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The Role of Supervised Community Service and Socio-Economic Status in Recidivism Pertaining to Financial Crimes among Ex-Convicts

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By

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ABSTRACT

THE ROLE OF SUPERVISED COMMUNITY SERVICE AND SOCIO-ECONOMIC STATUS IN RECIDIVISM PERTAINING TO FINANCIAL CRIMES AMONG EX-CONVICTS

by

David Adu-Boateng

An individual's economic situation impacts the commission of crimes, and ex-convicts inability to earn a living and integrate into society increases their propensity to commit financial crimes. Researchers indicate that the high rate of recidivism points to the fact that ex-convicts face significant challenges in their bid to adjust to life outside prison. Prior research and extant literature show that most ex-convicts re-offend within three years after their initial release from prison. Generally, the propensity to commit a financial crime increases after prison time among convicted felons. However, an elevated socio-economic status reduces an ex-convict's propensity to commit financial crimes and recidivate. Therefore, it is expected that ex-convicts who participate in supervised community service will be less likely to commit financial crimes and recidivate.

If most repeat offenses involve financial crimes, then recidivism can be significantly reduced by controlling the propensity to commit financial crimes among ex-convicts. This study employs a multivariate regression analysis to investigate a nationally aggregated archival data of paroled ex-convicts to determine the impact of socio-economic factors and supervised community service on ex-convicts' inclination to commit financial crimes. The current study finds that elevated socio-economic status reduces financial crimes. However, there is no conclusive indication from the current study that supervised community service reduces recidivism pertaining to financial crimes among ex-convicts.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I: INTRODUCTION

Background

This research paper examines the impact of supervised community service and socio-economic status on the propensity of ex-convicts to commit financial crimes. Researchers indicate that the high rate of recidivism points to the fact that ex-convicts face significant challenges in their bid to adjust to life outside prison. Prior research and extant literature show that about sixty-seven percent (67%) of ex-convicts re-offend within three years after their initial release from jail (Nuñez-Neto, 2008). However, about seventy-seven percent (77%) of re-convictions involve financial crimes in which perpetrators unlawfully converted another's property to their personal use and benefit, even though just about twenty-four percent (24%) of initial crimes involve financial crimes (James, 2004). It means that the propensity to commit a financial crime increases after jail time among convicted felons. Research findings show that personal traits, environmental factors, and economic status are dominant players in the propensity to commit crime (Aaltonen, Kivivuori, & Martikainen, 2011; Farrall, Bottoms, & Shapland, 2010; Parnaby, 2007). For instance, income inequality and unemployment are significant predictors of property crimes (Hooghe, Vanhoutte, Hardyns, & Bircan, 2011), and unfavorable social structures influence offenders to recommit crimes either to deliberately return to prison or in their bid to obtain financial benefits (Parnaby, 2007). Therefore, ex-convicts are more likely to commit a financial crime than other crimes.

Further, programs designed to moderate antisocial behaviors, social disorganization, and financial hardships are likely to reduce the propensity to commit crimes, and in turn reduce recidivism involving financial crimes (Bouffard & Muftic, 2007; Killias, Aebi, & Ribeaud, 2000; Lockwood, Nally, Ho, & Knutson, 2012; Rex &

Gelsthorpe, 2002; Wermink, Blokland, Nieuwbeerta, Nagin, & Tollenaar, 2010). The behavior characteristics of criminals and their tendency to obtain financial benefits play a significant role in recidivism. Additionally, offenders with low socio-economic status (low-SES), as defined by education, income, and occupation have a higher propensity to reoffend (Allen, 1996). Some study results imply that if prospective criminals expect adequate punishment, the propensity to commit crimes will reduce (Bodman & Maultby, 1997; Holtfreter, Piquero, & Piquero, 2008). However, other findings, in overwhelming majority, show that correctional intervention programs such as supervised community service can help reform offenders, improve their socio-economic situation and reduce recidivism (Hooghe et al., 2011). In particular, some findings indicate that community service is more effective in reducing recidivism than prison sentences or monetary fines. Therefore, community service is more effective in moderating recidivism in offenders, given that most repeat offenses tend to be financial crimes.

Problem Statement

This paper examines the influence of supervised community service and socio-economic status in reducing financial crimes among ex-convicts. Supervised community service and socio-economic status are coupled in this research to address the issue of effective community service and the need to resolve the incidence of joblessness and economic hardship among criminal offenders. Some have argued that sentencing policies which are focused solely on punishment without reformation of the criminal is not effective (Hooghe et al., 2011; Holtfreter et al., 2008). Ineffective sentencing policies place a financial burden on society, since members of society shoulder a significant financial burden to keep criminals in jail. Therefore, if sentencing policies influence a positive reformation by addressing the factors that influence financial crime, crime offenders will be less likely to reoffend, and the financial burden on society will lessen.

This study considers two factors in reformation. First, community service may help moderate a criminal's selfish posture. Persons with individualistic tendencies, as explained in the Theory of Individualism, are more likely to commit financial crimes (Pedelford & White, 2009). Therefore, community service geared towards a reduction in selfish tendencies is likely to reform an ex-convict and reduce financial crime offenses after jail time (Killias et al., 2000). Additionally, individuals with less financial pressure are less likely to commit financial crimes (English, 2011). For instance, States that provide offenders with training and employment assistance programs are more likely to reduce financial crimes and reduce recidivism (The Pew Center on the States, 2011). Hence, a pathway to self-dependence is likely to improve an ex-convict's socio-economic status and reduce the likelihood of committing a financial crime. Individuals with a criminal history often face difficulties in finding viable employment to make ends meet. The financial distress and pressure caused by unemployment will likely influence an ex-convict to commit a financial crime.

Some community services are not supervised to aid the ex-convict to reintegrate into society and are not effective in reforming the ex-convict (Rex & Gelsthorpe, 2002). Further, efforts to reduce recidivism have been focused more on punishment and deterrence. However, a focus on socio-economic status of the ex-convict will be more effective in reducing recidivism, since most offenses among ex-convicts involve financial crimes (James, 2004).

It is expected that an offender's socio-economic status is more likely to influence the propensity to commit a financial crime. It is more likely that adverse socio-economic effects, such as financial distress caused by unemployment will contribute more to recidivism (Coenen, 2009; Sullivan & Piquero, 2016), given that offenders have difficulty finding jobs. Therefore, recidivism is less likely if the ex-convict has a favorable socio-economic status, is self-dependent, and avoids a financial crime. The expectation is that effective supervised community service will provide ex-convicts with some occupational and social skills needed for obtaining gainful employment, and ultimately avoid a financial crime. This study employs a quantitative method in analyzing secondary data found in public records about crime offenders and their demographics, and the impact of supervised community service.

Dissertation Goal

This research gathers and analyzes data about crime offenders and their demographics, and reports on the role of supervised community service in recidivism pertaining to financial crimes.

Significance of the Study

Sentencing has focused more on punishment and has not been effective in curbing recidivism. This is supported by the fact that most ex-convicts re-offend within three years after their initial release from jail (Nuñez-Neto, 2008). Therefore, if sentencing policies influence a positive reformation by addressing the factors that influence financial crime after prison life, crime offenders will be less likely to reoffend. A convict's propensity to commit a financial crime is moderated by social and economic factors. If recidivism is unacceptably high or increasing, then the current sentencing and after-prison programs are not working (Farrall et al., 2010). Further, most recidivism cases involve financial crimes (James, 2004). Therefore, there is the need to design and implement innovative after-prison programs to reduce financial crimes and thereby reduce recidivism.

Commission of financial crimes is moderated by factors that tend to elevate the social status of persons convicted of a crime. Findings from the literature are consistent in explaining an offender's propensity to commit a financial crime given financial hardships (Aaltonen et al., 2011; English, 2011). Further, some research findings indicate that sentencing policies can be used to control recidivism involving financial crimes (Lockwood et al., 2012; Dean, Brame, & Piquero, 1996). If a person committed a crime and has possibly acquired expert knowledge about criminal schemes, denying the person economic opportunities is not likely to keep him or her out of jail (Nuñez-Neto, 2008). On the other hand, supervised community service that focuses on creating social and economic opportunities for a crime offender is more likely to reduce financial crimes in offenders and ultimately reduce recidivism. Therefore, recidivism stemming from financial crimes is less likely if the convicted person has a favorable socio-economic status and is self-dependent. Clearly, supervised community service which provides basic education, employment skills, and allowances, and influences future income potential is likely to moderate the incidence of recidivism involving crimes in general and financial crimes in particular (Lockwood et al., 2012).

Offenders with a criminal history often experience difficulties in finding gainful employment to alleviate their financial hardships (English, 2011). The financial distress associated with unemployment is likely to influence an offender to commit a financial crime. Supervised community service can be designed to provide reformation-oriented education to offenders, refocus their attention on playing a positive role in society, and provide offenders with work-ethic skills to improve employability. Evidently, gainful employment enables ex-convicts to make a living, and supervised community service can provide the pathway to obtaining gainful employment. First, supervised community service should be designed to reform crime offenders, moderate their selfish outlook, and be used as an effective intervening factor in recidivism in crime offenders. Secondly, supervised community service should be designed to assist crime offenders in obtaining gainful employment. This study examines the need to intervene with a pathway to socio-economic opportunities.

The purpose of this study is to investigate and analyze the impact of supervised community service and socio-economic status on the propensity of ex-convicts to commit financial crimes. If most repeat offenses involve financial crimes, then recidivism can be significantly reduced by controlling the propensity to commit financial crimes among ex-convicts.

Barriers and Issues

The variables in the study tend to be very broad. Supervised community service is subject to varying interpretations. For instance, electronic monitoring of an ex-convict or family member responses to an offender's activities after prison time may be construed to be supervision. Further, the effectiveness of the intervention is relative to the unique situation of the ex-convict. Therefore, the need to utilize proxy variables for supervised community service may be essential but challenging. This study assumes that providing ex-convicts with social and employment skills needed to obtain gainful employment is among the goals of a State's supervised community service program.

Additionally, measuring the effectiveness of intervention programs after the fact confounds the findings. For instance, an ex-convict may be gainfully employed due to other factors, such as social network and previously acquired skills, and not necessarily the outcome of supervised community service. This study assumes that an ex-convict avoids a financial crime mainly because he or she was a participant in a community service program, and that participation in a community service program will reduce financial crimes in offenders more than other factors. Even though, supervised community service may produce such influencers of socio-economic status, it cannot be determined by this study whether the ex-convict would have committed a financial crime with or without the intervention program. This study does not determine whether community service participants actually obtained and maintained gainful employment over a period of time. The nature of this study and the timeline do not afford such a determination. In order to resolve the complexity, this study assumes that community service that is supervised will be effective in producing socio-economic opportunities more than pre-existing factors before the intervention program. Therefore, ex-convicts who participate in a supervised community service will be less likely to commit a financial crime compared to ex-convicts who do not participate in a supervised community service.

Definition of Terms

Independent Variables. The independent variables are 1) Supervised Community Service and 2) Socio-Economic Situation as determined by educational attainment, unemployment rate, and average household income. Supervised Community Service is a State or County-sponsored intervention program, as determined by supervised parole, designed to re-integrate ex-convicts into society and assist them in obtaining gainful employment. An example is supervised attachment to a prospective employer organization. Ex-convicts are crime offenders who have served a prison sentence in a State or Federal prison. Socio-Economic Situation is represented by educational attainment, unemployment rate, and average household income, and it is an indicator of the social and economic opportunities available to ex-convicts. The socio-economic situation of an ex-convict is a proxy for financial means and the existence of social responsibility and opportunities.

Dependent Variables. Financial Crime in ex-convicts is the dependent variable. Financial crimes are crimes against properties (property crimes), and involve a crime in which the perpetrator gained or sought to gain an economic benefit. Examples of financial crimes include kickback fraud, robberies, credit card fraud, money laundering, and securities or investment fraud. Financial crime offenders are those who are sentenced for their involvement in property crimes (Hopwood, Leiner & Young, 2008). In this study, property crimes comprise burglary, larceny-theft, and motor vehicle theft. Financial Crime Rate is the number of financial crimes per 100,000 population per year in the United States. Ex-convicts who committed property crimes are studied.

Control Variables. This study controls for the Year Crime Occurred, Gender, Educational Level of ex-convict, Age of ex-convict, Race of ex-convict, and number of Years to Recidivism after release of convict. These demographics have been found to influence a person’s ability to obtain a favorable social status and gainful employment.

For instance, males, Non-Caucasians, persons with criminal record in family, high school dropouts, individuals with prior adjudications, and those with learning disabilities are more at risk of repeating criminal behaviors. Therefore, personal traits (intrinsic with offender) and environmental factors (extrinsic to offender) are significant players in the propensity to commit crimes (Dean et al., 1996).

Gender represents the sex of the offender (Male or Female). The level of education is determined by high school graduation, university degree or vocational training. The age of the offender is a categorical variable based on age brackets in years. Race is determined by whether the ex-convict is White Caucasian or Non-White (Native American, Black, Hispanic, Asian, or Other Race).

Summary

The high rate of recidivism points to the fact that ex-convicts face significant challenges in their bid to adjust to life outside prison. For ex-convicts, obtaining favorable social status and gainful employment empowers them financially and reduces their propensity to recidivate (Parnaby, 2007). This section introduced the research background and problem, and stated the dissertation goal. Further, the section presented the research questions and hypotheses, and explained the significance of the research. Additionally, the likely barriers to be encountered and the limitations and delimitations of the research were introduced, and the definitions of research terms were stated.

CHAPTER II: LITERATURE REVIEW

This literature review explores the role that supervised community service and socio-economic status play in the propensity of ex-convicts to commit financial crimes. In this section, a review of extant literature about recidivism pertaining to financial crime among ex-convicts and two influencing factors is presented.

Recidivism among Ex-convicts

Recidivism is a behavior in which incarcerated offenders reoffend. Nuñez-Neto (2008) indicates that sixty-seven percent (67%) of ex-convicts re-offend within three years after their initial release from jail. However, about seventy-seven percent (77%) of re-convictions involve financial crimes in which perpetrators unlawfully converted another's property to their personal use and benefit, even though just about twenty-four percent (24%) of initial crimes involve financial crimes (James, 2004). Financial crimes are crimes against properties, and involve a crime in which the perpetrator gained or sought to gain an economic benefit. Examples include kickback fraud, robberies, credit card fraud, money laundering, and securities or investment fraud. Financial crime offenders are those who are sentenced for their involvement in property crimes (Hopwood, Leiner & Young, 2008). In this review, ex-convicts who commit financial crimes are studied, and some associated research studies are presented.

The rate of recidivism indicates that punishment has not been effective in deterring crimes (Nuñez-Neto, 2008). However, some research findings show mixed results about the role of punishment in curtailing criminal activities. For instance, Bodman and Maultby (1997) applied the economic theory of crime to determine whether punishment acts as deterrence against property crimes or moderates the propensity to commit property crimes. Economic theory posits that individuals commit certain types of crimes in order to maximize their benefits or utility of resources, or to avoid losing resources. Therefore, the propensity to commit crime depends on the costs and benefits of the criminal act. The study selected 60 criminal cases from six (6) Australian States between 1982 and 1991, and used regression analysis to determine whether the probability of imprisonment and expected sentence length influence the propensity to commit property crimes. The authors find a significant deterrent effect (from probability of imprisonment and expected sentence length) on the propensity to commit property crimes. The findings are consistent with those of other researchers (Benson, Iljoon & Rasmussen, 1994; Pedelford & White, 2009). Further, the findings indicate that sentencing policies may be used to control recidivism pertaining to financial crimes in some cultures. However, based on the rate of recidivism in the United States (Nuñez-Neto, 2008), punishment has not been effective. Therefore, other factors need to be examined.

