THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF SOCIOLOGY & CRIMINOLOGY

AN ANALYSIS OF THE AGE-CRIME RELATIONSHIP USING FBI SERIOUS OFFENSES

KRISTEN L. SWIGART
Spring 2014

A thesis
submitted in partial fulfillment
of the requirements
for a baccalaureate degree
in Criminology
with honors in Criminology

Reviewed and approved* by the following:

Darrell Steffensmeier
Professor of Sociology and Criminology
Thesis Supervisor

Stacy Silver
Associate Professor of Sociology and Human Development
Honors Adviser

* Signatures are on file in the Schreyer Honors College.

ABSTRACT

This document presents the analysis of the relationship between age and crime for offenses considered serious by the FBI. A dataset of over 1000 defendants involved in crimes prosecuted by the Federal Bureau of Investigation (FBI) was created for this thesis by analyzing weekly press releases on what the FBI defined as the *Top Ten Cases*. The dataset covers the 2010 and 2011 time frame. The findings observed from the analysis of this dataset were compared to the UCR arrest data for the offense category of burglary, used to represent ordinary crime. The purpose of this analysis was to shed light on the claim of invariance in the age distribution of crime across offense types as proposed by Hirshi and Gottfredson (1983). Findings show that peak offending for serious offenses occurs much later than ordinary crimes, and variation in parameters (i.e. mean, median, rate of descent) exists between offense types. The “older” crime curves observed for offenders who comprised the FBI Top Ten dataset contrasts sharply with the much “younger” age curves observed for burglary offenders. Overall, the evidence was considerably at odds with the age-crime invariance hypothesis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

I would like to acknowledge several people who were integral in the completion of this project. First, I would like to express sincere appreciation to Dr. Darrell Steffensmeier for his guidance and mentorship over the past four years. In addition to advising this thesis, he has provided me numerous research opportunities and inspired my passion for original research, for which I am extremely grateful. I would also like to thank Dr. Jeffrey Ulmer, for his guidance and support throughout the past two years, as well as Dr. Stacey Silver for her help in the final stages of this process. I would also like to express gratitude to my mother, Lore Swigart and my father, Robert Swigart, as well as many close friends for their unending support throughout my academic career. I could not have accomplished my goals without them.

Chapter 1
INTRODUCTION

Sociologists and criminologists have studied the relationship between age and criminal involvement for centuries. The findings of data from the 1800s found that the highest proportion of the population involved in crime were adolescents and those in early adulthood, and these proportions declined with age (Quetelet, 1984). It has been widely accepted throughout the long history of research that criminality generally peaks in the teens or young adulthood and then diminishes with age. This finding has remained relatively stable and has been supported by researchers as methodology has advanced. Most importantly for the purpose of this thesis, moreover, this central finding about the timing of crime has led some sociologists (Hirshi and Gottfredson, 1983) to propose~~d~~ the theory that the age distribution of crime is everywhere invariant.

While the term ‘invariance’ itself has sparked debate (Britt, 1992), broadly speaking Hirshi and Gottfredson claimed that the age-crime relationship is universal across time, place, offense type and demographic groups. However, this conclusion has become the subject of much debate, with some researchers finding significant differences in strength and parameters of the age-crime curves (Steffensmeier, Allan, Harer & Streifel, 1989). As statistical methodology and record keeping have advanced, the ability for researchers to understand this relationship has increased. However, much is still unclear about the link between age and crime for serious offenses.

The main goal of this thesis is to determine whether variation in the age-crime relationship exists between ordinary, low-yield crimes and serious lucrative crimes. In addition to this goal, the researcher also aims to discover if variation exists between different types of serious offenses.

While a bountiful amount of arrest data is made available to researchers and the public each year by agencies like the Department of Justice (DOJ) and the Federal Bureau of Investigation (FBI), data focusing on serious crimes is often lost in the vast amount of summary and low-yield offenses handled annually by law enforcement. In an effort to better understand the characteristics of serious crimes and criminals; a dataset of over 1,000 defendants arrested and/or prosecuted by the FBI in 2010 and 2011 was developed using information made available to the public in the form of weekly press releases on what the FBI defined as the "Top Ten" cases for that week. Offenders represented in this database were involved in a variety of serious lucrative crimes including high-level fraud, bribery, drug trafficking, violent crime, terrorism, and corruption.

The age-crime distribution of these serious criminals was compared to the age-curves taken from the Uniform Crime Reports for the offense category of burglary, a method employed by Steffensmeier et al. (1989). Burglary was chosen because it is representative of low-yield, ordinary offenses and because it closely matches the invariant age-curve~~,~~ as described by Gottfredson and Hirshi (1986) as peaking "in the middle to late teens and then declining rapidly throughout life."

In the following sections of this chapter, I will review literature both in support of the invariance theory and in opposition before offering additional information on the hypothesis I aim to test.

The Invariance Debate

Hirshi and Gottfredson claim the age-crime distribution is invariant using data from several sources, including US arrest statistics made available in the Uniform Crime Reports. Considering the lack of longitudinal data available in the US, let alone other cultures, a claim of invariance is hard to substantiate. To demonstrate invariance, Hirshi and Gottfredson use data from England and Whales from the mid-1800s and the early 1900s, as well as UCR data from 1979 (Hirschi and Gottfredson 1983). No statistical analyses are provided in their article, so it is presumed that assumptions are made based on eyeball comparisons. Based on these data, as well as data from Argentina in 1960, Hirshi and Gottfredson assert "the shape or form of the distribution has remained virtually unchanged for about 150 years" (1983). Gottfredson and Hirshi suggest that invariance also holds true for race and sex, offering only visual analysis of age-crime curves as evidence.

Most relevant to the topic of this paper is the evaluation of the invariance argument based on offense type. Hirshi and Gottfredson acknowledge that in official data the peak offending age for person crimes is higher (late-teens, early-20s) than for property crimes (mid-teens). However, this relationship is not found when self-response data are analyzed. It is believed that the reason for this discrepancy between the two types of crime in official data could be "age-related differences in the consequences of person and property crimes" (1983). One said difference being the seriousness of the offense. The researchers contend that 'injury' crimes committed by youth do not attract the same attention from law enforcement as do those committed by older offenders, thus leading to a higher peak age in official data for violent crimes (1983). Hirshi and Gottfredson contend that self-report data should be taken at face value, as the difference in official data "is a function of differential response by age rather than a function of differential causal factors" (1983).

The implications of the age-crime invariance hypothesis are broad and far reaching. The hypothesis, while contested by some sociologists and criminologists, has been widely accepted by other criminologists and social scientists (see review by Ulmer and Steffensmeier 2014. Based on the assumption of invariance in the age distribution of crime, an evolutionary perspective was advanced—proposing that crime is biologically determined (Kanazawa and Still, 2000). While Kanazawa and Still (2000) point to greater competitiveness and higher testosterone levels among youth, other biologists have focused on physical aging and neurological development (see Steinberg, 2007; Farrington et al., 2012). However, sociologists have pointed out that these biological markers do not directly track on to the age peaks of most street crimes (Ulmer and Steffensmeier, 2014). While these biological approaches are not without merit, it would be a vast misgiving to ignore the role of social factors in criminality, even if the invariance hypothesis were true.

Opposition to Invariance

Due to its bold assertions, the theory of invariance was widely contested very shortly after its publication in the 1983 *American Journal of Sociology* article by Hirschi and Gottfredson. Many social scientists believe the claim to be "overstated, and that sociologically important variation exists across historical periods, societies, groups, and by offense type in specific features of the age-crime relationship" (Ulmer and Steffensmeier, 2014). Some findings in contradiction to the invariance theory will be reviewed in this section as regards the age-crime distribution by time, place and offense type.

Time and Place

Most sociological researchers will admit the availability of data to study the age-crime relationship over time and across locals is limited, at best (Steffensmeier et al., 1989; Greenberg, 1985; Ulmer and Steffensmeier, ?) Nonetheless, researchers have utilized the data available to contest the claim of invariance.

