data.* Lexington, MA: Lexington Books, D.C. Heath and Company.

Gibbs, Jack P. 1975. *Crime, Punishment and Deterrence.* New York: Elsevier.

Goldkamp, John S. and Michael Gottfredson. 1985. *Policy Guidelines for Bail: An Experiment in Court Reform.* Philadelphia, PA: Temple University Press.

Gordon, Robert. 1976. "Prevalence: The Rare Datum in Delinquency Measurement and Its Implications for the Theory of Delinquency," in Malcolm W. Klein (ed.), *The Juvenile Justice System.* Beverly Hills, CA: Sage.

Gottfredson, Michael R. and Don M. Gottfredson. 1988. *Decisionmaking in Criminal Justice.* New York: Plenum.

Gottfredson, Michael and Travis Hirschi. 1986. "The True Value of Lambda would Appear to be Zero: An Essay on Career Criminals, Criminal Careers, Selective Incapacitation, Cohort Studies, and Related Topics." *Criminology* 24:213-233.

Gottfredson, Michael and Travis Hirschi. 1987. "The Methodological Adequacy of Longitudinal Research on Crime." *Criminology* 25:581-614.

Gottfredson Michael and Travis Hirschi. 1988. "Science, Public Policy, and the Career Paradigm." *Criminology* 26:37-55.

Gottfredson, Michael and Travis Hirschi. 1990. *A General Theory of Crime.* Palo Alto, CA: Stanford University Press.

Greenberg, David F. 1985. "Age, Crime, and Social Explanation." *American Journal of Sociology* 91(1):1-21.

Greenberg, David F., Ronald C. Kessler, and Charles H. Logan. 1979. "A Panel Model of Crime Rates and Arrest Rates."*American Sociological Review* 44:843-850.

Greenberg, David F. and Nancy J. Larkin. 1985. "Age-Cohort Analysis of Arrest Rates." *Journal of Quantitative Criminology* 1:227-240.

Greenwood, Peter. 1982. *Selective Incapacitation.* Santa Monica, CA: The Rand Corporation.

Greenwood, Peter. 1983. "Controlling the Crime Rate through Imprisonment," in James Q. Wilson (ed.), *Crime and Public Policy*, pages 251-269. San Francisco: ICS Press.

Heckman, James J. 1976. "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models." *Annals of Economic and Social Measurement* 5:475-492.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 45:153-161.

Heineke, James M. 1978a. "Economic Models of Criminal Behavior: An Overview," in James M. Heineke (ed.), *Economic Models of Criminal Behavior*. Amsterdam: North-Holland.

Heineke, James M. 1978b. "Substitution Among Crimes and the Question Of Deterrence," in James M. Heineke (ed.), *Economic Models of Criminal Behavior*. Amsterdam: North-Holland.

Herrnstein, Richard. 1983. "Some Criminogenic Traits of Offenders," in James Q. Wilson (ed.), *Crime and Public Policy*, pages 31-49. San Francisco: ICS Press.

Hindelang Michael J. 1981. "Variation in Sex-Race-Age Specific Incidence Rates of Offending." *American Sociological Review* 46:461-474.

Hindelang, Michael, Travis Hirschi, and Joseph G. Weis. 1981. *Measuring Delinquency*. Beverly Hills: Sage.

Hirschi, Travis. 1969. *Causes of Delinquency*. Berkeley: University of California Press.

Hirschi, Travis. 1979. "Separate and Unequal is Better." *Journal of Research in Crime and Delinquency* 16:34-37.

Hirschi, Travis and Michael Gottfredson. 1983. "Age and the Explanation of Crime." *American Journal of Sociology* 89:552-584.

Hirschi, Travis and Michael Gottfredson. 1985. "Age and Crime, Logic and Scholarship: Comment on Greenberg." *American Journal of Sociology* 91:22-27.

Hobbes, Thomas. 1962. *Leviathan*. London: Collier Books.

Judge, George G., William E. Griffiths, R. Carter Hill, Helmut Lutkephol, and Tsoung-Chao Lee. 1985. *The Theory and*

Practice of Econometrics, 2 ed. New York: Jown Wiley and Sons.