Holtfreter, Piquero and Piquero (2008) examined the perceptions of fraud investigators in relation to punishment for fraud perpetrators and the propensity to commit fraud. The study evaluated 663 fraud investigators' perceptions of white-collar crimes, using secondary data previously collected by the Association of Certified Fraud Examiners (ACFE) from April 2001 to February 2002. All the cases examined involved occupational fraud (or fraud committed against organizations), and summarized self-reported survey responses from Certified Fraud Examiners (CFEs) about their most recently investigated cases. The methodology employed was designed to avoid skewed distribution of cases. Further, cases reported were ones in which the perpetrators were identified, and the investigation and legal proceedings were completed. The study used bivariate and regression models to test the relationships between "respondent characteristics, organizational context, case characteristics, and perpetrator characteristics" (p. 406) and "general and specific punishment perceptions" (p. 406). The results of the study indicate that organizational context (e.g. working for a government agency) and case characteristics were positively associated with general punishment perceptions of adequacy for persons who commit occupational fraud. Additionally, case characteristics (incarceration and civil suit) and organizational resources increased the perceptions of specific punishments being adequate. Further, the study results imply that if prospective criminals expect adequate punishment, the propensity to commit financial crimes in general will be moderated. However, punishment alone did not show conclusive results.

Clearly, punishment alone is not effective in reducing financial crimes among ex-convicts, and other factors that tend to address the root causes of financial crimes, such as supervised community service and socio-economic status, should be prominent in crime reduction programs. In one of the studies that address the root causes of criminal behavior, Yarbrough, Jones, Sullivan, Sellers and Cochran (2012) examined the likelihood of committing crime by assessing the role of social learning and self-control in moderating the potential of criminal propensity. Yarborough et al. employed the social learning theory (social amplification), which posits that individuals with antisocial characteristics are more likely to commit crime, and analyzed the moderating impact of self-control. The study selected a sample of 1,674 students and used self-reported survey response to test the extent to which self-control moderates antisocial behaviors (and impliedly the propensity to commit crime). The result of the bivariate relationships test and multivariate analyses show that 1) the model explained sixty percent (60%) of the variability in antisocial behaviors ($F = 308.83$, $p < .001$) and 2) self-control is significant in moderating antisocial behaviors ($\beta = -.24$). Hence, programs designed to moderate antisocial behaviors are likely to reduce the propensity to commit crime, which implies that financial crime among ex-convicts may be moderated by intervention programs. Clearly, effective supervised community service and improved socio-economic status are likely to moderate antisocial behaviors and curtail financial crime among ex-convicts.

Some studies show that the presence of financial pressures influences individuals to commit financial crimes (Bodman & Maultby, 1997). English (2011) studied the distribution of property offences in the Atlanta, GA area, and concludes that property crimes differed based on socio-economic status. According to English, the City of Atlanta experienced twenty-four and one-half percent (24.5%) increase in property crimes in 2008 from the previous year. The study used raw crime data from the Atlanta Department of Police, the U.S. Census, Reference USA, and the Bureau of Labor Statistics. The study used Point Density analysis and Moran's I model to determine whether offenses were clustered or randomly dispersed. Additionally, the Manhattan Distance Method and Z-Score were used in determining where offenses occurred most. The author analyzed where property crimes were prevalent, and which environmental factors played a role in the crime. The study documents that criminals targeted more affluent areas, and that neighborhood design played a significant role in the propensity to commit property crimes in the Atlanta area. The study also shows the behavior characteristics of criminals and their tendency to obtain the maximum financial gain per crime. For instance, residential burglaries occurred most (1,073 times) in December, compared to 773 in July. Possibly, financial pressure on individuals is more in the period around the Christmas season. Clearly, programs geared toward alleviating financial distress in ex-convicts are more likely to reduce recidivism pertaining to financial crimes.

Nevertheless, other intervening factors, such as gender, educational level, age, and race, need to be examined and isolated in order to correctly identify the role of supervised community service and improved socio-economic status. For instance, Dean, Brame and Piquero (1996) examined the propensity to commit crime based on an analysis of criminal behaviors in various groups of individuals. Their study finds that prior convictions influenced recidivism in general, more for financial crimes, in older individuals compared to juveniles. The authors took a sample of 848 post-age-16 individuals who had repeated criminal records in North Carolina institutional releases. The study applied the concept of Survival Time Analysis to determine whether recidivism is similar across two groups of individuals: "those who experienced their first adjudication at an early age and those who were first adjudicated at a later age" (p. 547). In general, criminals reoffended within 78.04 weeks after their initial offense within the observed time frame. Additionally, the results indicated that the risk of recidivism approaches one hundred percent (100%) as the time frame extends towards infinity. This implies that all individuals in the sample are likely to reoffend if observed within an extensive time frame. It also means that individuals with a heavier financial burden were more likely to reoffend. Further, males, Non-Caucasians, persons with criminal record in family, individuals with prior adjudications and those with learning disabilities were more at risk of repeating criminal behaviors. It is clear from the results that personal traits and environmental factors are dominant players in the propensity to commit crime, and therefore, need to be controlled in order to isolate the impact of supervised community service and socio-economic status on recidivism pertaining to financial crimes among ex-convicts.

Socio-Economic Status

Unemployed ex-convicts are more likely to recommit crimes (Hooghe, Vanhoutte, Hardyns and Bircan, 2011). Hence, an ex-convict's socio-economic situation is more likely to influence the propensity to commit a financial crime. This section reviews the literature about the post-conviction socio-economic situation of offenders. The prevalence of unemployment is high among persons convicted of a crime, since they have difficulty in finding jobs. Unemployment leads to financial distress, which in turn contributes to recidivism pertaining to financial crimes. The literature indicates that convicted persons who can meet their basic economic needs and play their role in society are less likely to repeat a crime (The Pew Center on the States, 2011). Therefore, financial crime is less likely if the convicted person has a desirable socio-economic status and is self-dependent.

Hooghe et al. (2011) studied the role of unemployment, inequality and poverty in the propensity to commit crime in Belgium. High poverty levels, lack of resources and other social disorganization factors tend to explain a high incidence of criminal behaviors. The state of unemployment indicates a lack of income and increased poverty level. Additionally, the concomitant loss of a socially meaningful role in the community increases the risk of crime commission and provides an incentive or the rationalization to perform criminal acts. Hooghe et al. selected 589 Belgian municipalities for the period

2001 to 2006. Using spatial regression analysis, the authors find that unemployment explained the variability in violent crimes more than income levels. However, income inequality and unemployment were both significant in predicting property crimes. It implies that financial crime is less likely if an ex-convict has economic opportunities and can maintain a desirable social status.

Parnaby (2007) examined the role of environmental factors in crime prevention. The study assessed the impact of financial hardship, power dynamics, and effective governance. The author used semi-structured interviews and a snow-ball sampling technique to collect responses from 25 professionals involved in crime prevention and city planning and protection. The author finds that abundant financial resources, empowerment of persons assigned to implement crime protection strategies, and the prospect of effective community government are likely to reduce crime. Therefore, an ex-convict's propensity to commit crime is moderated by social and economic factors.

Social structures and available opportunities play a role in the commission of crimes. For instance, Farrall, Bottoms and Shapland (2010) investigated the impact of social structures on desistance from crime. The authors compared the strength of the desistance with that of employment prospects, family links and peer pressure. The study examined the likelihood of an individual to desist from criminal behavior given a set of social structures, including class, affluence, societal practices and values. In particular, the authors find that employment practices in the United Kingdom (UK) has changed to the extent that there are less low-skilled jobs which were effective in attracting potential criminals away from crimes. Further, punitive approaches to sentencing yielded an ever-increasing prison population from 49,000 in 2005 to 82,100 in 2009, and reduced ability to obtain gainful employment. The result is that the changing social structures influence offenders to recommit crimes either to deliberately return to prison or in their bid to obtain financial benefits.

Additionally, Aaltonen, Kivivuori, and Martikainen (2011) examined the strength and nature of socio-economic status (SES) in predicting crime. Criminal behavior is more present "when structural factors block people's striving to fulfill cultural expectations of affluence" (p. 162). The study used a sample of 28,485 Finnish citizens involved in property offenses, violent offences and driving while intoxication (DWI) offenses to determine crime risk factors. The authors find a strong association between SES and all three types of crime. In particular, long-term unemployment and lack of basic education were the strongest predictors of crime. Using survival analysis statistical method and a regression model, the study finds that persistent unemployment and low education predicted all three criminal behaviors examined in the study. The study results are consistent with others shown in preceding sections and suggest that recidivism is moderated by factors that tend to elevate the social status of persons convicted of a crime.

Further, Benson, Kim and Rasmussen (1994) developed a deterrence hypothesis, based on the economics of crime, to determine the propensity to commit crime. If individuals can derive a benefit from crime, the likelihood of a criminal act is increased. In particular, in cases where the derived benefit satisfies a financial need or a social-status need, the incidence of crime increases. Reviews of meta-analyses indicate that the economics of crime is more influential in predicting crime deterrence than policing and other deterrence policies. The study results are consistent with the notion that the propensity to commit crime is increased in the presence of financial hardships.

Supervised Community Service

Extant literature show that supervised community service will help an ex-convict to “reform”. People who exhibit individualistic tendencies are more likely to commit crimes (Pedelford & White, 2009). Supervised community service moderates individualistic tendencies and reduce the propensity to repeat a crime. For instance, States with supervised community service as part of their sentencing policy tend to reduce the incidence of recidivism. Further, supervised community service which provides basic education, employment skills and allowances tend to moderate the incidence of recidivism (The Pew Center on the States, 2011).

Others find consistent results. Lockwood, Nally, Ho, and Knutson (2012) used a 5-year study in Indiana to investigate the impact of correctional education and post-release employment on the propensity to reoffend. Research results show that ex-convicts are likely to reoffend if they are uneducated and unemployed upon their release from prison. Lockwood et al. selected a sample of 6,561 offenders who were ex-convicts from the Indiana Department of Correction in 2005, and studied the impact of education and employment on the offenders’ propensity to reoffend. The Indiana Department of Correction used state funds and federal grants to provide released offenders with educational and vocational programs in a community service setting. The authors find that education and employment were the strongest predictors of post-release recidivism. In particular, offenders who did not complete high school were most at risk to reoffend. The propensity to reoffend increased from thirty-one percent (31%) for college educated offenders to almost sixty percent (55.9%) for offenders who did not complete high school. By implication, education reforms offenders’ ability to obtain employment, and gainful employment enables ex-convicts to make a living. Additionally, the results are consistent with other findings which suggest that supervised community service reforms offenders, moderates their selfish outlook, and it is a strong intervening factor in recidivism pertaining to financial crimes (Pedelford & White, 2009).

However, research on community service as a correctional intervention had yielded mixed results due to differing research designs. Some researchers found a positive association between community service and recidivism, while others found a negative association. Bouffard and Muftic (2007) examined the effectiveness of community service sentences in comparison to traditional fines for low-level offenders. Bouffard and Muftic used quasi-experimental research method to compare recidivism among 200 offenders who completed community services and 222 offenders who paid monetary fines, using data from RESTORE, a non-profit corrections agency. The authors find that multiple factors are at play in reducing recidivism, and that isolating the impact of community service is a daunting task. Nevertheless, their results indicate that offenders who completed community service were less likely to recidivate ($B = -0.926$, $p < .05$) than offenders who paid monetary fines, after controlling for confounding variables. The results imply that community service is more effective in reducing recidivism than monetary fines.

The effectiveness of community service in reducing recidivism has been confirmed in other parts of the world. For instance, Rex and Gelsthorpe (2002) investigated the role of community service in reducing recidivism in the United Kingdom (UK). The study evaluated the effectiveness of the Pathfinder Projects in community service to determine whether they influenced a reduction in recidivism, using self-reported questionnaires between March and September 2000 and post-program evaluations for 638 offenders. Offenders enrolled in the project comprised ninety-two percent (92%) male and averaged 27 years. Offenders achieved a high-compliance rating (83%) and a high-performance rating (86%). The authors identified the products of community service in reducing recidivism to include 1) pro-social modeling 2) skills accreditation and 3) addressing problems underlying offending (p. 318). The study results show that pro-criminal attitudes and post-criminal behaviors in about thirty-three percent (33%) of offenders who successfully completed the program significantly reduced. The findings indicate that supervised community service may be effective in reforming offenders and in moderating recidivism.

Additionally, Wermink, Blokland, Nieuwbeerta, Nagin, and Tollenaar (2010) compared the impact of community service and short-term imprisonment on the propensity to reoffend in the Netherlands. The authors show that sixty percent (60%) of imprisoned offenders in the Netherlands recidivate compared to forty percent (40%) for those who have performed community service. Wermink et al. however argue that the difference may just be explaining the selection process for community service and not causality. The study selected 4,246 adult offenders from longitudinal official data in the Netherlands. Additionally, the study utilized “matching variable” and “propensity score matching” to control confounding variables such as selection process for community service. Wermink et al. find that offenders who performed community service after imprisonment were less likely to recidivate compared to offenders who did not perform community service but spent time in prison. The study results are consistent with other findings which indicate that supervised community service assist in reforming offenders, refocuses their attention on playing a respectable role in society, and provides offenders with work-ethic skills to improve employability in offenders.

Further, Killias, Aebia and Ribeaud (2000) investigated the effectiveness of community service in rehabilitating offenders compared to short-term imprisonment in a controlled experiment in Switzerland. The authors show that various studies have attempted to predict the effectiveness of various sentencing policies in reducing recidivism and found mixed results. The study examined 123 convicts in a controlled experiment over 14 days in Switzerland. Killias et al. find that re-arrest were more frequent in offenders who served a prison sentence than in those who completed community service. Further, prisoners adopted a more negative attitude toward their sentence and the criminal justice system. The results imply that community service has the potential to reform offenders than a prison sentence. Additionally, the results are consistent with other study results which suggest that supervised community service is an effective tool for correctional intervention.

Research Questions and Hypotheses

The propensity to commit crime increases with lower educational attainment and decreased economic opportunities (Ehrlich, 1973; Lochner & Moretti, 2004). It means that socio-economic factors influence crime rate. Therefore, socio-economic situation, as represented by educational attainment, employment rate, and household income levels, is associated with crime rates.

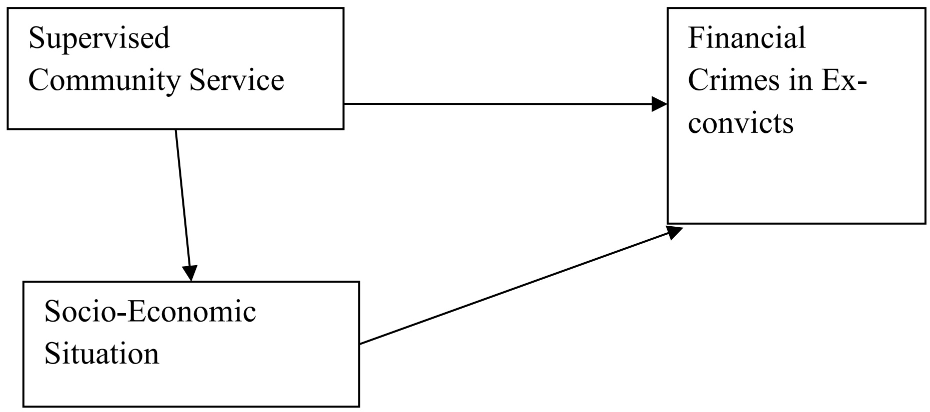
Further, research results indicate a stronger and a positive association between unemployment rates and property crime rates (Raphael & Winter-Ebmer, 2001). The trend implies that individuals are more likely to commit financial crimes with lower or no disposable income. This study postulates that supervised community service designed to assist ex-convicts to reform is likely to reduce recidivism stemming from financial crimes. Some community services are not supervised to aid the ex-convict to reintegrate into society and are not effective in reforming the ex-convict (Rex & Gelsthorpe, (2002). Further, efforts to reduce recidivism through community services and the maintenance and display of offender records in public databases have been focused more on punishment and deterrence (Holtfreter et al., 2008). However, an increased focus on socio-economic status of the ex-convict will be more effective in reducing recidivism, since most offenses among ex-convicts involve financial crimes (James, 2004). Therefore, financial crimes, as represented by property crimes, are more likely to increase in periods of decreasing disposable incomes and or increasing unemployment rate.