Greenberg (1985) compared arrest statistics from the US across time. In the US, "in 1933, 39% of all arrests were of persons under the age of 25; in 1980, 56%" a finding that could not be explained away by population demographics. Steffensmeier, Allan, Harer and Streifel (1989) also examined the age-crime relationship in the US over time. Using UCR data from 1940, 1960 and 1980; the researchers calculated indices of dissimilarity and other statistical tests and concluded that in more recent times "the age curves peak earlier and become progressively steeper, so that the offenders of today tend to be younger and less variable in age than in 1940 or in 1960" (Steffensmeier et al., 1989).

Greenberg found similar results for England and Norway; peak age of offending has become younger as time has progressed. Ulmer and Steffensmeier (2014) also found substantial variation in the percent age involvement of homicide offenders in Japan, over time. Homicide data from 1960 yielded an age-curve sharper and higher than other decades. In addition, the homicide offending patterns in Japan differed greatly from US offending; peak age was 25 in 1960 and 35 in 1980 and 2000 whereas peak offending occurred in the teens in the US (Ulmer and Steffensmeier, 2014). In addition to studying the age-crime distribution for industrialized societies like England and Norway, offending in India was also examined (Greenberg, 1985). Greenberg found very few arrests were accounted for by youth (3%), even though over half the population was under the age of 21 (1985). The differences in offending between industrialized societies and non-industrialized societies (e.g. India) point to sociological factors as influencing the age relationship to criminal involvement.

The findings of multiple researchers presented in this section suggest that there is indeed variability across the dimensions of time and place for the age-crime relationship, directly contradicting Gottfredson and Hirshi's invariance claim. Greenberg notes, "although a decline in criminality at older ages is common to all these distributions, the parameters of the distributions are quite different" (Greenberg, 1985).

Offense Type

Most relevant to the focus of this thesis is the assertion of invariance across offense type. While Hirshi and Gottfredson acknowledge some small differences in peak age for person and property crimes in official data, they suggest this is an artifact due to the perception of seriousness by law enforcement. However, analysis of 20 different offenses using UCR data suggests invariance is not the case~~;~~ :"although a decline in criminality at older ages is common to all age-crime distributions, the parameters—both in modal age and in shape—of the distributions are quite different" (Steffensmeier et al., 1989). Steffensmeier and his fellow researchers compared all UCR offenses against the norm category of burglary. As mentioned in the introduction, the offense of burglary was chosen because it closely represents the norm curve of invariance described by Gottfredson and Hirshi (1986). Steffensmeier et al. found that more than half of all offenses studied yielded index of dissimilarity values of 33 or higher when compared to the offense of burglary. This can be interpreted to mean, "more than one-third of all arrests would have to shift for the comparison crime to achieve an age distribution identical to that of burglary" (Steffensmeier et al., 1989). Clearly, offense categories were found to be dissimilar from one another.

In more recent research Greenberg used statistical methodology to test the invariance theory by fitting a modified chi-squared distribution to the age distribution of UCR Index crimes for several years. Greenberg not only found variation in the age-crime curves over time, but also found differences in peak offending among the 7 Index Crimes, ranging from 16-21 in 1987, the most recent year examined (Greenberg, 1994).

Like previous sections, these data suggest the claim proposed by Hirshi and Gottfredson is overstated in asserting invariance across offense types. While it is clear variation exists among offense categories, the extent and magnitude of this variation is still under debate. Steffensmeier et al. (1989) recognize a current limitation of their analysis is the likely shift of older offenders into less visible criminal roles or as a spinoff of legitimate roles, committing crimes like fraud, bribery or price fixing—crimes less likely to be reported to the authorities. “Unfortunately, we know very little about the age distribution of persons who commit these and related lucrative crimes” (Steffensmeier et. al, 1989). Instead, most of what is known about the age distribution of crime is based on ordinary, low-yield crimes like burglary. The work of this thesis will be to extend our knowledge of such lucrative crimes and will be described in the next section.

Age-Crime Relationship for Serious Crimes

As Steffensmeier et al. (1989) acknowledged, less is known about the relationship between age and crime for lucrative offenses and offenders. One major reason for this gap in knowledge is a lack of data on serious offenses that are high-yield and lucrative. The data most often utilized in studying the age-crime relationship ~~is~~ are taken from the Uniform Crime Reports, published annually by the FBI. This report is comprised of reporting from local, state and federal agencies and provides data on *all* arrests known to police for a wide variety of offense categories. While this dataset offers a good composite of criminality, serious offenses are lost in the broad summary offense categories. In order to better understand the age-crime relationship of serious criminals, a dataset comprised only of serious crimes and their offenders needs to be analyzed. It is the goal of this thesis to shed more light on this relationship by taking advantage of information provided to the public by the FBI in what is called the *FBI Top Ten News Stories of the Week*. More details on the specifics of this dataset will be offered in the following sections of this paper.

FBI Top Ten News Stories of the Week. Insert this nomenclature elsewhere in text or something close to it – e.g., per my earlier edits.

While steps have been taken by researchers to examine the invariance claim across offense type, examining a subset of serious offenders will further this effort. Hence, the main question this thesis seeks to answer is whether evidence for invariance will be found in examining a subset of serious offenders. Steffensmeier et al. (1989) predict that "in contrast to the age curves for ordinary crimes, which tend to be sharply peaked, it may be that the age curves for lucrative criminality not only peak much later, but tend not to decline with age." Many high-yield offenses, such as white-collar fraud, drug trafficking, and organized crime activity, are less likely to be committed by youth offenders because they lack the skills, resources, reputation, and access to crime opportunity. However, the extent to which resources and opportunity are lacking may differ for each offense type. For example, young adults can still find themselves involved in drug trafficking and violent crimes through gangs and peer groups, whereas the opportunity for mortgage, securities and health care fraud is extremely rare for youth. Based on the above information, two hypotheses will be examined:

> *Hypothesis 1: In comparison to ordinary crimes, serious offenses will have later peak ages of offending and older or flatter age-crime curves, as well as larger variance in the age of offenders.*

> *Hypothesis 2: Variation in the age curves will be present between different types of serious offenses.*[1]

In addition to offering data aimed at testing the invariance hypothesis, an analysis of serious crimes prosecuted by the FBI will allow for a better understanding of where

[1] Variation will be determined by differences in peak age of offending, mean age and other summary measures. More information will be given in following chapters.

the FBI devotes time and resources. If these serious crimes are, in fact, being committed by an older population, this could imply a need for new crime-prevention efforts. The following sections of this paper will offer the methods, analyses and results of testing the proposed hypotheses.

Chapter 2

DATA AND METHODS

In order to test the hypothesis presented in the previous section, two sets of data were used: one for serious, high-yield crimes (i.e., FBI Serious Crimes dataset); the other for ordinary crimes (i.e., UCR-burglary). This chapter will first provide information on the dataset of serious crimes established by the researcher, including coding criteria and caveats of data collection. Information regarding the use of the FBI Uniform Crime Report arrest data for ordinary crime will then be given, followed by a description of the procedures used for analyses.

FBI Serious Crimes Dataset

Since 2007, the Federal Bureau of Investigation has published a weekly press release titled, “The Top Ten News Stories of the Week.” This document includes links to 10 press releases based on indictments of cases prosecuted by the FBI, often in partnership with other state and local agencies. These releases, dating back to 2007, are archived on the FBI’s website and are readily available to the public. The cases presented by the FBI as the Top 10 News Stories offer specific information on the offense committed as well as demographic information of the offender(s). While the specific threshold for inclusion in the Top 10 press release is unknown, it is believed that the Bureau deems cases released in the Top 10 as both serious and important.

Previous age-crime research, both in support and in opposition to the invariance theory, has relied heavily on arrest data from the Uniform Crime Reports (UCR) for their analyses. While the UCR offers a massive collection of all crimes known to police, the cases in the Top 10 press releases offer a much more selective look at serious crimes and serious criminal offenders. These cases have been given ample attention and resources by the FBI, and represent a sample of serious offending. For this reason this untouched source of information was considered very relevant to the research questions posed in this manuscript. If the invariance hypothesis is indeed true, the age-crime data and curves obtained from this compiled dataset will also “peak in the middle to late teens and then decline rapidly throughout life,” (Gottfredson and Hirshi, 1986), matching analyses based on the UCR arrest data for ordinary property crimes like burglary.