Katz, Jack. 1988. *Seductions of Crime*. New York: Basic Books.

Kempf, Kimberly. 1987. "Specialization and the Criminal Career." *Criminology* 25:399-420.

Krohn, Marvin D., James L. Massey, and Mary Zielinski. 1988. "Role Overlap, Network Multiplexy, and Adolescent Deviant Behavior." *Social Psychology Quarterly* 51:346-356.

Little, Alan. 1965. "The Prevalence of Recorded Delinquency and Recidivism in England and Wales." *American Sociological Review* 30:260-263.

Long, J. Scott and John Fox. 1989/90. "Introduction." *Sociological Methods and Research* 18:195-199.

Long, Sharon K., Ann D. Witte, and Patrice Karr. 1983. "Family Violence: A Microeconomic Approach." *Social Science Research* 12:363-392.

Maddala, G.S. 1983. *Limited Dependent and Qualitative Variables in Econometrics*. New York: Cambridge University Press.

Manski, Charles F. 1978a. "Prospects for Inference on Deterrence Through Empirical Analysis of Individual Criminal Behavior," in James M. Heineke (ed.), *Economic Models of Criminal Behavior*. Amsterdam: North-Holland.

Manski, Charles F. 1978b. "Prospects for Inference on Deterrence through Empirical Analysis of Individual Criminal Behavior," in Alfred Blumstein, Jacqueline Cohen, and Daniel Nagin (eds.), *Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates*, pages 400-424. Washington, D.C.: National Academy of Sciences Press.

Mason, William M. and Stephen E. Fienberg. 1985. "Introduction: Beyond the Identification Problem," in William M. Mason and Stephen E. Fienberg (eds.), *Cohort Analysis in Social Research: Beyond the Identification Problem*. New York: Springer-Verlag.

Massey James L. and Marvin D. Krohn. 1986. "A Longitudinal Examination of an Integrated Social Process Model of Deviant Behavior." *Social Forces* 65:106-134.

McCleary, Richard, Barbara C. Nienstadt, and James M. Erven. 1982. "Uniform Crime Reports as Organizational Outcomes: Three Time- Series Experiments." *Social Problems* 29:361-372.

Merton, Robert M. 1938. "Social Structure and Anomie." *American Sociological Review* 3:672-682.

Moitra, Soumyo D. 1981. *The Analysis of Sentencing Policies Considering Crime Switching Patterns and Imprisonment Constraints*. Unpublished Ph.D. Dissertation. School of Urban and Public Affairs, Carnegie-Mellon University.

Monahan, Thomas. 1960. "On the Incidence of Delinquency." *Social Forces* 39:66-72.

Nagin, Daniel. 1978. "General Deterrence: A Review of the Empirical Evidence," in Alfred Blumstein, Jacqueline Cohen, and Daniel Nagin (eds.), *Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates*. Washington,D.C.: National Academy of Sciences Press.

O'Brien, Robert M. 1985. *Crime and Victimization Data*. Beverly Hills, CA: Sage.

Paternoster, Raymond. 1989. "Absolute and Restrictive Deterrence in a Panel of Youth: Explaining the Onset, Persistence/Desistance, and Frequency of Delinquent Offending." *Social Problems* 36:289-309.

Paternoster, Raymond and Ruth Triplett. 1988. "Disaggregating Self-Reported Delinquency and Its Implications for Theory." *Criminology* 26:591-625.

Poulsen, C.S. 1982. *Latent Structure Analysis with Choice Modeling Applications*. Unpublished Ph.D. Dissertation. The Aarhus School of Business Administration and Economics, The University of Pennsylvania.

Pyle, Donald J. 1983. *The Economics of Crime and Law Enforcement*. London: The Macmillan Press LTD.

Quinney, Richard. 1970. *The Social Reality of Crime.* Boston: Little, Brown.

Rapoport, Anatol. 1983. *Mathematical Models in the Social and Behavioral Sciences.* New York: John Wiley and Sons.