RQ #1: Is socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, associated with financial crimes?

If financial crimes are more likely to increase with decreasing disposable incomes and or increasing unemployment rate, then socio-economic factors are associated with recidivism stemming from financial crimes in offenders incarcerated for various crimes. By implication, crime offenders who successfully participate in supervised community service are more likely to improve their socio-economic status (more social and economic opportunities) and are less likely to commit financial crimes compared to ex-convicts who do not participate in any supervised community service. Therefore, supervised community service, as represented by supervised parole, is more likely to reduce financial crimes among ex-convicts (Figure 1).

RQ #2: Do ex-convicts who undergo supervised community service less likely to commit a financial crime compared to ex-convicts who do not?

Figure 1. Conceptual Model of Intervening Factors



Socioeconomic factors play a significant role in the commission of crime, as explained in the economic model of crime (Ehrlich, 1973). Individuals with higher educational attainment often have a higher social standing and more economic opportunities, and hence are less likely to commit crimes. The opposite is true for individuals with lower educational attainment and less economic opportunities. For instance, a high school dropout has less opportunities for furthering his or her education, has less employable skills, and is more risk-tolerant to the consequences of illegal behaviors and may be more inclined to commit crime.

Additionally, the economic theory of crime helps to explain the influence of punishment in deterrence against property crimes and in the propensity to commit financial crimes. The economic theory posits that individuals commit certain types of crimes in order to maximize their benefits or utility of resources, or to avoid losing resources. Therefore, the propensity to commit crime depends on the costs and benefits of the criminal act. Further, the presence of financial pressures influences individuals to commit financial crimes (Bodman and Maultby (1997). By implication, the presence of economic opportunities moderates the incidence of financial crimes as individuals try to minimize their costs and maximize their financial benefits.

H1: Socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes.

Furthermore, the likelihood of crime commission is moderated by social learning and self-control, and in turn reduces criminal propensity (Yarbrough, Jones, Sullivan, Sellers and Cochran, 2012). Individuals with antisocial characteristics are less likely to obtain gainful employment and more likely to commit crime. Hence, programs designed to moderate antisocial behaviors are more likely to aid the ex-convict to increase their economic opportunities and reduce the propensity to commit a financial crime (Yarborough et al., 2012). Further, prisoners who participate in supervised community service are likely to adopt a more positive attitude toward their sentence and the criminal justice system (Killias et al., 2000). The results imply that community service has the potential to reform offenders than a prison sentence. Additionally, the expectation is consistent with other study results which suggest that supervised community service is an effective tool for correctional intervention (Lockwood et al., 2012).

H2: Ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to ex-convicts who do not.

Summary

Prior research and extant literature show that about sixty-seven percent (67%) of ex-convicts re-offend within three years after their initial release from jail (Nuñez-Neto, 2008). However, about seventy-seven percent (77%) of re-convictions involve financial crimes, even though just about twenty-four percent (24%) of initial crimes involve financial crimes (James, 2004). The research findings reviewed in this study show that personal traits, environmental factors and economic status are dominant players in the propensity to commit a financial crime among ex-convicts (Aaltonen et al., 2011; Farrall et al., 2010; Parnaby, 2007). For instance, income inequality and unemployment were found to be significant predictors of property crimes (Hooghe et al., 2011), and unfavorable social structures influenced offenders to recommit crimes either to deliberately return to prison or in their bid to obtain financial benefits (Parnaby, 2007). The findings from a review of the literature show that programs designed to moderate antisocial behaviors, social disorganization, and financial hardships are likely to reduce the propensity to commit a financial crime among ex-convicts (Bouffard & Muftic, 2007; Killias et al., 2000; Lockwood et al., 2012; Rex & Gelsthorpe, 2002; Wermink et al., 2010).

A review of the literature shows that the behavior characteristics of criminals and their tendency to obtain financial benefits play a significant role in the propensity to commit a financial crime among ex-convicts. Further, offenders with low socio-economic status have a higher propensity to reoffend. Some study results imply that if prospective criminals expect adequate punishment, the propensity to commit crimes will reduce (Bodman & Maultby, 1997; Holtfreter et al., 2008). However, other findings (in overwhelming majority) show that correctional intervention programs such as supervised community service can help reform offenders, increase employability, and reduce recidivism pertaining to financial crimes (Hooghe et al., 2011). In particular, some findings indicate that community service is more effective in reducing recidivism than prison sentences or monetary fines. Therefore, community service is more effective in moderating financial crimes among ex-convicts.

This study postulates that socio-economic status is associated with the commission of financial crimes among ex-convicts, and expects that individuals with economic hardships are more likely to reoffend. An ex-convict's propensity to commit a financial crime is moderated by social and economic factors. The results from extant literature are consistent in showing that recidivism pertaining to financial crimes is moderated by factors that tend to elevate the social status of persons convicted of a crime, and consistent in predicting an offender's propensity to commit crime given financial hardships. Further, the findings indicate that sentencing policies can be used to control recidivism pertaining to financial crimes (Bodman and Maultby, 1997; Holtfreter, Piquero and Piquero, 2008). However, supervised community service is more effective in reducing financial crimes among ex-convicts (Hooghe et al., 2011; Yarborough et al., 2012). Therefore, recidivism pertaining to financial crimes is less likely if the ex-convict has a desirable socio-economic status and is self-dependent. It implies that recidivism among ex-convicts in general is less likely if the ex-convict has economic opportunities and can maintain a desirable social status (Hooghe et al., 2011). For instance, States with supervised community service as part of their sentencing policy tend to reduce the incidence of recidivism. Further, supervised community service which provides basic education, employment skills and allowances tend to moderate the incidence of recidivism (Farrall, Bottoms and Shapland, 2010).

Additionally, this study posits that ex-convicts who undergo supervised community service are less likely to commit financial crimes. Offenders with a criminal history often experience difficulties in finding gainful employment to alleviate their financial hardships. The financial distress associated with unemployment is likely to influence an offender to commit a financial crime. Supervised community service can be designed to provide reformation-oriented education to ex-convicts, refocus their attention on playing a respectable role in society, and provide ex-convicts with work-ethic skills to improve employability in offenders. Evidently, social and economic opportunities enable ex-convicts to make a decent living, and supervised community service can provide the pathway to obtaining socio-economic opportunities. Additionally, supervised community service should be designed to reform offenders, moderate their selfish outlook, and be used as an effective intervening factor in recidivism pertaining to financial crimes among ex-convicts (Lockwood et al., 2012).

Sentencing policies which are focused solely on punishment without reformation of the criminal may not be effective. Ineffective sentencing policies place a financial burden on society, cause dissatisfaction in offenders, and are likely to be ineffective in controlling financial crimes among ex-convicts. Clearly, sentencing policies that are designed to influence a positive reformation by addressing the factors that influence crime are likely to reduce financial crimes among ex-convicts. Hence, supervised community service designed to improve an ex-convict's socio-economic status is likely to reform the ex-convict and reduce the propensity to commit a financial crime.

CHAPTER III: METHODOLOGY

This chapter presents the research method to be employed. The chapter is organized as follows: the next section introduces the methodology, followed by 1) an explanation of the research method participants, 2) elaboration of the research instruments, 3) how the methodology procedures will aid in effective research design and appropriateness, 4) an identification of how data analysis and appropriateness will be performed and achieved, 5) a discussion of research limitations, and how internal and external validity will be achieved in addressing limitations, and 6) a summary of key points presented in the chapter.

Background

This paper examines the impact of supervised community service and socio-economic status on the propensity of ex-convicts to commit financial crimes. Researchers indicate that the high rate of recidivism point to the fact that ex-convicts face significant challenges in their bid to re-adjust to life after serving time in prison (Bouffard & Muftic, 2007; Killias, Aebi, & Ribeaud, 2000; Lockwood, Nally, Ho, & Knutson, 2012; Rex & Gelsthorpe, 2002; Wermink, Blokland, Nieuwbeerta, Nagin, & Tollenaar, 2010). Nuñez-Neto (2008) shows in a study that about sixty-seven percent (67%) of ex-convicts re-offend within three years after their release from jail. However, about seventy-seven percent (77%) of ex-convicts who recidivate commit financial crimes in which they unlawfully converted another’s property to their personal use and benefit, even though just about twenty-four percent (24%) of their initial crimes involve financial crimes (James, 2004). It means that the propensity to commit a financial crime increases after jail time among ex-convicts. Research findings show that personal traits, environmental factors and economic status are dominant players in the propensity to commit crime (Aaltonen, Kivivuori, & Martikainen, 2011; Farrall, Bottoms, & Shapland, 2010; Parnaby, 2007). For instance, income inequality and unemployment are significant predictors of property crimes (Hooghe, Vanhoutte, Hardyns, & Bircan, 2011), and unfavorable social structures influence offenders to recommit crimes either to deliberately return to prison or in their bid to obtain financial benefits (Parnaby, 2007). Therefore, ex-convicts are more likely to commit a financial crime than other crimes.

Individuals with antisocial characteristics are less likely to obtain gainful employment and more likely to commit crimes. Hence, programs designed to moderate antisocial behaviors are more likely to aid ex-convicts to improve their socio-economic opportunities and reduce the propensity to commit a financial crime (Yarborough et al., 2012).

This study explores the association among various variables of socio-economic trends, offender characteristics, and property crime trends. Secondary data is used in a predictive model for recidivism involving property crimes. If economic well-being is associated with reduced financial crimes, then effective supervised community service that provides a pathway to offenders to improve their social and economic opportunities is likely to reduce the propensity to commit financial crimes. The methodology in this study is designed to test 1) whether socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes and 2) whether ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to ex-convicts who do not.

Research Participants

This study utilizes archival data for crime trends, unemployment trends, household income levels, educational trends, and ex-convicts in the United States from the FBI's Uniform Crime Report, Bureau of Labor Statistics, the U.S. Census Bureau, National Center for Education Statistics, and the Bureau of Justice Statistics respectively, which are available between 1960 and 2015. The first dataset for the years 2005 to 2010 (United States Department of Justice, Office of Justice Programs, and Bureau of Justice Statistics, 2015) is used in testing whether socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes.

A second dataset comprises records of ex-convicts observed between the years 2005 to 2010 (Bureau of Justice Statistics, 2016; Cooper, Durose, & Snyder, 2014) who were released in 2005 and received supervised parole with community service is used in testing whether ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to other types of crimes. Further, this study will gain access to the National Archive of Criminal Justice Data (NACJD), the repository of original data for the Bureau of Justice Statistics, for further analysis and confirmations. The Bureau of Justice Statistics maintains data repository of ex-convicts, supervised parole for ex-convicts and the agencies involved, and ex-convicts who recidivate available from 1975 to 2012 (Cooper, Durose, & Snyder, 2014).

Further, the datasets and quantitative analysis of the results are compared with data from State Offender Supervision Agencies, The National Crime Victimization Survey, the FBI's Uniform Crime Reports, State Correction Agencies, and prison population and recidivism from The Pew Center.

Research Instruments

This study employs archival research (ex-post facto), in which existing data that is publicly available is analyzed in answering the research questions. The study analyzes publicly available data in aggregate form and does not include identifying ex-convicts information. Secondary data, as described above, is used in a multivariate regression (Gulumbe, Dikko & Bello, 2012; Zeintek & Thompson, 2007) in responding to the research questions 1) Is socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, associated with financial crimes?, and 2) Do ex-convicts who undergo supervised community service less likely to commit a financial crime compared to ex-convicts who do not? Further, a matched set of secondary data from the same sources is used for research question 2).

Research Design and Procedures

This study employs an explanatory research design to assess the impact of supervised community service on the propensity for ex-convicts to commit financial crimes. Supervised community service is a State or County-sponsored parole program designed to re-integrate ex-convicts into society and assist them in obtaining social and employment skills. This research examines the impact of supervised community service and socio-economic status on financial crimes. Researchers find that the propensity to commit crimes reduces with gainful employment (Bouffard & Muftic, 2007; Killias, Aebi, & Ribeaud, 2000; Lockwood, Nally, Ho, & Knutson, 2012; Rex & Gelsthorpe, 2002; Wermink, Blokland, Nieuwbeerta, Nagin, & Tollenaar, 2010). Therefore, ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to other types of crimes (Coenen, 2009).

This researcher uses datasets from the FBI's Uniform Crime Report, Bureau of Labor Statistics, the U.S. Census Bureau, National Center for Education Statistics, and the Bureau of Justice Statistics showing the following variables: financial crime (FINCRM); national unemployment rate (UNEMPR); average income (AVGINC); year crime report (YRCRPT); supervised community service with parole after release (SCSPAR); gender of the offender (GEN); level of education of ex-convict in years (EDU); age of ex-convict in years (AGE); race of ex-convict (RACE); financial crime rate (FINCRMRT); and years to recidivism (RECIDYRS).

Data Analysis and Appropriateness

This study utilizes descriptive statistics to examine and present crime trends and the characteristics of ex-convicts who commit property crimes and their supervised parole programs. Aggregate data for State parole programs is analyzed. Further analysis of the classes or types of property crimes and supervised parole programs is performed. Tables are used in presenting descriptive statistics for ex-convicts who receive supervised parole and their matched control set who did not receive supervised parole. Detailed analysis of the impact of the independent variables on the dependent variables is made, and an explanation of the regression test results is presented (see Table 1). It is expected that most of the variables are significantly correlated with each other. Therefore, a logistic regression analysis is used to assess the association of each of the variables, after controlling for the other variables in the study.

Data Reliability. The datasets for this study are collected from government data repositories for large scale surveys and censuses (Bureau of Labor Statistics, 2016; DeNavas-Walt & Proctor, 2015; FBI Uniform Crime Reporting Statistics, 2010; National

Center for Education Statistics, 2014; U.S. Census Bureau, 2014). The data collection approach employed in this study ensures that source bias is eliminated. The data have been analyzed by statisticians and researchers, and the collection methods have undergone periods of scrutiny and improvements. Further, national data in aggregate form are better suited for analyzing crime trends, for answering the research questions about recidivism in the general population, and for making conclusions about factors that moderate recidivism involving financial crimes. Additionally, the secondary data for this study are less impacted by resource constraints that usually inhibit primary data collection by a researcher. A multivariate regression is employed, and standard errors are analyzed (Jain, Singh, & Sharma, 2011; Lin, Zhu, Cao, & Li, 2011).

Ex-convicts who participated in state-administered supervised parole programs are studied for recidivism. The data is a national aggregate of state administered programs for offenders released from prison and are required to participate in a mandatory supervised parole. This study excludes probation participants and other non-supervised offenders from the dataset, in order to ensure that supervised community service is reliably defined in the data. This study uses data quality control measures to evaluate and verify the data sets for appropriateness and reliability. Unreliable data are excluded.

Multivariate Analysis. The impact of socio-economic status on the propensity to commit financial crimes among ex-convicts is tested, after controlling for other intervening variables. Table 1 provides a summary of the hypotheses and the regression equations. Some demographics have been found to influence a person’s socio-economic situation. For instance, males, Non-Caucasians, persons with criminal record in family, individuals with prior adjudications and those with learning disabilities are more at risk of repeating criminal behaviors. Therefore, personal traits and environmental factors are significant players in the propensity to commit crime (Dean et al., 1996).