The coding of the information in the Top 10 news stories will expand our understanding of the FBIs prosecution of serious crimes, and the relationship between age and crime for serious criminals. The press releases provide specifics concerning the demographics of the defendant and the details of the criminal act. This information was coded and compiled to form the FBI Serious Crime dataset. Cases from the first 26 weeks of 2010 and the first 26 weeks of 2011 were used in the following analyses. Specific information on coding criteria is offered in the following section.

Offender and Offense Characteristics

A scheme for coding was established to aid in the organization and description of the types of crimes and the criminal offenders involved. The coding scheme attempted to categorize several characteristics of each case. The coding criteria for these categories are defined and discussed for clarification purposes.

Sex of Defendant refers to the gender of the defendant as indicated by pronoun usage and general knowledge of nomenclature. When gender could not be determined by name, the Bureau of Prisons Inmate Locator tool and online searches were used for additional information.

Sex Composition refers to the composition of the group of defendants based on sex, if more than one person was charged. Six possible categories existed to account for cases with only one defendant. The categories were (1) solo male (2) all males (3) solo female (4) all females (5) mixed sex (6) missing/undetermined.

Age of Defendant refers to the age of the defendant at the time in which the press release was published. In most cases the age information was found within the press release, when not available the Federal Bureau of Prisons Inmate Locator tool was used to obtain age data. The age information was then standardized to represent the defendant's age at the time of the release.

Type of Crime. Due to the breadth of types of cases prosecuted by the FBI, creating categories for coding was difficult. In order to identify the best coding scheme, 200 cases were first coded into broad categories in order to obtain frequency information, then narrowed the scope to 10 different categories. These categories do not necessarily represent an exhaustive list of the types of offenses prosecuted by the FBI, nor are they necessarily mutually exclusive. Both of these facts are recognized as current limitations of the data. A description of each category is included for clarification purposes.

Fraud broadly refers to intentionally misrepresenting the truth in order to fraudulently obtain money, property or securities under false pretenses. Examples include securities fraud, mortgage fraud and healthcare fraud.

Terrorism broadly refers to acts both international and domestic in nature, and involves threats against the United States. This category would also include counterintelligence. Examples of charges included in this category are: disclosing documents/secrets to foreign governments, material support of terrorists or terrorist groups (foreign or domestic), attempted attacks and completed attacks.

Hate Crimes broadly refers to a traditional offense with an element of added bias. “Congress has defined a hate crime as a ‘criminal offense against a person or property motivated in whole or in part by an offender’s bias against a race, religion, disability, ethnic origin or sexual orientation.’” (FBI Civil Rights, 2013) Included in this category are solicitations of hate crimes, and violations of civil rights.

Drug Offenses broadly refers to crimes concerning the illegal trafficking or large-scale distribution of drugs including prescription narcotics. Specific drug types included in the sample were: methamphetamine, cocaine/crack, heroin, marijuana and narcotics.

Violent Crime broadly refers to crimes violent in nature including, but not limited to: murder, attempted murder, armed robbery, arson, piracy, threats, and assaults.

Sexual Offenses broadly refers to crimes with a sexual element including sexual assault, pedophilia and rape.

Racketeering/Corruption broadly refers to crimes of bribery, bribery of public officials, money laundering and extortion. It also frequently includes crimes punishable by the Racketeering Influenced and Corrupt Organizations Act (RICO), a statute created to prosecute organized crime. While this category was not exclusively focused on RICO cases, many indictments involved RICO charges.

Smuggling broadly refers to the bringing of goods or individuals into or out of the United States by illegal means. This category includes, but is not limited to the smuggling of illegal aliens, sex traffickers or regulated goods.

Vice Crimes refer to crimes said to be ‘without victims’ and include offenses such as gambling or prostitution.

Miscellaneous broadly refers to crimes that do not fall within the categories listed above. Examples of cases in this category include obstruction of justice, copyright infringement, and false impersonation of a law enforcement officer.

Missing and Omitted Data

While the majority of the news stories presented by the FBI in the “Top Ten” weekly press releases involved indictments of criminal prosecutions in which criminal defendants were identified, occasionally information not concerning defendants was presented. These stories often included information on the release of new FBI statistics (such as the annual UCR report), announcements concerning leadership positions, and infrequently information concerning wanted criminals. These cases (N = 17) were initially included in the dataset to maintain integrity, but were omitted for the analysis of the data. In addition to cases that were not related to criminal prosecution, several prosecution cases targeted organizations rather than specific defendants. Because no person was being charged, and thus age information was not available or relevant, these cases (N = 16) were also omitted. Finally, cases in which age was not listed and could not be determined by additional research were also omitted from the analysis of data (N =78). In total, 156 cases were removed from the dataset before analysis, leaving 1146 defendants.

UCR Burglary as "Norm"

In order to test the invariance hypothesis, the age-crime patterns based on the FBI Serious Crime dataset will be compared to the UCR age-crime statistics for the offense category of burglary, a procedure employed by Steffensmeier & Allan (1989). Recall from Chapter 1, the category of burglary was used as the norm due to its representativeness of the invariant age-crime relationship, as described by Hirshi and Gottfredson.

The UCR is a report published annually by the FBI, containing arrest data "from over 18,000 city, university/college, county, state, tribal, and federal law enforcement agencies voluntarily participating in the program" (FBI.gov). The UCR contains arrest information for 28 different offenses and breaks offenses into Part 1 or Part 2 categories based on seriousness. Part 1 crimes make up the Crime Index and include 8 offenses: criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft and arson. The other 20 offenses comprise the Part 2 category and are considered less serious. Notably, the Part 2 category includes the offense categories of fraud and drug violations.

UCR data are presented in the form of tables for all crimes and by offense type. These tables can provide information on gender, age and race. For the present analysis, age tables were the main focus. Included in the age table were offense types, the total number of arrests in a given year per offense type, a breakdown of arrest counts per age and offense type, and percent distribution for each age category and offense type.

The Bureau of Justice Statistics' Arrest Data Analysis Tool gives published age-specific arrest rate calculations and plots age-crime curves based on the UCR arrest data, allowing users to select a specific year and offense type. This tool also provides population information for each age grouping. All data used in the present analysis were taken from the year 2010. In order to make comparisons between the two datasets as consistent as possible, 10 age categories were used: 18-20, and then 5-year age grouping for 20-24, 25-29, etc. up to age 64.

Procedures

The procedures used in this paper followed those applied in Steffensmeier et al. (1989), and include the calculation of rate and percent age involvement, which were then used to calculate summary measures such as peak age and variance in the age distribution. First, age-specific arrest rates were calculated for the total of FBI Top Ten offenses, and for each offense type. The rate was calculated by dividing the arrest count for an age category by the population for that category and then multiplying by 100,000. Due to the low N in the Serious Crimes dataset, the number was instead multiplied by 1,000,000 in order to yield whole numbers (reflected in the formula below). Using the rate for calculations, as opposed to the event count, allows for the control of the age composition of the population during 2010 and makes the data more stable. The formula for rate is:

$$r_{ij} = C_{ij} \div P_i \times 100{,}000{,}000$$

where C = count of offenders, P = population count, i = age category and j = offense type.

The second type of computation used in the study is known as percent age involvement (PAI), and represents the percentage of total arrests that is accounted for by each age grouping. PAI controls for population size, and is thus demographically sensitive and "provides a robust comparison of crime levels across age groups as well as easy identification of shifts in the age-crime distribution across offense" (Steffensmeier et al, 1989). The PAI calculation aids in the understanding of the differences across age groups when rates differ greatly. This is especially beneficial due to the differences in N values between the FBI Serious Crimes data and the UCR data. The formula for PAI is:

$$\mathrm{PAI}_{ij} = r_{ij} \div \sum r_{ij} \times 100$$

where r = age-specific arrest rate, i = age category and j = offense type.

Means were also calculated and will be included in the following analysis. For the FBI Serious Crimes data, age information was available for each defendant, making the calculations simple. However, raw age data were not available for the UCR-Burglary data, so calculations were done based on age categories that yielded close approximations. In order to calculate the mean for each age category, PAI was calculated based on event count and was used to weight the age categories, which were assigned ordinal values. The estimate of the mean was then discerned as the midpoint of the age-category.