Reiss, Albert J., Jr. 1975. "Inappropriate Theories and Inadequate Methods as Policy Plagues: Self-Reported Delinquency and the Law," in N.J. Demerath, III, Otto Larsen, and Karl F. Schuesler (eds.), *Social POlicy and Sociology*, pages 211-222. New York: Academic Press.

Rojek, Dean G. and Maynard L. Erickson. 1982. "Delinquent Careers: A Test of the Career Escalation Model." *Criminology* 20:5-28.

Rowe, David C. and D. Wayne Osgood. 1984. "Heredity and Sociological Theories of Delinquency: A Reconsideration." *American Sociological Review* 49:526-540.

Rowe, David C., D. Wayne Osgood, and W. Alan Nicewander. 1990. "A Latent Trait Approach to Unifying Criminal Careers." *Criminology* 28:237-270.

Shavit, Yossi and Arye Rattner. 1988. "Age, Crime, and the Early Life Course." *American Journal of Sociology* 93:1457-1470.

Steffensmeier, Darrell. 1989. "On the Causes of 'White-Collar' Crime: An Assessment of Hirschi and Gottfredson's Claims." *Criminology* 27:345-358.

Schmidt, Peter and Ann D. Witte. 1984. *An Economic Analysis of Crime and Justice.* New York: Academic Press.

Steffensmeier, Darrell J. and Michael Cobb. 1981. "Sex Differences in Urban Arrest Patterns, 1934-79." *Social Problems* 29:37- 49.

Steffensmeier, Darrell J. and Miles D. Harer. 1986. "Is the Crime Rate Really Falling? An 'Aging' U.S. Population and its Impact on the Nation's Crime Rate, 1980-1984." *Journal of Research in Crime and Delinquency* 24:23-48.

Steffensmeier, Darrell J., Emilie Andersen Allan, Miles D. Harer, and Cathy Streifel. 1989. "Age and the Distribution of Crime." *American Journal of Sociology* 94:803-831.

Steffensmeier, Darrell, Cathy Streifel, and Miles D. Harer. 1987. "Relative Cohort Size and Youth Crime in the United States, 1953-1984." *American Sociological Review* 52:702-710.

Thompson, Patrick A., William R. Bell, John F. Long, and Robert B. Miller. 1989. "Multivariate Time Series Projections of Parameterized Age-Specific Fertility Rates." *Journal of the American Statistical Association* 84:689-699.

U.S. Department of Commerce. Bureau of the Census. 1965. *Current Population Reports: Estimates of the Population of the United States by Single Years of Age, Color, and Sex 1900 to 1959.* Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Commerce. Bureau of the Census. 1974. *Current Population Reports: Estimates of the Population of the United States, by Age, Sex, and Race: April 1, 1960 to July 1, 1973.* Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Commerce. Bureau of the Census. 1981. *Current Population Reports: Estimates of the Population of the United States by Age, Sex, and Race, 1970-1981.* Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Commerce. Bureau of the Census. 1987. *Current Population Reports: Estimates of the Population of the United States by Age, Sex, and Race, 1980-1987.* Washington, D.C.: U.S. Government Printing Office.

U.S. Sentencing Commission. 1989. *Sentencing Guidelines and Policy Statements for Organizations.* Washington, D.C.: U.S.G.P.O.

Varian, Hal R. 1984. *Microeconomic Analysis*, 2 ed. New York: W.W. Norton.

Witte, Ann D. 1980. "Estimating the Economic Model of Crime with Individual Data." *Quarterly Journal of Economics* 94:57-84.

Wolfgang, Marvin E., Robert M. Figlio, and Thorsten Sellin. 1972. *Delinquency in a Birth Cohort.* Chicago: University of Chicago Press.

Wolfgang, Marvin E., Robert M. Figlio, Paul E. Tracy, and Simon I. Singer. 1985. *The National Survey of Crime Severity.* Washington, D.C.: U.S.G.P.O.

Wolfgang, Marvin E., Terrence F. Thornberry, and Robrt M. Figlio. 1987. *From Boy to Man: From Delinquency to Crime.* Chicago: University of Chicago Press.

Zimring, Franklin and Gordon Hawkins. 1973. *Deterrence.* Chicago: University of Chicago Press.