The following logistic regression is used in testing H1:

$$FINCRM = \beta_0 + \beta_1 YRCRPT + \beta_2 GEN + \beta_3 EDU + \beta_4 AGE + \beta_5 RACE + \beta_6 UNEMPR + \beta_7 AVGINC + \varepsilon$$

The following logistic regression is used in testing H2:

$$FINCRM = \beta_0 + \beta_1 SCSPAR + \beta_2 RECIDYRS + \beta_3 GEN + \beta_4 AGE + \beta_5 RACE + \varepsilon$$

Where:

UNEMPR = national unemployment rate; the percentage of unemployed persons who are employable and seeking gainful employment averaged for the year;

AVGINC = average income; national average household income in dollars;

FINCRM = financial crime; 1 if an offender committed a property crime, 0 otherwise;

YRCRPT = year crime report; year crime occurred;

GEN = gender of the offender; 1 if male, 0 if female;

EDU = level of education of convict; 1 if below high school, 2 if high school or higher;

AGE = age of convict at admission; 1 if 18-24 years, 2 if 25-34 years, 3 if 35-44 years, 4 if 45-54 years, 5 if 55 or more years;

RACE = race of convict; 1 if White Caucasian; 0 otherwise

SCSPAR = supervised community service with parole after release; 1 if ex-convict received supervised parole, 0 otherwise

RECIDYRS = years to recidivism; number of years ex-convict returned to prison after prior release; 1 if re-arrested within 5 years after prior release, 0 otherwise

Table 1

Methodology and Hypotheses Testing

Hypothesis	Test	Result Implication
H1	FINCRM = $\beta_0 + \beta_1$YRCRPT + β_2GEN + β_3EDU + β_4AGE + β_5RACE + β_6UNEMPR + β_7AVGINC + ε	If true, then socio-economic status plays a role in financial crime commission.
H2	FINCRM = $\beta_0 + \beta_1$SCSPAR + β_2RECIDYRS + β_3GEN + β_4AGE + β_5RACE + ε	If true, then supervised community service reduces financial crime commission among ex-convicts; else results are inconclusive.

Internal Validity. The study examines 1) whether socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes and 2) whether ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to ex-convicts who did not undergo supervised community service, after controlling for the Year Crime Occurred, Gender, Educational Level of ex-convict, Age of ex-convict, Race of ex-convict, and number of Years to Recidivism after release (control variables). These control variables affect the socio-economic situation of individuals and their propensity to a commit crime (Lockwood et al., 2012; Aaltonen et al., 2011; English, 2011). Hence, it is necessary to separate the influence of the control variables in socio-economic status and the propensity to commit crime, or suppress their strengths in the prediction model, in order to correctly measure the effect of the intervention program. This helps to ensure that any conclusions reached support the propositions presented in the study. In particular, the research methodology validates any claim that supervised community service yields socio-economic status and reduces the propensity to commit financial crimes among ex-convicts.

External Validity. In an attempt to eliminate any plausible alternative explanation of the role of socio-economic status and to validate any generalization of test results, this study examines a matched sample of ex-convicts who did not participate in a supervised parole program. Otherwise, it will be difficult to establish that since supervised community service was not administered an ex-convict committed a financial crime. Further, ex-convicts who fall within the working ages of 18 and 65 years are sampled to include ex-convicts who are more able and willing to work for a living, and whose avoidance of a financial crime is not explained by dependence on others (McMenamin, Miller & Polivka, 2006).

CHAPTER IV: RESULTS

Introduction

This paper examined the impact of supervised community service and socio-economic status on the propensity of ex-convicts to commit financial crimes. Studies indicate that the challenges ex-convicts face in their bid to adjust to life outside prison influence the high rate of recidivism. Is the socio-economic situation of ex-convicts associated with their propensity to commit financial crimes? If so, does supervised community service play an intervening role in moderating their propensity to commit financial crimes? This chapter presents empirical results in response to the foregoing questions. The section shows findings from descriptive statistics, multivariate regression analysis, and hypothesis testing.

Demographics of Ex-Convicts and Hypothesis Testing for H1

H1 Demographics. Data set for H1 comprises 1,403,792 cases of offenders admitted in prison between the period 2005 and 2010. The final data set was culled from the original data set of 3,898,157 cases of prison and parole admissions. The final data set excludes cases with missing or incomplete offender information. Further, ex-convict admission cases from Alabama, California, Connecticut, Delaware, the District of Colombia, Illinois, Kansas, Louisiana, Maryland, Michigan, Montana, New Jersey, New Mexico, Ohio, and Vermont were excluded from the final data. These states had many reporting inconsistencies or missing data over the study period. For instance, California and Louisiana had unusually high crime rates of 339.9 and 338.9 per 100,000 residents respectively over the study period and reporting inconsistencies. Additionally, drug cases are unevenly reported by the individual states. Therefore, drug cases were excluded from the final data set (Appendix A, Table A9). Table 2 and Table 3 below show the states with the five (5) highest and five (5) lowest crime rates respectively.

Table 2

Ex-Convicts Admitted to Prison – Top 5 by Total Crime Rate

	5-Level Categorization of Crime Type Excluding Drug Offenses					
	Violent	Property	Public order	Other/unspecified	Property Crime Rate*	Total Crime Rate*
Rhode Island	6413	5583	6670	129	87.9	296.0
Alaska	2889	1858	6599	25	45.1	275.8
Arizona	24381	35411	26707	76	95.5	233.6
North Carolina	33166	44609	39544	196	81.0	213.4
Arkansas	9683	19249	4379	2653	112.3	209.8
Total	76532	106710	83899	3079		

This table presents summaries of ex-convicts admitted to prison between 2005 and 2010 and used for testing Hypothesis 1

Top 5 Total Crime Rate represents the top five states with the highest crime rates

*Property Crime Rate is the number of property crimes per 100,000 state residents

*Total Crime Rate is the number of total crimes per 100,000 state residents

*(N) Total Cases Excluding Missing Cases and Drug Offenses = 1,403,792 cases of ex-convicts

Out of the 1,403,792 cases, forty-one and a half percent (41.5%) represented property crimes (FINCRM) and fifty-eight and a half percent (58.5%) comprised non-property crime cases (non-FINCRM). Non-property crime cases consisted of violent crimes, public order cases, and unspecified cases. The number of FINCRM present (one) and absent (zero) in the dataset is 1,403,792.

Table 3

Ex-Convicts Admitted to Prison – Bottom 5 by Total Crime Rate

	5-Level Categorization of Crime Type Excluding Drug Offenses

	Violent	Property	Public order	Other/unspecified	Property Crime Rate*	Total Crime Rate*
Virginia	2830	3489	1488	42	7.5	16.8
Mississippi	1255	1104	235	54	6.3	15.0
Nebraska	466	452	246	14	4.2	11.0
New Hampshire	112	91	381	1	1.2	7.4
Massachusetts	1172	542	475	37	1.4	5.7
Total	5835	5678	2825	148		

This table presents summaries of ex-convicts admitted to prison between 2005 and 2010 and used for testing Hypothesis 1

Bottom 5 Total Crime Rate represents the bottom five states with the lowest crime rates

*Property Crime Rate is the number of property crimes per 100,000 state residents

*Total Crime Rate is the number of total crimes per 100,000 state residents

*(N) Total Cases Excluding Missing Cases and Drug Offenses = 1,403,792 cases of ex-convicts

Descriptive Statistics for H1. Table 4 below presents, for ex-convicts admitted to prison, the descriptive statistics of the variables. Additionally, a Pearson Correlation Matrix is presented to show the relationship between FINCRM and the independent variables (Appendix B, Table B1). Due to the large size of the dataset, a 0.01 (p value) significance level was used in producing the correlations. Hence, an association with FINCRM is significant if the observed p-value is 0.01 or less. In the univariate analysis, Unemployment Rate has a negative association with FINCRM ($r(1403792) = -0.011$, $p < 0.01$), and Average Income has a positive association with FINCRM ($r(1403792) = 0.012$, $p < 0.01$). The univariate analysis indicates that Level of Education does not have a statistically significant relationship with FINCRM ($r(1403792) = -0.002$, $p > 0.01$).

The univariate analysis of the intervening variables, after recoding Female and Non-White to zero (0), indicates that Gender (Male) has a positive association with FINCRM ($r(1403792) = 0.105$, $p < 0.01$), Year Crime Occurred has a negative association with FINCRM (r(1403792) = -0.012, $p < 0.01$), Race (White) of offender has a negative association with FINCRM (r(1403792) = -0.095, $p < 0.01$), and Age of offender has a negative association with FINCRM (r(1403792) = -0.022, $p < 0.01$) (Appendix B, Table B1).

Table 4

Descriptive Statistics of Financial Crimes and Non-Financial Crimes Cases

	Financial Crimes			Non-Financial Crimes			
Variable	Mean	Median	Std. Deviation	Mean	Median	Std. Deviation	Two-tailed p-value
YRCRPT	2007.53	2008.00	1.703	2007.58	2008.00	1.703	0.000
GEN	1.15	1.00	0.357	1.08	1.00	0.276	0.000
EDU	1.49	1.00	0.500	1.49	1.00	0.500	0.019
AGE	2.28	2.00	1.031	2.33	2.00	1.055	0.000
RACE	1.47	1.00	0.499	1.57	2.00	0.495	0.000
UNEMPR	6.53*	5.80*	2.133*	6.58*	5.80*	2.146*	0.000
AVGINC	75.32**	75.01**	1.826**	75.28**	75.01**	1.821**	0.000

This table presents descriptive statistics on a sample of 1,403,792 cases of ex-convicts between 2005 and 2010.

(N) FINCRM = 582,758 cases of ex-convicts (property crimes)

(N) Non-FINCRM = 821,034 cases of ex-convicts (non-property crimes)

Maintained DOJ codes for Male (1), Female (2), White (1), and Non-White recoded (2)

*UNEMPR in percentage

** AVGINC in thousands of US Dollars

Regression Analyses for H1. This study used a logistic regression to analyze the relationship between FINCRM (dependent variable) and 1) YRCRPT 2) GEN 3) EDU 4) AGE 5) RACE 6) UNEMPR and 7) AVGINC (independent variables). Table 5 below shows the regression results for the logistic regression model used for estimating the impact of each variable on financial crime. The first regression (Full Logistic Regression) contains the full set of variables. The variables which were not significant ($p > 0.01$) in the first regression were excluded from the second regression (Partial Logistic Regression) in a bid to strengthen the Pseudo-R^2 (regression model fitness). The second regression was produced to ascertain whether excluding variables that were not statistically significant will lead to different regression model results. The association between each of the statistically significant variables and FINCRM was identical in direction and in predictive strength in both the full and partial regression models. Further, both regression models produced the same Pseudo-R^2.

Table 5

Logistic Regression for Financial Crimes – H1

$$FINCRM = \beta_0 + \beta_1 YRCRPT + \beta_2 GEN + \beta_3 EDU + \beta_4 AGE + \beta_5 RACE + \beta_6 UNEMPR + \beta_7 AVGINC + \varepsilon$$

Dependent Variable = Financial Crimes

	Full Logistic Regression		Partial Logistic Regression	
Variables	Coefficient	p-value	Coefficient	p-value
Intercept	-0.343	0.000	-0.343	0.000
YRCRPT	-0.008	0.072		
GEN	0.635	0.000	0.634	0.000
EDU	-0.033	0.000	-0.035	0.000
AGE	-0.062	0.000	-0.062	0.000
RACE	-0.373	0.000	-0.373	0.000

UNEMPR	-0.003	0.063
AVGINC	0.000	0.644

This table presents regression results for financial crimes.
(N) FINCRM = 582,758 cases of ex-convicts
(N) Non-FINCRM = 821,034 cases of ex-convicts
Female and Non-White recoded (zero)
Full regression Pseudo R-square = 0.026
Partial regression Pseudo R-square = 0.026
Full regression Chi-square = 27821.29
Statistic is significant at p-value equal to or less than 0.01

A 0.01 (p value) significance level was used in producing the multivariate regression results, after recoding Female and Non-White to zero (0). Hence, the model results and the association between each of the independent variables and FINCRM are significant if the observed p-value is 0.01 or less. In the multivariate analysis, the model was significant in predicting FINCRM (B = -0.343, $p < 0.01$). The model's Pseudo-R^2 indicates that the variables in the regression models predicted about 2.6% of the variability in FINCRM. In the full regression, Year Crime Occurred, Unemployment Rate, and Average Income are not statistically significant ($p > 0.01$) in predicting FINCRM. The full regression and the partial regression produce identical and statistically significant association ($p < 0.01$) between each of the remaining independent variables (GEN, EDU, AGE, and RACE) and FINCRM.

Results for H1 variables are presented in Table 5. The multivariate analysis shows that GEN is positively associated with FINCRM, r(1403792) = 0.635, $p < 0.01$, and there is a negative association between EDU and FINCRM, r(1403792) = -0.033, $p < 0.01$. Also, the model shows that AGE is negatively associated with FINCRM, r(1403792) = -0.062, $p < 0.01$, and RACE is negatively associated with FINCRM, r(1403792) = -0.373, $p < 0.01$.

Demographics of Ex-Convicts and Hypothesis Testing for H2

H2 Demographics. Data set for H2 comprises 85,954 cases of offenders re-admitted to prison in 2010, of which 42,977 are re-offenders who were on parole and observed between the period 2005 and 2010, and a matching set of 42,977 non-parole (probation) re-offenders. The number of supervised Community Service with Parole (SCSPAR) present (one) and absent (zero) in the dataset is 85,954. The samples of supervised releases who returned to prison were taken from State parole and Federal probation recidivism cases. The final data set excludes cases with missing or incomplete offender information.

Out of the 85,954 cases, about twenty-seven percent (27.3%) represented property crimes (financial crimes) and approximately seventy-three percent (72.7%) comprised non-property crime cases (non- financial crimes). Non-property crime cases consisted of violent crimes, public order cases, and unspecified cases. The number of FINCRM present (one) and absent (zero) in the dataset is 85,954.

Descriptive Statistics for H2. Table 6 below presents, for ex-convicts readmitted to prison, the descriptive statistics of the variables. A Pearson Correlation is presented in Appendix B, Table B5 to show the association between FINCRM and the independent variables. Due to the large size of the dataset, a 0.01 (p value) significance level was used in producing the correlations. Hence, an association with FINCRM is significant if the observed p-value is 0.01 or less. In the univariate analysis, supervised Community Service with Parole (SCSPAR) has a positive association with FINCRM ($r(85954) = 0.071$, $p < 0.01$).

The univariate analysis of the intervening variables, after recoding Female and Non-White to zero (0), indicates that the number of years from prison release to readmission, Years to Recidivism (RECIDYRS) within 5 years, has a positive association with FINCRM ($r(85954) = 0.360$, $p < 0.01$), Gender (Male) has a negative association with FINCRM ($r(85954) = -0.155$, $p < 0.01$), Age of offender has a negative association with FINCRM ($r(85954) = -0.344$, $p < 0.01$), and Race (White) of offender has a negative association with FINCRM ($r(85954) = -0.378$, $p < 0.01$), and (Appendix B, Table B5).

Table 6

Descriptive Statistics of Parole and Non-Parole Recidivism

	Parole Recidivism			Non-Parole Recidivism			
Variable	Mean	Median	Std. Deviation	Mean	Median	Std. Deviation	Two-tailed p-value
FINCRM	0.300	0.00	0.460	0.240	0.00	0.428	0.000
RECIDYRS	0.330	0.00	0.470	0.380	0.00	0.485	0.000
GEN	1.100	1.00	0.294	1.20	1.00	0.402	0.000
AGE	2.500	2.00	1.005	2.88	3.00	1.240	0.000
RACE	1.610	2.00	0.488	1.590	2.00	1.492	0.000

This table presents descriptive statistics on a sample of 85,954 cases of recidivated ex-convicts observed between 2005 and 2010.
(N) Parole Recidivism = 42,977 cases of recidivated ex-convicts
(N) Non-Parole Recidivism = 42,977 cases of recidivated ex-convicts
Maintained DOJ codes for Male (1), Female (2), White (1), and Non-White recoded (2)
*Non-Parole Recidivism comprises supervised probation cases of recidivated ex-convicts

Table 7 below compares recidivism rates among supervised releases (parole and probation) and the overall total releases of both supervised and non-supervised.