Chapter 3

FINDINGS

In the following sections, the results of the calculations performed on the FBI Serious Crimes Dataset will be analyzed and compared to the calculations performed on the UCR-burglary data. The goals of these analyses are to shed light on the distribution of age for various serious crimes~~,~~ and to discern whether Gottfredson and Hirshi's assertion of invariance across offense type holds true for serious crimes. Section 1 of this chapter will offer general information on serious offenses and offenders prosecuted by the FBI. Section 2 will offer an analysis of the FBI Serious Crimes dataset by offense type, while Section 3 will present findings on all offenses included in the dataset.

Section 1: General Offender and Offense Characteristics

Table 1, found on the following page, provides an overview of the general offender and offense type for the total sample. Key observations are as follows:

Sex. As shown in Table 1, Males were predominately the offenders (87%) of serious crimes, while females accounted for the remaining (13%) of the sample.

Sex Composition. Of the total sample, 228 defendants (20%) acted alone, with males (about 18%) accounting for the majority of solo offenders. In terms of groups of offenders, the data shows that a majority committed crime with a mixed-sex criminal group (43%). However, it is important to note that in order for a group to be considered mixed sex only one female needed to be involved. In many of the cases involved in the sample a very large number of defendants were charged in one release, in which one or two were female. All male criminal groups were the second highest prevalence (32.5%). While female involvement in serious crime was found to be low, even fewer acted alone (2%) or with only fellow females (<1%).

Table 1. FBI Serious Crimes Dataset General Characteristics

General Characteristics (N = 1146)	N	%
Sex		
Male	997	87
Female	149	13
Sex Composition		
Solo Male	205	18
All Male	373	32.6
Solo Female	23	2
All Female	11	1
Mixed Sex	494	43.1
Unknown	40	3.5
Offense Type		
Fraud	282	24.6
Terrorism	57	5.0
Hate Crimes	13	1.1
Drug Offenses	241	21
Violent Crime	139	12.1
Sex Crimes	16	1.4
Racketeering/Corruption	260	22.7
Illegal Smuggling	34	3.0
Vice	3	0.3
Miscellaneous	101	8.8
Age		
Range	18-89 yrs.	
Mean	40 yrs.	
Median	37 yrs.	
Mode	38 yrs.	

Age. As shown in Table 1, offenders ranged from 18-89 years old. Within this age range, 50% of offenders were age 37 or younger. However, in order for comparisons between the Serious Crimes data and the UCR data to be made in the following section, only offenders age 18-64 were considered. This reduced the total sample size by 55 individuals, making N = 1091. More detail concerning age will be presented in later sections.

Offense Type. Four offense types were found to be particularly prevalent. Fraud cases were most prevalent (N = 282) and accounted for 24.6% of the total sample. The offense category of racketeering/corruption was second most prevalent (N = 260) and accounted for 22.7% of the total sample, while drug offenses (N = 241) followed closely behind accounting for 21% of the total sample. Over 2/3rds of the sample was accounted for by these three offense categories alone. While less prevalent than the previous three categories, violent crimes accounted for 12.1% of the total sample. Together the offense categories of Fraud, Drug, Racketeering/Corruption and Violent crimes accounted for roughly 75% of the cases of serious crimes prosecuted by the FBI.

Taken together, the typical offender in the FBI Serious Crimes dataset is a male, acting in a mixed sex or an all male criminal group, and is likely to have committed a fraud, drug or racketeering crime. In the following section, an analysis of the age-crime curves for the four most prevalent offense types will be compared to the curve of UCR-burglary to specifically address the invariance claim of Gottfredson and Hirshi.

Section 2: Age-Crime Distribution by Offense Type

This section addresses the main focus of this study, the age distribution of crime by offense type for the FBI Serious Crimes dataset as compared to the age curve for burglary. Table 2, shown on the following two pages, provides the calculations for rate and PAI summarized in the previous chapter. These calculations were then used to derive the summary measures for analysis found in Table 3. Key results from the analyses are presented in Tables 2 and 3 and Figures 1-4.

Table 2. Age-Crime Calculations by Offense Type

Age Range	**Count**	**Rate (per 1 million)**	**PAI (%)**	**Cumulative PAI (%)**
All Crimes (N = 1091)				
18-19	15	1.66	3.1	-
20-24	96	4.42	8.28	11.38
25-29	172	8.13	15.22	26.6
30-34	185	9.22	17.25	43.85
35-39	135	6.72	12.58	56.43
40-44	138	6.6	12.35	68.78
45-49	134	5.92	11.08	79.86
50-54	96	4.3	8.04	87.9
54-59	72	3.64	6.81	94.71
60-64	48	2.83	5.29	100
Total	**1091**	**53.44**	**100.0**	**-**
Fraud (N = 266)				
18-29	0	0	0	-
20-24	0	0	0	0
25-29	21	0.99	7.69	7.69
30-34	33	1.64	12.74	20.43
35-39	35	1.74	13.51	33.94
40-44	42	2.1	15.57	49.51
45-49	40	1.77	13.69	63.2
50-54	39	1.74	13.52	76.72
54-59	35	1.77	13.7	90.42
60-64	21	1.24	9.58	100
Total	**266**	**12.99**	**100**	**-**
Drug Offenses (N =238)				
18-19	2	0.22	1.91	-
20-24	24	1.11	9.56	11.47
25-29	56	2.65	22.89	34.36
30-34	65	3.24	27.99	62.35
35-39	41	2.04	17.65	80
40-44	20	0.96	8.27	88.27
45-49	15	0.66	5.73	94
50-54	11	0.49	4.25	98.25
54-59	4	0.20	1.75	100
60-64	0	0	0	100
Total	**238**	**11.57**	**100**	**-**
Racketeering/Corruption (N = 242)				
18-20	2	0.22	1.87	-
21-24	27	1.24	10.54	12.41
25-29	45	2.13	18.04	30.45
30-34	30	1.49	12.67	43.12
35-39	15	0.75	6.33	49.45
40-44	38	1.82	15.41	64.86
45-49	30	1.33	11.23	76.09
50-54	19	0.85	7.21	83.3
54-59	18	0.91	7.71	91.01
60-64	18	1.06	8.98	99.99
Total	**242**	**11.8**	**99.99**	**-**

Table 2. Age-Crime Calculations by Offense Type cont.

Age Range	**Count**	**Rate (per 1 million)**	**PAI (%)**	**Cumulative PAI (%)**
Violent Crimes (N = 134)				
18-19	5	0.55	8.26	-
20-24	19	0.88	13.1	21.36
25-29	20	0.95	14.15	35.51
30-34	18	0.9	13.42	48.93
35-39	16	0.8	11.93	60.86
40-44	14	0.67	10.02	70.88
45-49	19	0.84	12.56	83.44
50-54	14	0.63	9.37	92.81
54-59	6	0.3	4.54	97.35
60-64	3	0.18	2.64	99.99
Total	**134**	**6.7**	**99.99**	**-**
UCR- Burglary (N = 224,012)		**(per 100,000)**		
18-29	41,722	460.46	18.60	
20-24	60,714	279.74	27.90	46.50
25-29	36,796	174.01	15.10	61.60
30-34	24,991	124.52	10.20	71.80
35-39	18,460	91.94	7.50	79.30
40-44	16,441	78.65	6.70	86.00
45-49	13,277	58.66	5.40	91.40
50-54	7,629	34.13	3.10	94.50
54-59	2,889	14.60	1.80	96.30
60-64	1,093	6.43	1.00	97.30
Total	**224,012**	**1323.14**	**97.3**	**-**

Table 3, found on the following page, gives the summary measures for each offense (calculated as based on Table 2, above). Peak age (row 1) represents the midpoint of the age group where PAI was the highest. One-half peak descending represents the age where the arrest rate dropped to half the maximum rate. Row 3, 4 and 5 show the percentages of total arrests accounted for by persons below a particular age, expressed as 25^{th}, 50^{th} (median), and 75^{th} percentiles. The mean is listed in the final row. (See Chapter 3 for how mean was calculated for UCR-Burglary arrest data).