Approximately eighty-two percent (82.1%) of ex-convicts who recidivated within 5 years by the year 2010 committed property crimes (Cooper et al., 2014), about thirty percent (30.4%) in the parole sample committed property crimes, and about twenty-four percent (24.1%) in the non-parole probation sample committed property crimes.

Table 7

Recidivism Rates of Parole and Probation Ex-convicts in 2010

Variable	Parole	Probation*	Total Recidivism**
PROPERTY CRIMES	30.4%	24.1%	82.1%
GEN (MALE)	90.4%	79.7%	84.6%
AGE (<34 YEARS)	54.7%	44.5%	60.9%
RACE (NON-WHITE)	60.8%	58.7%	76.5%
RECIDIVISM IN 5 YEARS	33.0%	38.0%	63.5%

This table presents descriptive statistics on a sample of 85,954 cases of recidivated ex-convicts observed between 2005 and 2010.

(N) Non-Parole Recidivism = 42,977 cases of recidivated ex-convicts

(N) Parole Recidivism = 42,977 cases of recidivated ex-convicts

Property Crimes rate is the percentage of recidivated ex-convicts who committed property crimes

*Non-Parole Recidivism comprises supervised probation cases of recidivated ex-convicts

**Total Recidivism comprises supervised parole and probation cases and non-supervised cases of recidivated ex-convicts (Cooper et al., 2014)

Regression Analyses for H2. This study used a logistic regression to analyze the relationship between FINCRM (dependent variable) and 1) SCSPAR 2) RECIDYRS 3) GEN 4) AGE 5) RACE (independent variables). Table 8 below shows the regression results for the logistic regression model used for estimating the impact of each variable on financial crime.

Table 8

Logistic Regression for Financial Crimes – H2

$$FINCRM = \beta_0 + \beta_1 SCSPAR + \beta_2 RECIDYRS + \beta_3 GEN + \beta_4 AGE +$$

$\beta_5 RACE + \varepsilon$

Dependent Variable = Financial Crimes

Variables	Coefficient	p-value
Intercept	-0.981	0.000
SCSPAR	0.704	0.000
RECIDYRS	0.993	0.000
GEN	-0.296	0.000
AGE	-0.508	0.000
RACE	-1.174	0.000

This table presents regression results for financial crimes for parole and non-parole ex-convicts who recidivated.
(N) Parole Recidivism = 42,977 cases of recidivated ex-convicts
(N) Non-Parole Recidivism = 42,977 cases of recidivated ex-convicts
Female and Non-White recoded (zero)
Regression Pseudo R-square = 0.308
Regression Chi-square = 20563.941
Statistic is significant at p-value equal to or less than 0.01

In the multivariate analysis for H2 using a 0.01 (p value) significance level, after recoding Female and Non-White to zero (0), the model was significant in predicting FINCRM (B = -0.981, $p < 0.01$). The variables in the regression model predicted about 30.1% of the variability in FINCRM (Pseudo-R^2=0.308). Each of the variables in the model (SCSPAR, RECIDYRS, GEN, AGE, and RACE) produces a statistically significant ($p > 0.01$) association with FINCRM. However, the association between SCSPAR and FINCRM was positive (r(85954) = 0.704, $p < 0.01$).

Results for H2 control variables are presented in Table 8. The multivariate analysis shows a positive association between RECIDYRS and FINCRM, r(85954) = 0.993, $p < 0.01$, and GEN is negatively associated with FINCRM, r(85954) = -0.296, p <

0.01. Further, the model produced a negative association between AGE and FINCRM, r(85954) = -0.508, $p < 0.01$, and RACE is negatively associated with FINCRM, r(85954) = -1.174, $p < 0.01$.

Summary of Results

This chapter presented results of archival data to determine whether 1) socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes (H1), and whether 2) ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to ex-convicts who do not (H2). A regression model was used to test each of the hypotheses. For H1, the model was significant in predicting FINCRM (B = -0.343, $p < 0.01$). H1 model's Pseudo-R^2 indicates that the variables in the regression predicted about 2.6% of the variability in FINCRM.

Year Crime Occurred, Unemployment Rate, and Average Income were not statistically significant ($p > 0.01$) in predicting FINCRM. The model produced statistically significant association ($p < 0.01$) between each of the remaining independent variables (GEN, EDU, AGE, and RACE) and FINCRM. GEN was positively associated with FINCRM, r(1403792) = 0.635, $p < 0.01$. Financial crimes increased with male convicts (coded 1) as compared to female convicts (coded 0). Also, there was a negative association between EDU and FINCRM, r(1403792) = -0.033, $p < 0.01$. Financial crimes decreased with convicts who have high school or higher education (coded 2) compared to convicts with below high school education (coded 1). Further, AGE was negatively associated with FINCRM, r(1403792) = -0.062, $p < 0.01$. Financial crimes decreased with age among the adult sample of convicts or with increase in the category of age brackets (1 if 18-24 years, 2 if 25-34 years, 3 if 35-44 years, 4 if 45-54 years, 5 if 55 or more years). Additionally, RACE was negatively associated with FINCRM, r(1403792) = -0.373, $p < 0.01$. Financial crimes decreased with White convicts (coded 1) as compared to Non-White convicts (coded 0).

Likewise for H2, the model was significant in predicting FINCRM (B = -0.981, $p < 0.01$). The variables in the regression model for H2 predicted about 30.1% of the variability in FINCRM (Pseudo-R^2=0.308). Further, each of the variables in the model (SCSPAR, RECIDYRS, GEN, AGE, and RACE) produced a statistically significant ($p > 0.01$) association with FINCRM. However, the model produced a positive association between SCSPAR and FINCRM (r(85954) = 0.704, $p < 0.01$). Financial crimes among ex-convicts increased with supervised community service (coded 1 for supervised parole) as compared to ex-convicts who did not receive supervised parole (coded 0 for probation).

There was a positive association between RECIDYRS and FINCRM, r(85954) = 0.993, $p < 0.01$. Financial crimes among ex-convicts increased within five years after release from prison, and the propensity to commit a financial crime increased with time during the five years counting from the initial release from prison (coded 1 if re-arrested within 5 years after prior release) compared to the period after five years from release (coded 0). Further, GEN was negatively associated with FINCRM, r(85954) = -0.296, $p < 0.01$. Financial crimes decreased with male ex-convicts (coded 1) as compared to female ex-convicts (coded 0). Also, AGE was negatively associated with FINCRM, r(85954) = -0.508, $p < 0.01$. Financial crimes decreased with age among the adult sample of ex-convicts or with increase in the category of age brackets (1 if 18-24 years, 2 if 25-34 years, 3 if 35-44 years, 4 if 45-54 years, 5 if 55 or more years). Additionally, RACE was negatively associated with FINCRM, $r(85954) = -1.174$, $p < 0.01$. Financial crimes decreased with White ex-convicts (coded 1) as compared to Non-White ex-convicts (coded 0).

CHAPTER V: DISCUSSION

Introduction

This study examined the impact of supervised community service and socio-economic status on the propensity of ex-convicts to commit financial crimes. A regression model was utilized in analyzing archival data to determine whether 1) socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes (H1), and whether 2) ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to ex-convicts who do not (H2). This chapter provides an interpretation of the study results, discusses the conclusions and limitations of this study, and presents the implications of the conclusions.

Interpretation of Results

Socio-economic Situation and Financial Crime for H1. This study examined the relationship between socio-economic situation and financial crime. Usually, socio-economic situation is more likely to influence the propensity to commit a financial crime (Yarbrough et al., 2012). Socio-economic situation is represented by educational attainment, unemployment rate, and average household income. The regression model was significant in predicting a negative association between socio-economic situation and financial crime (FINCRM) ($B = -0.343$, $p < 0.01$). It means that the propensity to commit a financial crime reduces with a higher level of socio-economic situation (Pieszko, 2016). This is the expectation of the current study, and it is consistent with the Criminal Justice literature. The model's Pseudo-R^2 indicates that the variables in the regression models predicted about 2.6% of the variability in FINCRM. The model's fitness and predictive strength is very small. However, given the very large data set ($n = 1403792$) and low interactivity among the variables, the multivariate result is reasonably significant. This confirms the first hypothesis:

H1: Socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, is associated with financial crimes.

The findings from the current study indicate that elevating an individual's socio-economic situation is likely to aid the individual to avoid financial crimes. Therefore, programs that have been designed to reform convicts and elevate their socio-economic situation are expected to aid ex-convicts to avoid financial crimes. The ultimate result is reduced recidivism.

In the univariate analysis, Year Crime Occurred (YRCRPT) was negatively associated with FINCRM ($r(1403792) = -0.012$, $p < 0.01$), Unemployment Rate (UNEMPR) was negatively associated with FINCRM ($r(1403792) = -0.011$, $p < 0.01$), and Average Income (AVGINC) was positively associated with FINCRM ($r(1403792) = 0.012$, $p < 0.01$). However, findings from the multivariate regression model indicate that YRCRPT, UNEMPR, and AVGINC were not statistically significant ($p > 0.01$) in predicting FINCRM (Table 5). These variables were significant in predicting crimes in earlier studies (Aaltonen et al., 2011; Hooghe et al., 2011). It is expected that with more relaxed drug laws and modernization of Criminal Justice, including the use of advanced monitoring systems and better policing, financial crimes will significantly decrease over time. Further, lower unemployment rate is expected to be associated with lower financial crimes as the economic situations of individuals improve. Similarly, higher income levels are expected to be associated with lower financial crimes as the financial pressure on individuals is lowered. The findings from the regression model did not confirm these expectations.

The univariate analysis indicates that Gender (GEN) was positively associated with FINCRM ($r(1403792) = 0.105$, $p < 0.01$). Similarly, the multivariate regression model indicates that GEN is positively associated with FINCRM, $r(1403792) = 0.635$, $p < 0.01$ (Table 5). As expected, financial crimes increased with male convicts as compared to female convicts. A male ex-convict is more likely to commit a financial crime than a female ex-convict. Additionally, GEN in the study population is largely driven by Male (88.9%), and it has the highest co-efficient in the multivariate regression model. Extant literature indicates that males are more likely to commit crimes than in females. This may stem from the level of risk aversion, the inclination to avoid punishment by females, or better social support system for females (Schnappauf & DiDonato, 2017; Skilling, 2014). The literature indicates that males are more likely to take risks and succumb to peer-pressure as compared to females, and females are more likely to accept learned behaviors that enable them to avoid unlawful choices as compared to males (Yarbrough et al., 2012).

The univariate analysis shows that Level of Education (EDU) does not have a statistically significant relationship with FINCRM ($r(1403792) = -0.002$, $p > 0.01$). However, the multivariate regression model indicates that there is a negative association between EDU and FINCRM, $r(1403792) = -0.033$, $p < 0.01$ (Table 5). Financial crimes decreased with convicts who have high school or higher education compared to convicts with below high school education. Therefore, the higher the level of education the less likely it is for an individual to commit financial crimes. This is consistent with the literature. For instance, university graduates or individuals with vocational skills beyond high school level have lower unemployment rate, higher incomes, and better job stability as compared with those will lower education (Lockwood, 2012; Sharlein, 2018).

The univariate analysis indicates that Age of the Offender (AGE) was negatively associated with FINCRM ($r(1403792) = -0.022$, $p < 0.01$). Similarly, the multivariate regression model indicates that AGE is negatively associated with FINCRM, $r(1403792) = -0.062$, $p < 0.01$ (Table 5). Financial crimes decreased with age among the adult sample of convicts or with increase in the category of age brackets. It is expected that older adults will be less likely to commit crimes than younger adults. Clearly, aging is associated with a less inclination to commit a financial crime given the experience and sense of responsibility among older individuals (Sharlein, 2018).

The univariate analysis shows that there is a negative association between Race of Offender (RACE) and FINCRM ($r(1403792) = -0.095$, $p < 0.01$). Similarly, the multivariate regression model predicts that RACE is negatively associated with FINCRM, $r(1403792) = -0.373$, $p < 0.01$ (Table 5). Financial crimes decreased with White convicts as compared to Non-White convicts. As expected, a White ex-convict is less likely to commit a financial crime than a Non-White ex-convict. RACE in the study population is about even for White (47.2%) and Non-White (52.8%), in spite of the significantly higher percentage of Whites in the United States. Extant literature indicates that Whites are less likely to commit crimes than Non-Whites. A more favorable socioeconomic status among Whites explains the lower propensity to commit financial crimes. Therefore, Whites are less likely to recidivate partly due to a stronger social support after spending time in prison, compared with Non-Whites (Tyler & Brockmann, 2018).

Supervised Community Service and Financial Crime for H2. This study examined the relationship between supervised community service (SCSPAR) and financial crime, using 85,954 cases of offenders, of which 42,977 were ex-convicts on parole and 42,977 were non-parole offenders on probation. The expectation is that supervised community service will be more likely to moderate participants' behaviors and improve employable skills, and ultimately help to reduce the propensity to repeat a crime. The regression model, given the interactions of all variables, was significant in predicting financial crime (FINCRM) ($B = -0.981$, $p < 0.01$). The model's Pseudo-R^2 indicates that the variables in the regression model predicted about 30.1% of the variability in FINCRM. The model's fitness and predictive strength is moderate. However, holding all other variables fixed, SCSPAR does not reduce FINCRM, $r(85954) = 0.704$, $p < 0.01$ (Table 8). Financial crimes among paroled ex-convicts increased with supervised community service as compared to ex-convicts on probation who did not receive supervised parole. This does not confirm the second hypothesis:

H2: Ex-convicts who undergo supervised community service are less likely to commit a financial crime compared to ex-convicts who do not.

The hypothesis test results indicate that the propensity to commit a financial crime after participating in a supervised community service program (n=42977) is more likely compared to a matched set of those who did not participate (n=42977). This is unexpected as compared to extant studies, which indicate that participation in community service reduces recidivism (Killias et al., 2000; Wermink et al., 2010). Also, it is expected that supervised community service programs will aid in elevating an ex-convict's socio-economic situation, which has been confirmed in the first part of this study to be a significant moderating factor in financial crime commission. However, most of the other variables in the model have the expected association with FINCRM. Clearly, the control variables in the model were important considerations in the study. As with the first regression model, AGE, and RACE have negative associations with FINCRM. Unexpectedly, GEN has a negative association with FINCRM. Also, the number of years ex-convict returned to prison after prior release, Years to Recidivism (RECIDYRS) within five (5) years, is positively associated with FINCRM.

The univariate analysis shows that there is a positive association between RECIDYRS and FINCRM ($r(85954) = 0.360$, $p < 0.01$). Similarly, the multivariate regression model predicts a positive association between RECIDYRS and FINCRM, $r(85954) = 0.993$, $p < 0.01$ (Table 8). Financial crimes among ex-convicts increased within five years after release from prison, and the propensity to commit a financial crime increased with time during the five years counting from the initial release from prison compared to the period after five years from release. Therefore, ex-convicts who returned to prison within five (5) years after prior release were more likely to have committed financial crimes, compared to those who returned to prison after five (5) years. This is consistent with the literature. The first few years after release from prison are critical to recidivism. Ex-convicts recidivate more during the years they have difficulty in obtaining gainful employment. Employment history, crime reports, and credit history improve significantly over time (Wolff & Baglivio, 2017).

In the univariate analysis, GEN is negatively associated with FINCRM ($r(85954) = -0.155$, $p < 0.01$). Similarly, the multivariate regression model shows that GEN is negatively associated with FINCRM, $r(85954) = -0.296$, $p < 0.01$ (Table 8) in the sample of parole ex-convicts with a matched offenders on probation. Unexpectedly, a male ex-convict is less likely to commit a financial crime than a female ex-convict. Extant literature indicates that males are more likely to commit crimes than in females. Males are more likely to take risks and succumb to peer-pressure as compared to females, and females are more likely to accept learned behaviors that enable them to avoid unlawful choices as compared to males (Yarbrough et al., 2012). However, based on a population of parole and non-parole offenders, it was not confirmed that males are more likely to commit financial crimes compared with females. It is possible that participating in a supervised community service moderates the effect of GEN on the propensity to commit financial crimes (Schnappauf & DiDonato, 2017; Skilling, 2014), and the large percentage of males (85.1%) in the sample weighed heavily on the co-efficient. One plausible explanation for the positive association with FINCRM, in spite of the overwhelming majority of males in the data set, is that Male is interacting with multiple variables in the multivariate analysis. In the univariate analysis, Male is negatively associated with FINCRM as expected. Most likely, males were reformed to accept learned behaviors that enable them to avoid unlawful choices.

AGE has a negative association with FINCRM ($r(85954) = -0.344$, $p < 0.01$) in the univariate analysis. Similarly, the multivariate regression model predicts that AGE is negatively associated with FINCRM, $r(85954) = -0.508$, $p < 0.01$ (Table 8). In the sample of parole ex-convicts with a matched set of offenders on probation, older adults are less likely to commit financial crimes than younger adults. Financial crimes decreased with age among the adult sample of ex-convicts or with increase in the category of age brackets. It is evident that aging is associated with a less inclination to commit a financial crime given the experience and sense of responsibility among older individuals. Also, older persons have more work experience and a more effective professional network, and they have a higher capacity to undergo reformation and avoid past mistakes (Sharlein, 2018).

The univariate analysis shows that RACE has a negative association with FINCRM ($r(85954) = -0.378$, $p < 0.01$). Similarly, the multivariate regression model predicts that RACE is negatively associated with FINCRM, $r(85954) = -1.174$, $p < 0.01$ (Table 8). In the sample of parole ex-convicts with a matched set of offenders on probation, Whites are less likely to commit a financial crime compared to Non-White ex-convicts. Financial crimes decreased with White ex-convicts as compared to Non-White ex-convicts. RACE in the study population comprises White (40.3%) and Non-White (59.7%), in spite of the significantly higher percentage of Whites in the United States. Extant literature indicates that Whites are less likely to commit crimes than Non-Whites. It is evident that a more favorable socioeconomic status among Whites partly explains the lower propensity to commit financial crimes (Kendler, Lönn, Sundquist, & Sundquist, 2017).

Conclusions

Socio-economic situation, as represented by educational attainment, unemployment rate, and average household income, was found to be negatively associated with financial crime (FINCRM). Therefore, it is expected that a program that is designed to elevate the socio-economic situation of an ex-convict is likely to reduce the propensity to commit a financial crime.

The negative association between socio-economic situation and FINCRM justified the testing of the second hypothesis (Table 9) to determine whether elevating the socio-economic situation of ex-convicts will reduce financial crimes. However, ex-convicts who participated in supervised community service were not less likely to re-offend, even though the impact of all variables taken together in the regression model show otherwise. It is possible that offenders on probation are more restrained in terms of crime commission, and the extent of restraint outweighs the benefits from supervised community service intended to reintegrate an ex-convict into society. Another plausible explanation is that the supervised parole programs were not effective enough to reform the participants and reduce recidivism pertaining to financial crimes. Further, offenders on probation possibly avoided significant depression of socio-economic status associated with prison time (Sharlein, 2018).

Table 9

Results from Hypotheses Testing

Hypothesis	Test	Result Implication
H1	$FINCRM = \beta_0 + \beta_1 YRCRPT + \beta_2 GEN + \beta_3 EDU + \beta_4 AGE + \beta_5 RACE + \beta_6 UNEMPR + \beta_7 AVGINC + \varepsilon$	H1 is confirmed. Socio-economic status plays a role in financial crime commission.

H2	$FINCRMRT = \beta_0 + \beta_1 SCSPAR + \beta_2 RECIDYRS + \beta_3 GEN + \beta_4 AGE + \beta_5 RACE + \varepsilon$	H2 is not confirmed. Supervised community service does not reduce financial crime commission among ex-convicts. Results are inconclusive.

In spite of the unexpected association between supervised community service and financial crimes, there are favorable outcomes from an ex-convict's participation in supervised community service. SCSPAR interacted with the control variables to produce a negative association between SCSPAR and FINCRM. It means that when all the variables in the study are considered together, parole ex-convicts who participated in supervised community service were less likely to commit financial crimes compared with offenders on probation who did not participate. The demographics in the study represent real life situation, and they cannot be ignored in measuring the outcome of a parole program. Therefore, the findings from this study are not conclusive in showing that ex-convicts who undergo supervised community service are less likely to re-offend compared to offenders on probation. However, the findings from this study indicate that improving supervised parole programs will lead to reduced recidivism pertaining to financial crimes.

Limitations and Delimitations

The effectiveness of intervening programs depends on the peculiar characteristics of ex-convicts and the effectiveness of State and Federal programs. The current study employed archival national data of crime arrests in aggregate form in determining the influence of intervening variables in controlling recidivism involving financial crimes. However, the predictive utility of the findings may not apply to some ex-convicts, and the findings from the current study should be cautiously interpreted. Using data for crime offenders somewhat mitigates the potential flaw, since offending characteristics of ex-convicts is expected to afford reasonable groupings. Also, national data in aggregate form are better suited for analyzing crime trends, for answering the research questions about recidivism in the general population, and for making conclusions about factors that moderate recidivism involving financial crimes.

Additionally, the secondary data did not capture the actual employment status of ex-convicts (before arrest and after parole), family financial support, and other social support systems. Also, offenders on probation tend to avoid prison time and the associated loss of socio-economic situation, and may already be in a better position to avoid the commission of a financial crime, compared to ex-convicts who have participated in a supervised parole program. The study method employed assumed that the sample from the secondary data was reasonably representative, and the use of a matched set of data comprising offenders on probation who did not participate in supervised parole moderates this limitation.

Further, this study did not use proxy variables to measure the extent of supervised community service. The use of specific programs (e.g. supervised parole in a specific institution, supervised attachment to specific organizations) may yield a better predictive utility. However, different programs need to be designed and modified to suit the unique needs of ex-convicts. Also, it is expected that supervised community service programs will evolve during the period of supervision, and therefore using static proxies may not be accurate.

Moreover, this study did not maintain any control over the operations of specific programs and their outcomes. The variability among programs was not addressed in the aggregate data, even though the aggregation can hide errors and variability of individual programs. This study has limited applicability to the role of supervised community service programs in reducing financial crimes. Therefore, the findings from this study should be taken with caution, given that the data might include errors presented over a long range of time and not evident in the aggregate.

Implications of Findings and Recommendations

The conclusions from this study present some implications and usefulness to the criminal justice literature, practitioners, intervention programs for ex-convict reform, and prison sentencing in general. It was evident from the study that socio-economic situation reduces the propensity to commit financial crimes. Therefore, programs designed to elevate the socio-economic situation should be embraced as a tool for reforming ex-convicts, in spite of the mixed results from this study.

Studies of this nature are scarce in the literature, partly because of the resource demands (among many legal constraints) for conducting firsthand observations of ex-convicts on parole and the lack of adequate secondary data for more meaningful studies. For instance, the Federal Government blocks researcher access to some offender information, such as employment status before and after parole. This study adds some weight to similar studies in demonstrating the usefulness of offender archival data and the need for more support from governments and all stakeholders, including the Department of Justice, to improve on researcher access to data and the quality of offender archival data.

Criminal Justice practitioners play a critical role in administering the legal system, and their approaches and belief systems in relation to their role are significant in determining the effectiveness of Criminal Justice. This study builds on the premise that ex-convicts have a difficulty in obtaining gainful employment and integrating into society. Also, it shows that elevating the socio-economic status of ex-convicts minimizes their propensity to reoffend. Even though the role of supervised community service is not conclusive from the results, this study adds to the rationale for practitioner and stakeholder support of rehabilitation programs that are geared towards the elevation of ex-convict socio-economic status.

This research study provides evidence that socio-economic situation of ex-convicts plays a role in their propensity to recidivate. Evidently, intervention programs, such as supervised community service, are critical to reforming ex-convicts. However, such programs should be deliberately designed and well-resourced to provide a meaningful pathway for offenders to obtain employable skills and ultimately be capable of maintaining a decent livelihood. The body of Criminal Justice literature points to the fact that the benefits from offender intervention programs outweigh the burden on society.

Offender sentencing may be designed to incorporate more supervised opportunities outside prison. This study indicates that both probation and parole are relevant considerations in sentencing. More probation time compared to prison time means the offender has an improved chance of avoiding prison time and the associated depression of socio-economic status. Therefore, more probation time compared to prison time is likely to reduce the likelihood that an offender will commit a financial crime. Similarly, the opportunity for parole implies that the convict has an improved chance of reducing prison time and the associated depression of socio-economic status, and it improves the likelihood of elevating an ex-convict's socio-economic status and the associated moderation on recidivism. Therefore, more parole time compared to extensive prison time is likely to reduce the likelihood that an offender will commit a financial crime.

Results from the second regression model used in testing H2 indicate that supervised community service does not reduce recidivism pertaining to financial crimes. Education, Unemployment Rate, and Income Level were excluded from the model, in part because supervised parole was supposed to elevate those variables or characteristics in ex-convicts. It is possible that most supervised programs are not sufficiently effective in elevating those variables or characteristics in ex-convicts, and they did not reduce recidivism relative to 1) family and professional networks and 2) probationers inclination to avoid financial crimes. The literature indicates that recidivism pertaining to financial crimes is higher than with other types of crimes. If programs designed to make offenders employable are not reducing recidivism significantly, then it is possible that the programs are not effective in themselves or not as effective as other enablers of improved socio-economic situation such as family and professional networks.

This study recommends a mixed-method approach for future research, in which the researcher employs archival data for quantitative analysis and observes a supervised parole program for qualitative analysis. Observing ex-convicts' situation pre and post-supervised community service period can eliminate the need to compare the study with offenders on probation and provide a stronger confirmatory analysis. Comparison with offenders on probation was the most viable option for the current study, given time and resource constraints.

Further, the current study may be advanced by using actual employment and educational status of ex-convicts during the post-community service period. This will eliminate the need to test for the impact of socio-economic status on an ex-convict's propensity to commit financial crimes, and will concentrate more resources on identifying social support variables or proxies. For instance, Whites are less likely to recidivate partly due to a stronger social support after spending time in prison, compared with Non-Whites. Social support comes in various forms, including access to accommodation, less competition for public services, race-induced access to employment, rehabilitation services outside parole, and the presence of family support (Kendler et al, 2017; Wolff & Baglivio, 2017). Therefore, using observed variables as a measure for the latent social support variable will improve on the current study (Zeintek & Thompson, 2007). However, social support variables are not present in archival data, and future studies may observe ex-convicts during and after supervised community service participation. It is expected that findings from ex-convict observations will improve on the utility and validity of the current study.

Additionally, results from this study do not imply the propensity to commit a crime in general. This study is designed to make conclusions about the propensity for ex-convicts to be re-arrested for committing financial crimes. Data about crime arrests may not be sufficient for making general conclusions about crime commissions, given that crime arrests typically do not capture all crime commissions and certain groups may be meticulously monitored for crime commissions more than other groups.

Summary

This study employed archival data to examine the role of supervised community service and socio-economic status in recidivism pertaining to financial crimes among ex-convicts. Findings from the current study indicate that socio-economic status reduces financial crimes. However, there is no conclusive indication from the current study that supervised community service reduces recidivism pertaining to financial crimes among ex-convicts.

The regression model used in testing the impact of supervised community service on financial crimes produced inconclusive results. The model taken together indicates that supervised community service interacts with demographic variables to reduce the propensity for ex-convicts to commit financial crimes. However, supervised community service per se (holding other variables constant), does not reduce the propensity for ex-convicts to commit financial crimes. Ex-convicts are more likely to commit financial crimes than other types of crimes. If programs designed to reform offenders and elevate their socio-economic situation are not reducing recidivism, then it is possible that the programs are not effective. Therefore, it is important for States and the Federal government to improve on parole programs and focus on elevating the socio-economic status of ex-convicts.

In spite of the inconclusive results and the limitations associated with this research, the current study presents some implications and usefulness to the Criminal Justice literature, practitioners, intervention programs for ex-convict reform, and prison sentencing in general. Elevating the socio-economic status of ex-convicts will likely reduce their propensity to commit financial crimes and return to prison. Further, future studies may be designed to overcome the limitations of the current study. A mixed-method approach involving archival data and actual parole program observations will likely improve the utility and validity of future research into the role of supervised community service and socio-economic status in recidivism pertaining to financial crimes among ex-convicts.

APPENDIX A

DEMOGRAPHICS

H1 Dataset and Demographics

Table A1: Type of Crime Frequency and FINCRM

Type of Crime

	Type of Crime	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	Non-Property	821034	58.5	58.5	58.5
	Property	582758	41.5	41.5	100.0
	Total	1403792	100.0	100.0	

Figure A1. Type of Crime Frequency and FINCRM

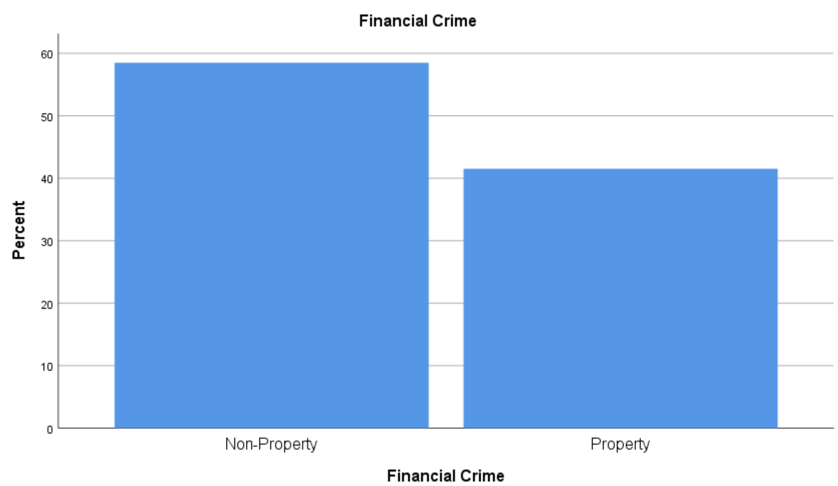


Table A2: Crime Frequency and YRCRPT

Year Crime Occurred

	YRCRPT	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	2005	219623	15.6	15.6	15.6
	2006	229989	16.4	16.4	32.0
	2007	230543	16.4	16.4	48.5
	2008	239933	17.1	17.1	65.5

	2009	238913	17.0	17.0	82.6
	2010	244791	17.4	17.4	100.0
	Total	1403792	100.0	100.0	

Crosstab

Count

		Financial Crime		
		Non-Property	Property	Total
Year Crime Occurred	2005	126695	92928	219623
	2006	132916	97073	229989
	2007	134425	96118	230543
	2008	140510	99423	239933
	2009	141209	97704	238913
	2010	145279	99512	244791
Total		821034	582758	1403792