Table 3. Age-Crime Distribution Summary Measures

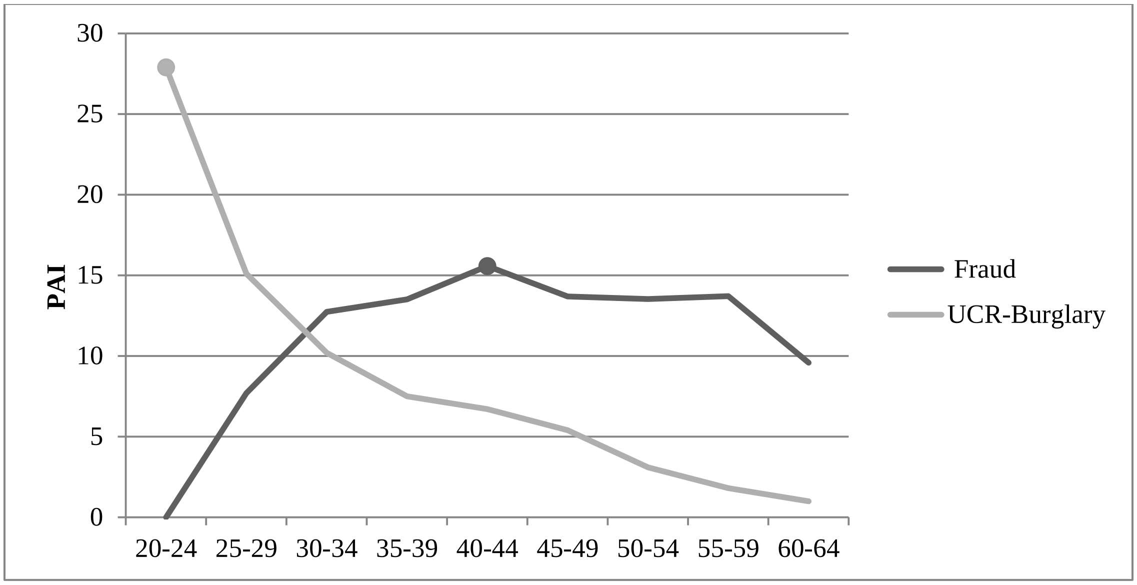
	Fraud	Drug Offenses	Racketeering/ Corruption	Violent Crimes	All Offenses	UCR- Burglary
Peak Age	42.5	32.5	27.5	27.5	32.5	20
½ peak descending	64+	39.5*	**	54.5*	50	27.5
25th percentile	34.5*	24.5*	25	24.5*	27.5	20
Median Age	45	32	40	37	37	25
75th percentile	52.5	34.5*	47.5	44.5*	44.5	34.5*
Mean Age	44.7	33.7	39.2	37.1	38.6	25

*This number is an estimate, and represents the midpoint between two age categories.

**Due to a bimodal distribution, ½ peak descending was not calculated for this offense category

Figures 1- 4 present plots that visually depict the age distribution of crime for each of the FBI serious crimes in comparison to the age curve for burglary (i.e., the standard or “norm” for the invariance claim). The plots provide a robust assessment of the invariance hypothesis. Combining results in Table 3 with the visual assessment displayed in these figures, key findings are as follows.

Figure 1. Fraud Age-Crime Curve[2]

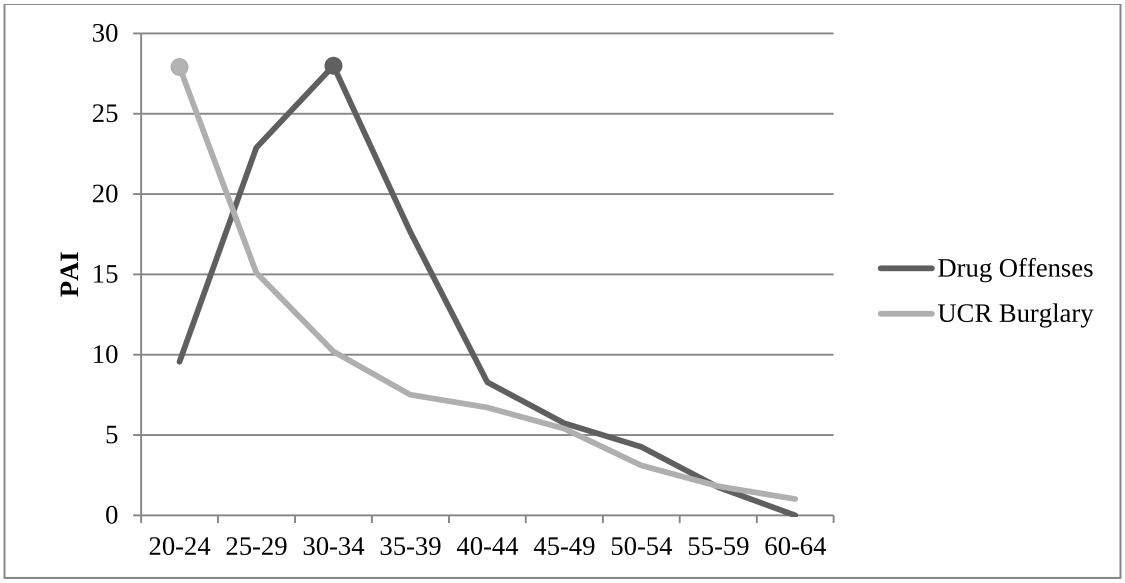


Fraud. The peak age of offending for fraud cases occurred in the 40-44 years old age category, the highest of all offense types analyzed. In this age category PAI reached 15.6%. 25% of arrests for fraud cases occurred somewhere between the age categories of 30-34 and 35-39. Half of all arrests were accounted for by age 45 and 75% of all arrests occurred among persons age 52.5 or younger. These numbers sharply contrast with the UCR-burglary data where 25% of arrests occur at the age of 20 and 75% occur before age 34.5. The differential between the 75th percentile for fraud and UCR-burglary is nearly 18 years. The mean age of offenders for fraud crimes at 44.7 years is also the highest among all offense categories. As seen in Figure 1, the variation in the percentiles demonstrates the large distribution of offenders at older ages, unlike the curve for UCR-burglary that is dominated by considerably greater involvement at younger ages. Instead, the serious-crime~~s~~ fraud curve peaks in middle adulthood, declines slowly over the course of the next 20 years. Furthermore, the arrest rate does not reach half the maximum rate until

[2] For the sake of uniformity, the age group of 18-20 is omitted from all of the age-crime curves. Only 5-year age groupings are shown, restricting the curves to age 20-64.

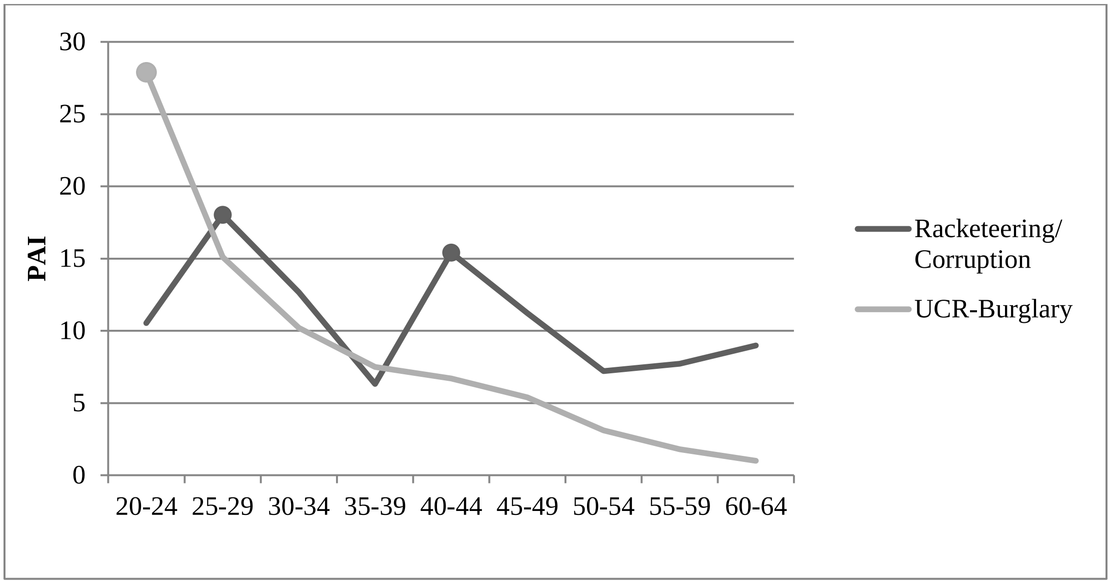
sometime after age 64.

Figure 2. Drug Offense Age-Crime Curve



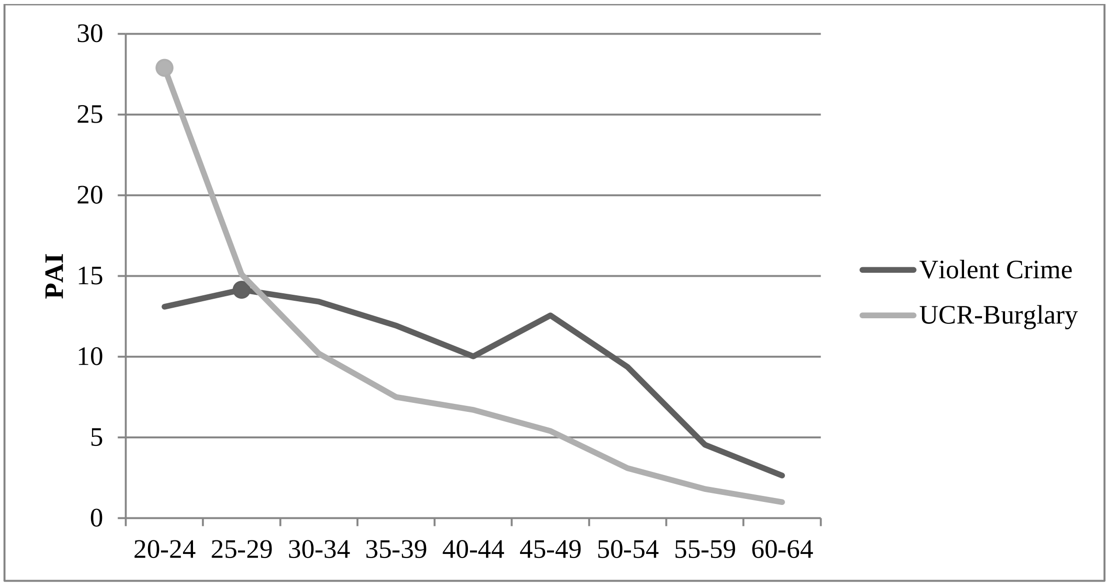
Drug Offenses. The peak age of offending for serious drug offenses is estimated to be 32.5, falling between ages 30-34. Within seven years of peak offending, arrest rates drop to one-half the maximum. About one-half of serious drug offending is accounted for by offenders falling between ages18-32, while 75% of offending occurred at age 34.5 or less. The mean age was also found to be within the 30-34 year age category (33.7). Figure 3 shows the age-crime curve for drug offenses in comparison to the UCR-burglary curve. While the peak age of serious drug offending is still nearly10 years higher than that of UCR- burglary, the PAI at peak offending is nearly identical and the rate of descent is similar, making their distributions appear somewhat alike. As Figure 2 shows, while the age curve for serious drug offenses age curve peaks sharply and declines rapidly with age, its peak age is much later than that for burglary.

Figure 3. Racketeering/Corruption Age-Crime Curve



Racketeering/Corruption. The offense category of racketeering/corruption showed the most varying results from the UCR-burglary category. The peak age was 27.5 years, with PAI being 18.04%. While PAI fell for age categories 30-34 (12.67%) and 35-39 (6.33%), it rose again for the 40-44 year age category (15.41%). As seen in Figure 4, these results represent both a bimodal curve and an overall "older" age distribution. While 25% of all arrests for this category occur at or before age 25, due to the bimodality of the curve 75% of arrests did not occur until age 47.5. The mean age was found to be 39.2 years. Again, the large variation is reflected in the bimodal nature of the curve. A discussion of the bimodality of this curve will be provided in the following chapter.

Figure 4. Violent Crimes Age-Crime Curve



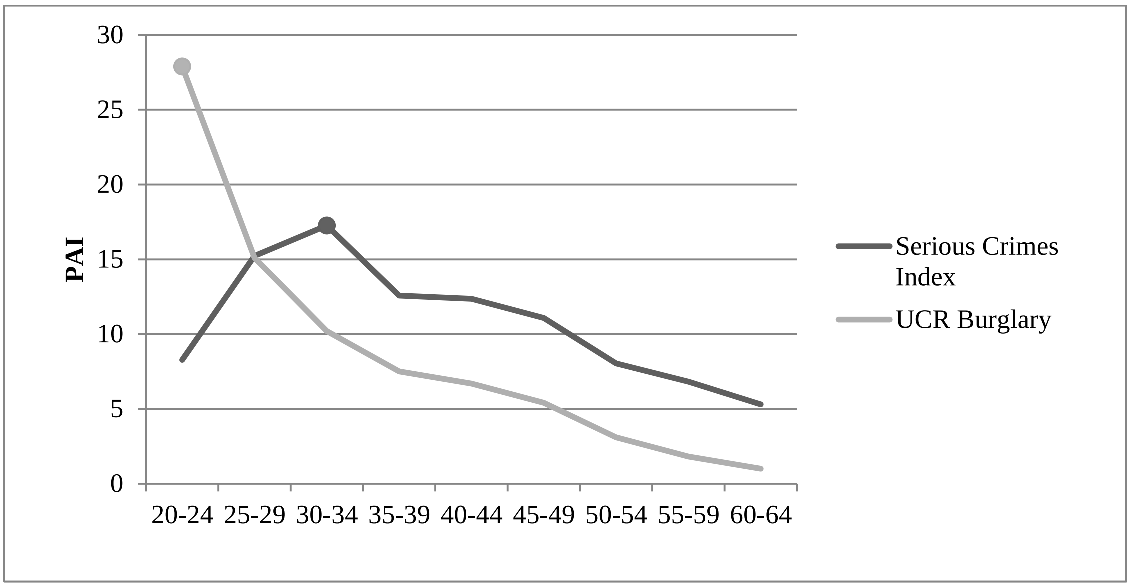
Violent Crime. The peak age of offending for violent crimes was also found to be 27.5 years, much older than the burglary peak; moreover, the mean age was found to be 37.1, nearly 10 years older. The large variation in age of offending is also evident when percentiles of offending are considered. While 25% of arrests were of persons age 24.5 or below, the median was 37 years and the 75th percentile was not reached until age 44.5. Added evidence for the older age distribution for serious violent offenses, is the fact that arrest rates do not drop to one-half the maximum rate until roughly age 55, nearly 28 years after peak involvement occurs. As seen in Figure 5, the curve for serious violent crimes also yields a bimodal distribution. However, it is believed this result is an artifact partly due to the small sample size for this category (N = 134).

Section 3: Age-Crime Distribution for Serious Crimes Index

This section will address the age distribution of crime across all offenses covered in the FBI Serious Crimes dataset (further referred to as the *serious crimes index)* and compare these results to that of the UCR-burglary category. As was the case with the previous section, Table 2 was used to calculate the summary measures found in Table 3.

As seen in Table 3, PAI for the serious-crimes index peaked in the age category of 30-34 —reflecting a peak age of 32.5, considerably higher than the peak age for UCR-burglary~~,~~ at18.5. While UCR-burglary fell to one-half peak descending just 6 years after peaking, it takes nearly 3 times as long for serious crime offending to do the same (roughly 17 years later). The sharp and rapid decline of the UCR-burglary curve~~,~~ as compared to the much and the more ‘flat’ and slower descent of the serious crimes index curve is vividly shown in Figure 5.