Figure A2. Crime Frequency and YRCRPT

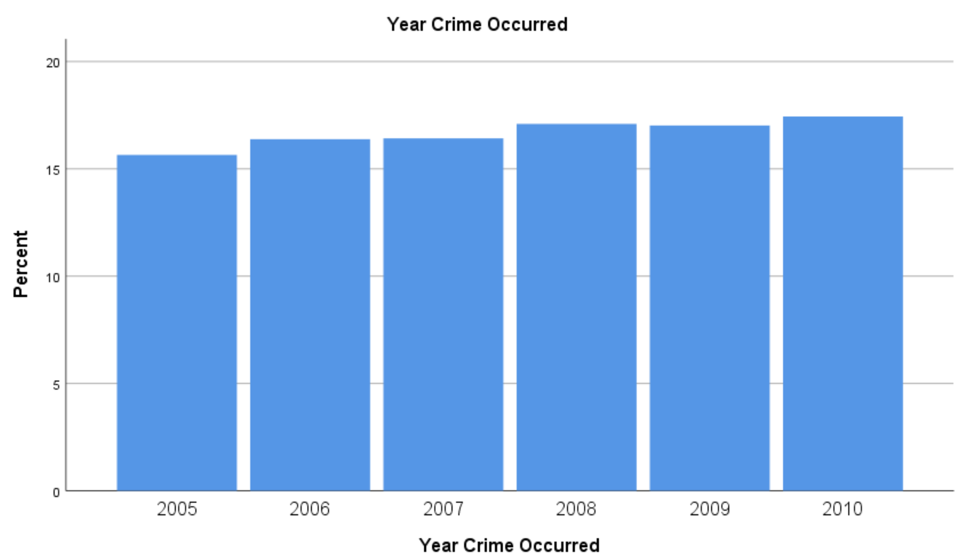


Table A3: Crime Frequency and GEN

Gender of Offender

	GEN	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	Male	1247839	88.9	88.9	88.9
	Female	155953	11.1	11.1	100.0
	Total	1403792	100.0	100.0	

Crosstab

Count

		Financial Crime		
		Non-Property	Property	Total
Gender of Offender	Male	752651	495188	1247839
	Female	68383	87570	155953
Total		821034	582758	1403792

Figure A3. Crime Frequency and GEN

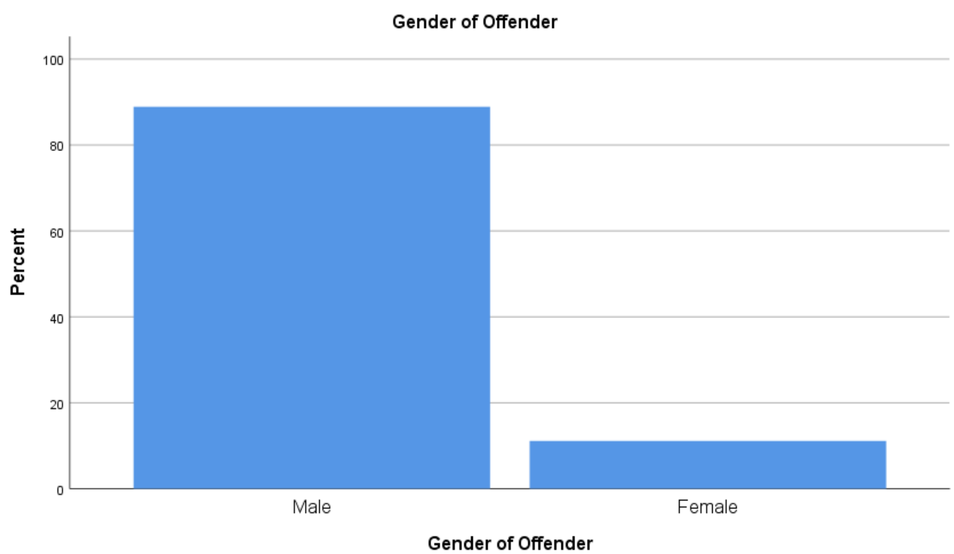


Table A4: Crime Frequency and EDU

Level of Education

	EDU	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	Below High School	714968	50.9	50.9	50.9
	High School or Higher	688824	49.1	49.1	100.0

Total	1403792	100.0	100.0	

Crosstab

Count

		Financial Crime		Total
		Non-Property	Property	
Level of Education	Below High School	417476	297492	714968
	High School or Higher	403558	285266	688824
Total		821034	582758	1403792

Figure A4. Crime Frequency and EDU

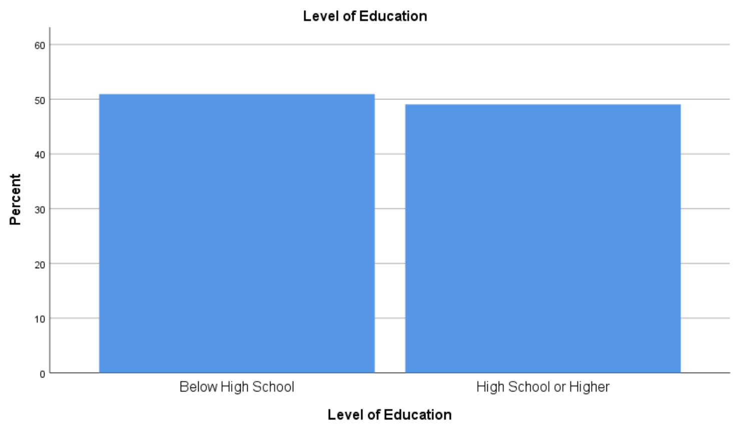


Table A5: Crime Frequency and AGE

Age of Offender

	AGE	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	18-24 years	367787	26.2	26.2	26.2
	25-34 years	461857	32.9	32.9	59.1
	35-44 years	359074	25.6	25.6	84.7
	45-54 years	198292	14.1	14.1	98.8
	55+ years	16782	1.2	1.2	100.0
	Total	1403792	100.0	100.0	

Crosstab

Count

		Financial Crime	Total

		Non-Property	Property	
Age of Offender	18-24 years	209592	158195	367787
	25-34 years	273555	188302	461857
	35-44 years	206507	152567	359074
	45-54 years	118720	79572	198292
	55+ years	12660	4122	16782
Total		821034	582758	1403792

Figure A5. Crime Frequency and AGE

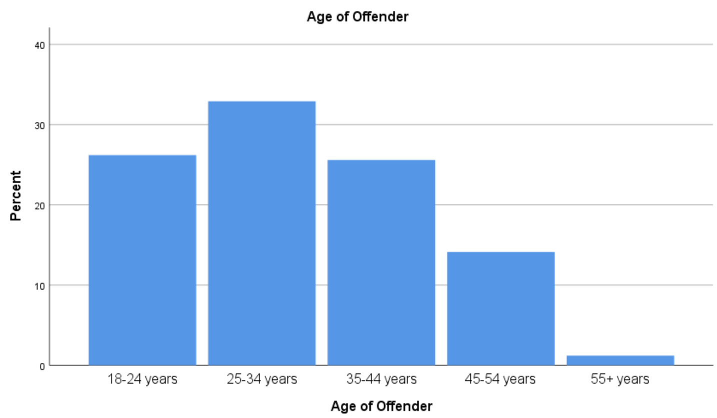


Table A6: Crime Frequency and RACE

Race of Offender

	RACE	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	White Caucasian	662145	47.2	47.2	47.2
	Non-White	741647	52.8	52.8	100.0
	Total	1403792	100.0	100.0	

Crosstab

Count

		Financial Crime		
		Non-Property	Property	Total
Race of Offender	White Caucasian	354418	307727	662145
	Non-White	466616	275031	741647
Total		821034	582758	1403792

Figure A6. Crime Frequency and RACE

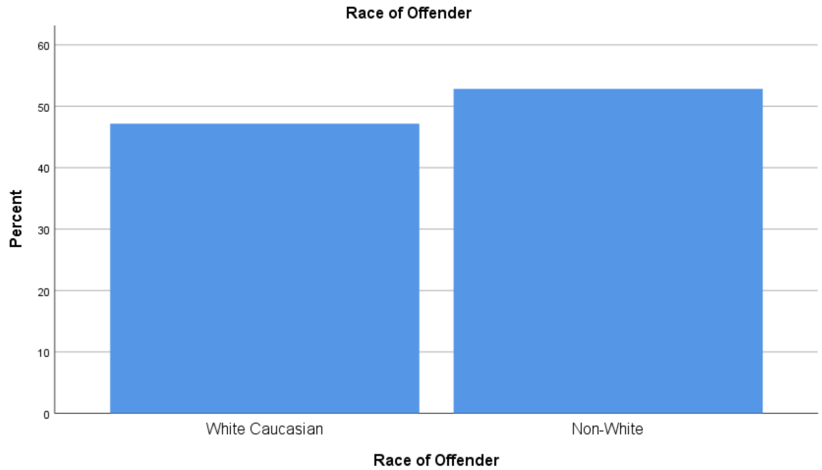


Table A7: Crime Frequency and UNEMPR

Unemployment Rate

UNEMPR		Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	4.60	460532	32.8	32.8	32.8
	5.10	219623	15.6	15.6	48.5
	5.80	239933	17.1	17.1	65.5
	9.30	238913	17.0	17.0	82.6
	9.60	244791	17.4	17.4	100.0
	Total	1403792	100.0	100.0	

Crosstab

Count

		Financial Crime		Total
		Non-Property	Property	
Unemployment Rate	4.60	267341	193191	460532
	5.10	126695	92928	219623
	5.80	140510	99423	239933
	9.30	141209	97704	238913
	9.60	145279	99512	244791
Total		821034	582758	1403792

Figure A7. Crime Frequency and UNEMPR

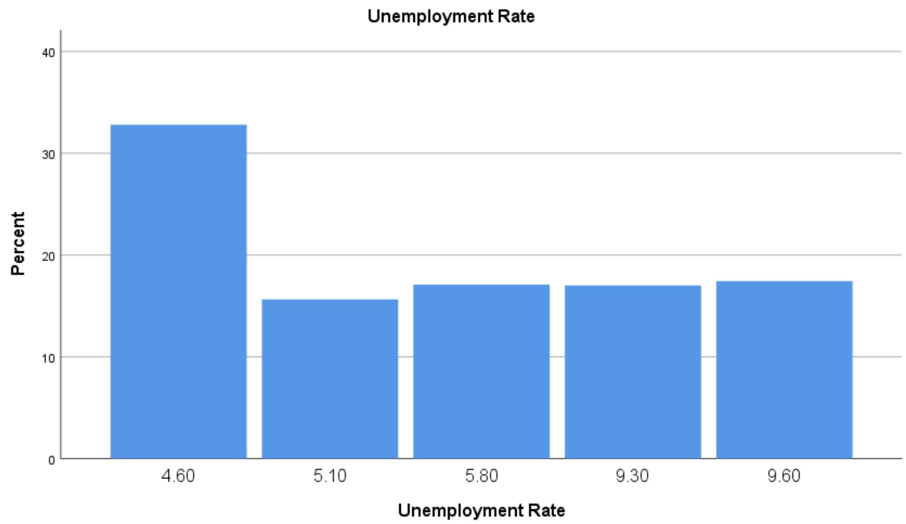


Table A8: Crime Frequency and AVGINC

Average Income

	AVGINC	Frequency OF Crime	Percent OF Crime	Valid Percent	Cumulative Percent
Valid	73178	238913	17.0	17.0	17.0
	73346	244791	17.4	17.4	34.5
	75007	239933	17.1	17.1	51.5
	75238	230543	16.4	16.4	68.0
	77198	229989	16.4	16.4	84.4
	78167	219623	15.6	15.6	100.0
	Total	1403792	100.0	100.0	

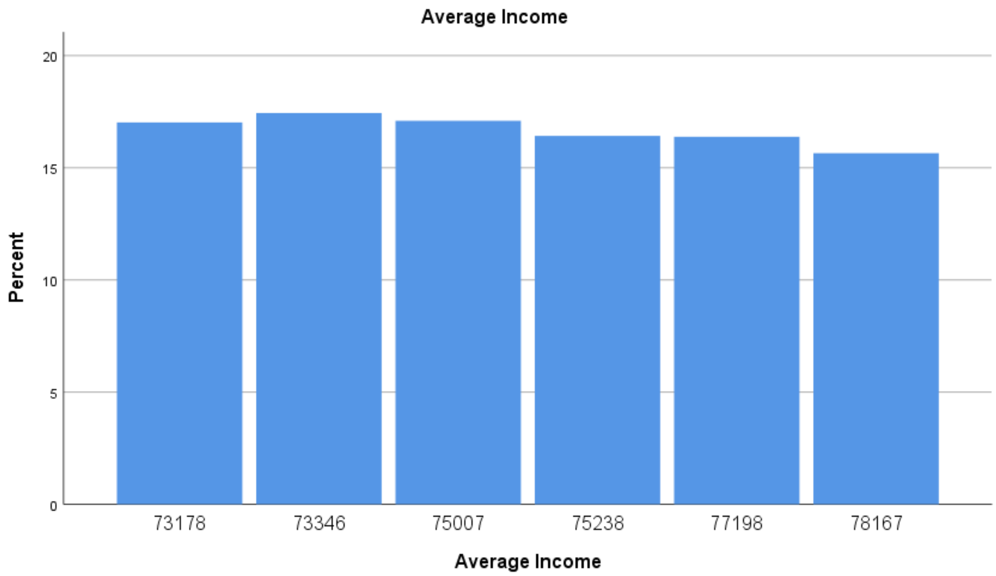
Crosstab

Count

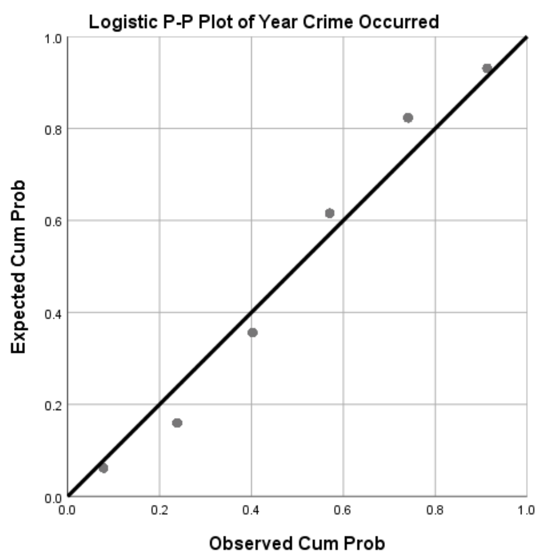
		Financial Crime		
		Non-Property	Property	Total
Average Income	73178	141209	97704	238913
	73346	145279	99512	244791
	75007	140510	99423	239933
	75238	134425	96118	230543
	77198	132916	97073	229989
	78167	126695	92928	219623