Figure 5. Serious Crimes Index Age-Crime Curve

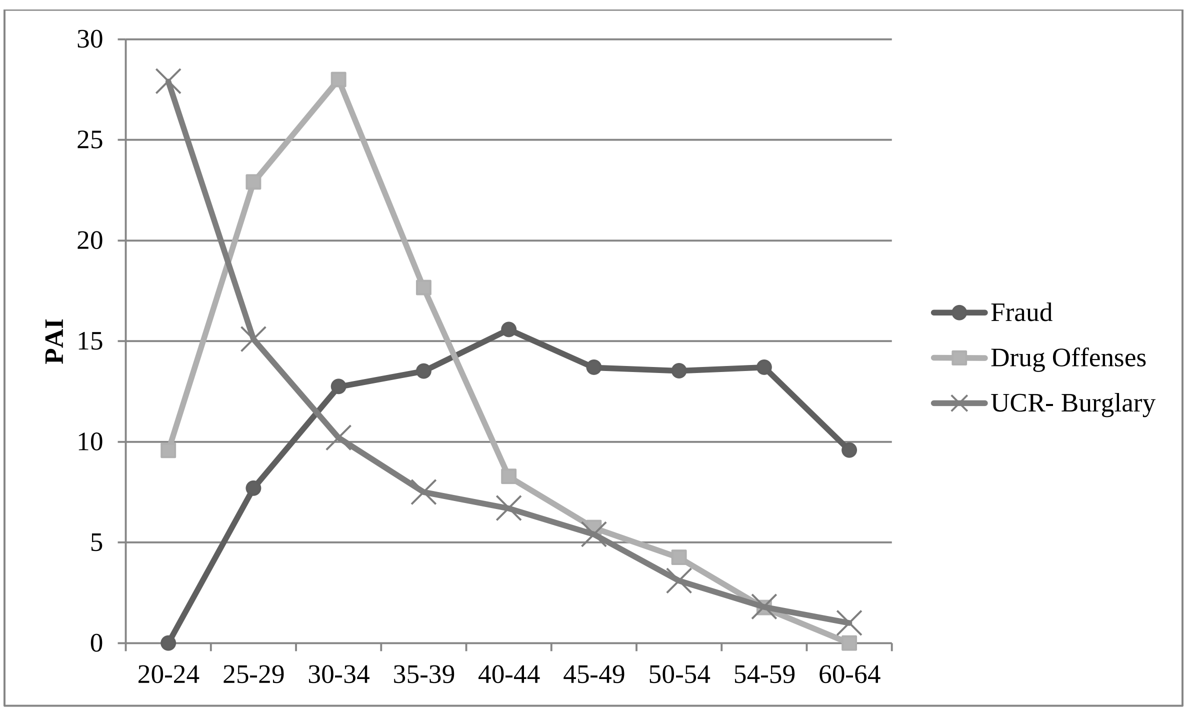


Further confirmation of the differences in age curves is reflected in the fact that 75% of all serious crime arrests were accounted for by age 44.5, a figure also represented in the ‘flatness’ of the curve. While the 25th and 75th percentiles were 17 years apart for serious crimes, they were only 5 years apart for burglary. [Note: focus here is only on serious-index category]. Again, the magnitude of the differences between the two age distributions (serious index vs burglary) is made clearer by the visual representation in Figure 5. For UCR-burglary age peaks at an early age (about age 18) and then rapidly descends, explaining the smaller variation and quick fall to one-half peak descent. The intersection of the two lines is very close to the ½ peak descending age and the 75th percentile for UCR-burglary. In contrast, the plot of the serious crimes index peaks later at roughly age 39 and has a more flat shape—representing a much slower decline during adulthood~~,~~ and an older age-crime distribution. Overall, the age curves representing ordinary crime and serious crime differ vastly, not only in peak age but also in shape.

Section 4: Inter-Offense Comparison of Age-Crime Distribution

After analyzing the curves for each offense type in comparison with the UCR-burglary category, it is worth noting that the categories of drug and fraud offenses have age distributions that are more similar in shape (e.g., unimodal) to the burglary curve than is the case with the other FBI Top Ten offenses. This section will shed light on these age-crime patterns.

Figure 6. Fraud and Drug Age-Crime Curves



As seen in Figure 6, the offense categories for fraud and drug crimes vary greatly.

While the peak age for drug offenses is much later than that of burglary, their curves are more similar in appearance than any other curve—peaking sharply and declining quickly. On the other hand, the age-crime curve for fraud peaks at 42.5, in middle age, nearly 24 years later than the UCR-burglary category and 10 years later than the drug offense category. As seen in Figure 6, this late peak makes the curve look more similar to a normal distribution than one skewed to the right, like the UCR-burglary and drug offense curves.

Taken together, the results presented in this section show that the peak age of offending for serious crimes occurs later than ordinary crime, as represented by the UCR-burglary category. As seen by the many figures included in the chapter, the age-curves representing serious crimes are much older than the age curve for UCR-burglary, and thus are robustly at odds with the invariance hypothesis. These differences will be discussed in detail in the following section.

Table 4. Findings In Comparison to UCR-Burglary by Offense Type*

Offense Type	**Peak Age**	**25th percentile**	**Median (50th percentile)**	**75th percentile**	**Mean**	**Skewness of Curve****	**Accept/Reject Invariance**
Fraud	Much later (+22.5)	Much later (+14.5)	Much later (+20)	Much later (+18)	Much later (+19.7)	Slight Left Skew	Reject
Drug Offenses	Later (+12.5)	Slightly later (+4.5)	Later (+7)	**Same**	Later (+8.7)	No Skew	Reject
Racketeering/ Corruption	Later (+7.5)	Slightly later (+5)	Much later (+15)	Later (+13)	Later (+14.2)	Left Skew, Bimodal	Reject
Violent Crime	Later (+7.5)	Slightly later (+4.5)	Later (+12)	Later (+10)	Later (+12.1)	Left Skew, Bimodal	Reject
Serious Crimes Index	Later (+12.5)	Later (+7.5)	Later (+12)	Later (+10)	Later (+13.6)	Left Skew	Reject

* number in parenthesis (#) represents the difference in years from UCR-burglary
** versus left skew in burglary age curve

Chapter 4

CONCLUSION

As stated in the introduction, the main goal of this paper was to determine whether variation in the age-crime relationship exists between ordinary, low-yield crimes and serious lucrative crimes. In addition to this goal, the researcher also aimed to discover if variation exists between different types of serious offenses. Both of these goals were formulated to shed light on the contested invariance hypothesis proposed by Hirshi and Gottfredson (1983). In this hypothesis, Hirshi and Gottfredson argue that the relationship between age and crime is invariant across time and place, demographics and offense type. While much research has accumulated on the topic since the hypothesis originated, specifically on offense type, our understanding of the age-crime relationship for serious, lucrative crimes is still lacking (Steffensmeier et al., 1989). Prior research (Hirshi and Gottfredson, 1983; Steffensmeier et al., 1989, etc.) has relied upon UCR arrest data to examine the age-crime relationship. However, in order to examine serious crime specifically, an original dataset of over 1,000 criminal defendants prosecuted by the FBI in years 2010 and 2011 was coded and analyzed. Table 4 summarizes the key findings of the analyses presented in Chapter 4. From this table I draw several conclusions.

[Insert Table 4 here]

First and foremost, Table 4 shows the vast differences in the age-crime distribution of serious offenses when compared to ordinary offenses like burglary. The comparison of the serious crime index to that of UCR-burglary shows that peak age occurs nearly 13 years later. In addition, each of the serious offense categories had later mean, median and peak ages of offending. The later ages for percentiles of offending and the differences between these ages show the considerable differences in the timing offending between serious and ordinary crimes. This information is consistent with the prediction of Steffensmeier et al. (1989) and supports hypothesis 1, stating that in comparison to ordinary crimes, serious or more lucrative offenses will have later peak ages of offending and will also have larger variance in the age of offenders. The age curve for the serious-index category is much older and flatter than the curve for ordinary crimes. The differences in the parameters of the age-crime distribution for the serious crime index and burglary provide strong evidence that the invariance hypothesis proposed by Hirshi and Gottfredson is invalid.

In addition to this finding, substantial differences were found between the various types of serious offenses examined in the FBI Serious Crimes dataset. The drug offenses curve most closely resembles that of UCR-burglary, while the fraud curve peaks later and declines far more slowly—giving it a ‘flatter’ shape. This finding could be reflective of the differences in opportunity for committing these types of serious crimes. Young adults can still gain access and develop means of serious drug offending, like distribution and trafficking through illegitimate opportunities, such as gang involvement or low-yield drug slinging. However, for serious fraud crimes, such as price-fixing, securities fraud or mortgage fraud, opportunity is most prevalent among middle-aged businessmen through legitimate means. Furthermore, the knowledge necessary to commit fraud is much greater than that necessary to commit drug related crimes.

While the age distributions for serious drug offenses and fraud yielded somewhat different shapes curves, both were unimodal. However, the curve for racketeering/corruption yielded extremely bimodal results. While this result could be due to a low sample size, the peaks in the age categories of 24-29 and 40-44 could also reflect the differences in the demographics of the syndicated criminal groups being charged with serious racketeering/corruption offenses. For example, street gangs tend to be comprised of younger offenders, while La Cosa Nostra (the Italian mafia) tends to recruit middle-aged men. Both of these organized crime groups are frequently charged with the Racketeering Influenced and Corrupt Organizations (RICO) act, and were included in this coding category.

In conclusion, the differences found in the summary measures of the various serious crimes analyzed in the FBI Serious Crimes dataset support hypothesis 2, stating that variation in age curves will be present for the different serious offenses. Taken together, the support for hypothesis 1 and 2 found in the present paper calls into question the invariance hypothesis proposed by Hirshi and Gottfredson, suggesting that all crime, regardless of offense type, “peak(s) in the middle to late teens and then decline(s) rapidly throughout life” (1986).

Based on the findings presented in this paper, it is clear that more substantial research must be done on the relationship of age and crime for serious offenses. While this paper sheds light on the vast differences in ages of offending, a much larger sample size might lead to more valid findings. In addition to a larger sample size, more detailed information about the kinds of crime falling into each of offense categories (e.g, types of racketeering/corruption or drug offending) would allow for more succinct coding and a more precise assessment of age-crime patterns. Furthermore, advanced statistical testing, such as the methods employed by Steffensmeier et al. (1989) and Greenberg (1994) would give more specific details about the relationship between age and crime for serious offenses.

BIBLIOGRAPHY

Britt III, C. L. (1992). Constancy and change in the US age distribution of crime: A test of the “invariance hypothesis”. *Journal of Quantitative Criminology*, *8*(2), 175 -187.

Farrington, David P., Rolf Loeber, and James C. Howell. 2012. “Young Adult Offenders: The Need for More Effective Legislative Options and Justice Processing.” Criminology and Public Policy 11(4):729-750.

Federal Bureau of Investigation. 2010. *Crime in the United States*. Washington, DC: U.S. Government Printing Office.

Gottfredson, M., & Hirschi, T. (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*(2), 213-234.

Greenberg, D. F. 1979. “Delinquency and the Age Structure of Society.” *Contemporary Crisis* 1:66-86.

Greenberg, D.F. 1982. “Age and Crime.” Pp. 30-35 in *Encyclopedia of Crime and Justice*, Vol. 1 (edited by S. Kadish). New York: Macmillan.

Greenberg, D. F. 1985. “Age, Crime, and Social Explanation.” *American Journal of Sociology* 91(1). 1-21.

Hirschi, T., & Gottfredson, M. (1983). Age and the explanation of crime. *American journal of sociology*, 552-584.

Kanazawa, S., & Still, M. C. (2000). Why men commit crimes (and why they desist). *Sociological Theory*, *18*(3), 434-447.

Quetelet, A. (1984). *Adolphe Quetelet's Research on the propensity for crime at different ages*. Anderson Publishing Company.

Steffensmeier, D., & Allan, E. (1996). Gender and crime: Toward a gendered theory of female offending. *Annual review of sociology*, *22*(1), 459-487.

Steffensmeier, D. J., Allan, E. A., Harer, M. D., & Streifel, C. (1989). Age and the Distribution of Crime. *American journal of Sociology*.

Steinberg, Laurence. 2007. "Risk Taking in Adolescence: New Perspectives from Brain and Behavioral Science." *Current Directions in Psychological Science* 16:55-59.

Ulmer, J.T., & Steffensmeier, D. (2014). "The Age and Crime Relationship: Social Variation, Social Explination." *At press*

ACADEMIC VITA

Kristen L. Swigart

Education:

The Pennsylvania State University, University Park, PA
May 2014
Schreyer Honors College
B.A. Criminology, Minor: Psychology

Research Experience:

January 2013- present
Undergraduate Lab Coordinator, *Leadership and Innovation Lab*
Under the supervision of Dr. Sam Hunter
Industrial-Organizational Psychology Department, PSU

- Aid graduate students in developing research projects through all phases including design, running subjects, as well as collecting and coding data.
- Participate in weekly meetings to discuss project work and relevant topics to I/O field.
- Coded written and audiovisual data for use in fellow students honors thesis.

August 2013- present
Undergraduate Research Assistant, *PNC Leadership Assessment Center*
Under the supervision of Dr. Rick Jacobs
Industrial-Organizational Psychology Department, PSU

- Develop and improve exercises used to elicit behavioral responses by participants such as case studies, presentations, and role-plays.
- Attend weekly meetings to discuss procedures and necessary work for upcoming assessment centers.
- Assemble all necessary materials for participants and assessors prior to assessment days.
- On day of assessment center, perform all roles necessary for success including orienting of students, compiling assessor ratings, and setting up and tearing down of the event.

May 2012- present
Undergraduate Research Assistant, *Department of Criminology*
Under the supervision of Dr. Darrell Steffensmeier

- Participated in the development of research plan for the purpose of analyzing demographic factors influencing corporate criminality.
- Compiled and coded Securities and Exchange Commission enforcement releases using self-developed codebook.
- Taught and managed other undergraduates coding methods and data collection process.

September 2012-present
Honors Thesis Project, *Schreyer Honors College*
An Analysis of the Age-Crime Relationship using FBI Serious Offenses

- Developed codebook for analysis of qualitative data from FBI Top 10 Crimes of the week database and personally coded over 1000 cases for use in thesis data .

Applied Experience:

May 2013- present

Consulting Intern, Select International

Pittsburgh, PA

- Work with consultants to plan and perform on-site job analyses.
- Participate in client meetings, compile necessary documentation and complete reporting.
- Managed Select's Executive Assessments by directly communicating with several clients, assessors and assesses.
- Gathered data for several validation studies of selection assessments.
- Based on success in position throughout summer was asked to continue project work through academic school year.

March 2013

Assessment Center Participant, *PNC Leadership Assessment Center*

- Completed the Wave, a personality assessment instrument, and analyzed a case study which was evaluated by professional assessors including local business leaders, alumni, and graduate students.
- Received a detailed management competency report including individual comprehensive feedback to discuss strengths, weaknesses, and areas of potential development.

Professional Affiliations:

2012 – present **Society for Industrial Organizational Psychology (SIOP)**

- Student Member
- Attended 2013 annual conference in Houston, TX

2013-present **Society for Social and Personality Psychology (SPSP)**

- Student Member
- Attended 2014 annual conference in Austin, TX

Certifications & Honors:

June 2013 **Certified Behavioral Interviewer**

Spring 2012 **President Sparks Award**

Spring 2011 **Presidents Freshman Award**

Fall 2010- present **The Pennsylvania State University Deans List**

Extra-Curricular Involvement:

October 2010- present
Committee Member, Penn State Dance Marathon (THON)

- Worked as a team member to aid in the success of the largest student run philanthropy for four consecutive years by setting up, tearing down, and maintaining a clean and safe environment during THON weekend as well as providing individualized support for a dancer committed to standing for 46 hours straight.

August 2013- present
Treasurer, Industrial Organizational Psychology Society (IOPS)

- Managed organizational budget, and ensure proper use of finances.
- Aided in planning and financing of undergraduate academic trip to Society of Personality and Social Psychology Conference.

January 2013 – May 2013
Note taker, Nittany Notes

- Compiled detailed written notes weekly for assigned courses.

August 2012- December 2012
Teaching Assistant, CRIM 425: Organized Crime

- Proctored exams and ensured the academic integrity of students at all times.
- Graded coursework and reported homework and exam scores for over 70 students.

August 2011- December 2011
Teaching Assistant, CRIM 12: Introduction to Criminology

- Graded coursework and reported homework and exam scores for over 125 students.
- Held office hours twice a week to assist students with assignments and questions.
- Led class lecture in absence of professor.