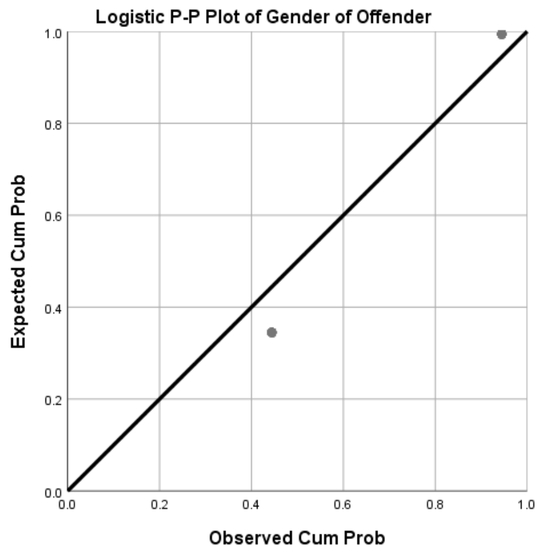
Total	821034	582758	1403792

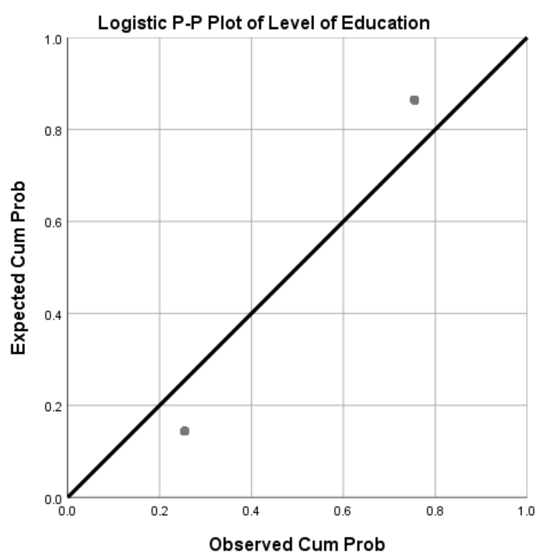
Figure A8. Crime Frequency and AVGINC

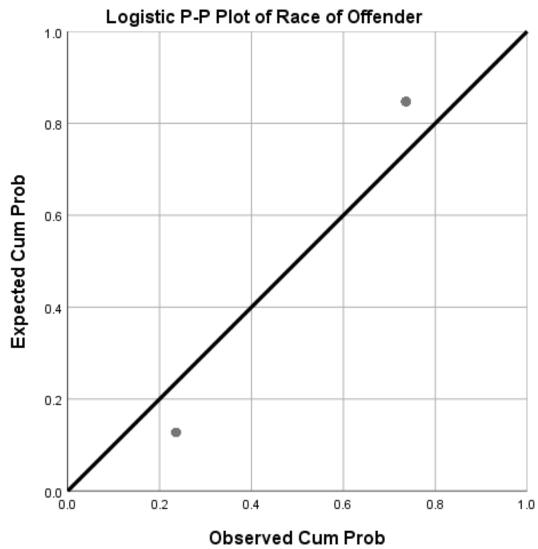


H1 Data Distribution Tests using Logistic P-P Plots

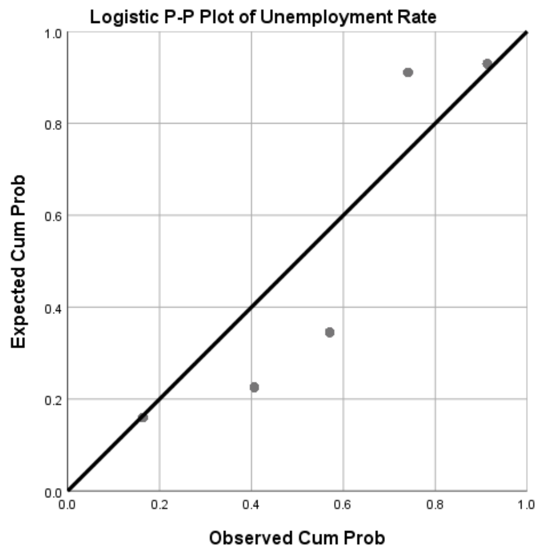


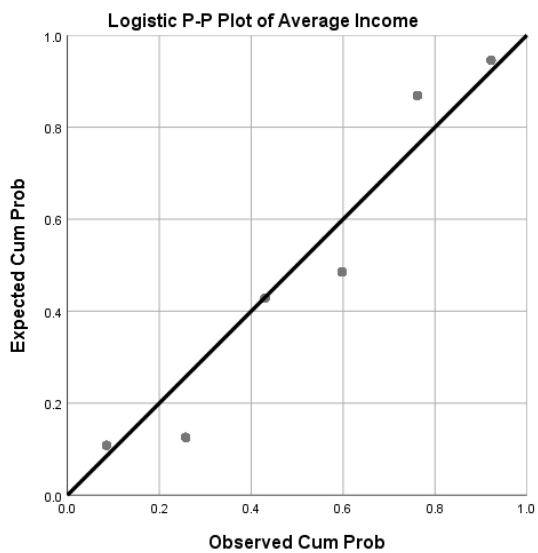

Logistic P-P Plot of Gender of Offender
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Level of Education
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Race of Offender
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Age of Offender
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0





H1 Final Data Set

Table A9

Ex-Convicts Admitted to Prison by State Excluding Drug Offenses

	5-Level Categorization of Crime Type Excluding Drug Offenses					
	Violent	Property	Public order	Other/unspecified	Property Crime Rate*	Total Crime Rate*
Alaska	2889	1858	6599	25	45.1	275.8

Arizona	24381	35411	26707	76	95.5	233.6
Arkansas	9683	19249	4379	2653	112.3	209.8
Colorado	14084	17774	12851	110	61.1	154.2
Florida	54662	58492	31666	272	53.0	131.4
Georgia	34776	37136	12767	154	66.0	150.8
Indiana	20683	28163	24501	4195	73.4	202.1
Iowa	4931	9334	6191	303	51.7	115.0
Kentucky	6606	14998	7004	1971	58.6	119.4
Massachusetts	1172	542	475	37	1.4	5.7
Minnesota	11693	6288	6455	8	20.1	78.0
Mississippi	1255	1104	235	54	6.3	15.0
Missouri	12621	24368	9607	3	68.8	131.6
Nebraska	466	452	246	14	4.2	11.0
Nevada	7752	12204	4570	426	78.2	160.0
New Hampshire	112	91	381	1	1.2	7.4
New York	36705	28125	15076	687	24.4	69.9
North Carolina	33166	44609	39544	196	81.0	213.4
North Dakota	807	802	401	20	20.3	51.5
Oklahoma	7928	10041	4453	184	45.8	103.1
Oregon	403	170	41	1	0.8	2.7
Pennsylvania	27770	14493	10247	5701	19.2	77.1
Rhode Island	6413	5583	6670	129	87.9	296.0
South Carolina	15765	26552	12191	1250	99.0	207.8
South Dakota	1860	3676	3771	22	77.0	195.5

Tennessee	15425	19831	3752	112	53.4	105.3
Texas	74860	127860	73453	3	88.6	191.4
Utah	4286	4253	1869	3	27.0	66.1
Virginia	2830	3489	1488	42	7.5	16.8
Washington	1941	3760	1482	62	9.6	18.5
West Virginia	3753	6288	1348	690	57.0	109.6
Wisconsin	16488	14262	11186	51	42.3	124.5
Wyoming	1413	1500	386	8	46.3	102.0
Total	459579	582758	341992	19463		

This table presents summaries of ex-convicts admitted to prison between 2005 and 2010 and used for testing Hypothesis 1

*Property Crime Rate is the number of property crimes per 100,000 state residents

*Total Crime Rate is the number of total crimes per 100,000 state residents

*(N) Total Cases Excluding Missing Cases and Drug Offenses = 1,403,792 cases of ex-convicts

H2 Dataset and Demographics

Table A9: Crime Frequency and FINCRM

Crime Type

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Non-Property Crime	62511	72.7	72.7	72.7
	Property Crime	23443	27.3	27.3	100.0
	Total	85954	100.0	100.0	

Crime Type * Community Service/Parole Crosstabulation

Count

		Community Service/Parole		
		Non-Parole Participant	Parole Participant	Total
Crime Type	Non-Property Crime	32620	29891	62511
	Property Crime	10357	13086	23443

Total	42977	42977	85954

Figure A9: Crime Frequency and FINCRM

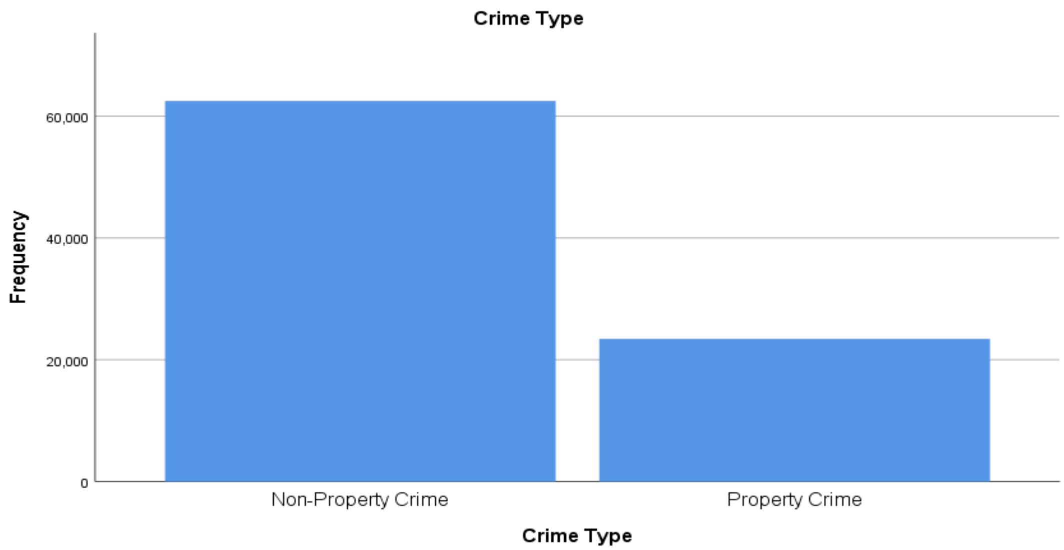


Table A10: Crime Frequency and SCSPAR

Community Service/Parole

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Non-Parole Participant	42977	50.0	50.0	50.0
	Parole Participant	42977	50.0	50.0	100.0
	Total	85954	100.0	100.0	

Figure A10: Crime Frequency and SCSPAR

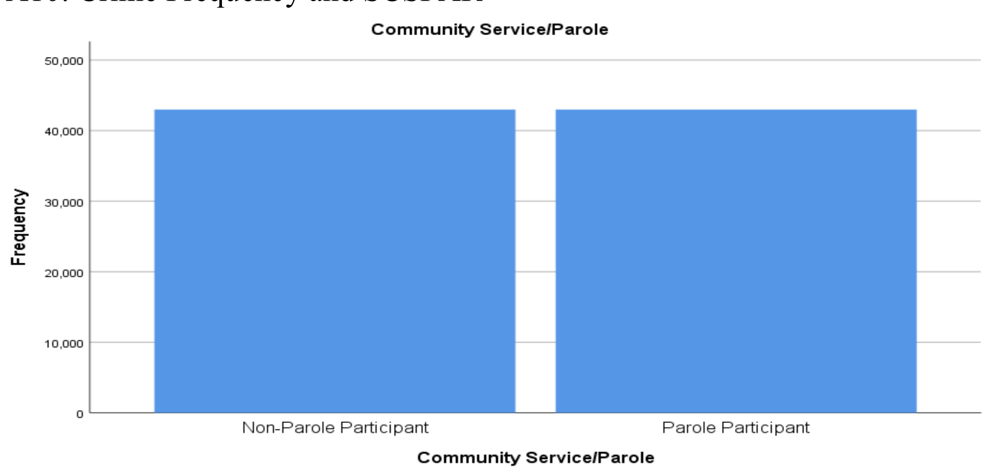


Table A11: Crime Frequency and RECIDYRS

Years to Recidivism

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No Re-Offense within 5 years	55439	64.5	64.5	64.5
	Re-Offended within 5 years	30515	35.5	35.5	100.0
	Total	85954	100.0	100.0	

Years to Recidivism * Community Service/Parole Crosstabulation

Count

		Community Service/Parole		
		Non-Parole Participant	Parole Participant	Total
Years to Recidivism	No Re-Offense within 5 years	26645	28794	55439
	Re-Offended within 5 years	16332	14183	30515
Total		42977	42977	85954

Figure A11: Crime Frequency and RECIDYRS

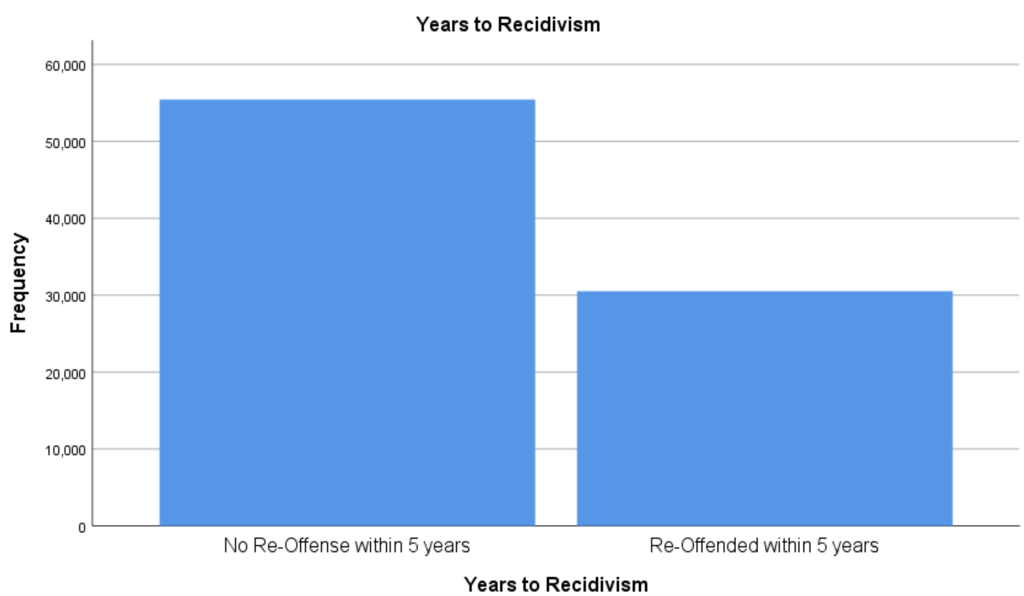


Table A12: Crime Frequency and GEN

Gender of Offender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	73111	85.1	85.1	85.1
	Female	12843	14.9	14.9	100.0
	Total	85954	100.0	100.0	

Gender of Offender * Community Service/Parole Crosstabulation

Count

		Community Service/Parole		
		Non-Parole Participant	Parole Participant	Total
Gender of Offender	Male	34253	38858	73111
	Female	8724	4119	12843
Total		42977	42977	85954

Figure A12: Crime Frequency and GEN

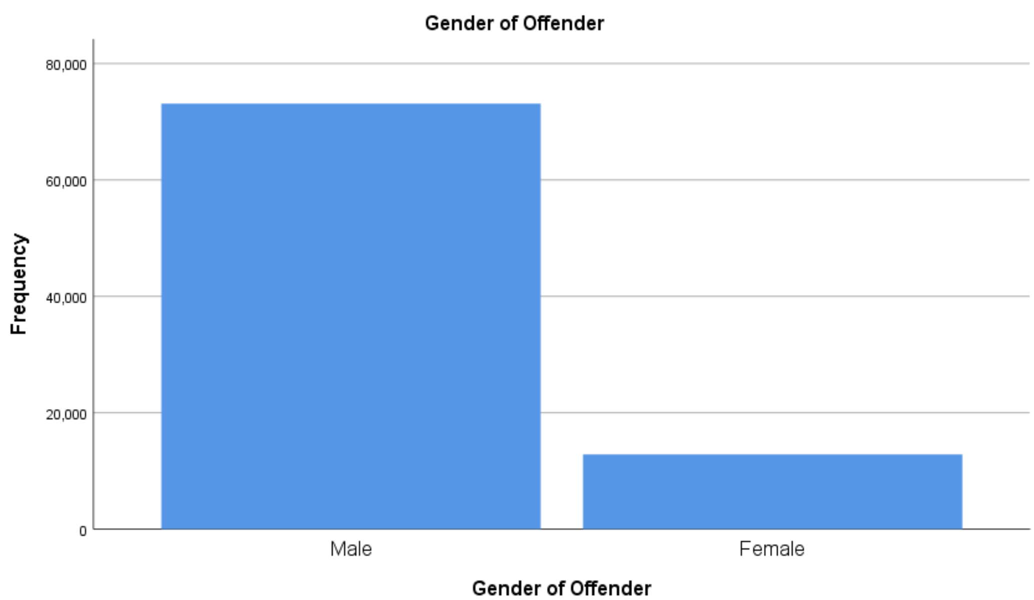


Table A13: Crime Frequency and AGE

Age of Offender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24 years	11777	13.7	13.7	13.7
	25-34 years	30854	35.9	35.9	49.6

	35-44 years	23326	27.1	27.1	76.7
	45-54 years	12365	14.4	14.4	91.1
	55+ years	7632	8.9	8.9	100.0
	Total	85954	100.0	100.0	

Age of Offender * Community Service/Parole Crosstabulation

Count

		Community Service/Parole		
		Non-Parole Participant	Parole Participant	Total
Age of Offender	18-24 years	4966	6811	11777
	25-34 years	14126	16728	30854
	35-44 years	12179	11147	23326
	45-54 years	4684	7681	12365
	55+ years	7022	610	7632
Total		42977	42977	85954

Figure A13: Crime Frequency and AGE

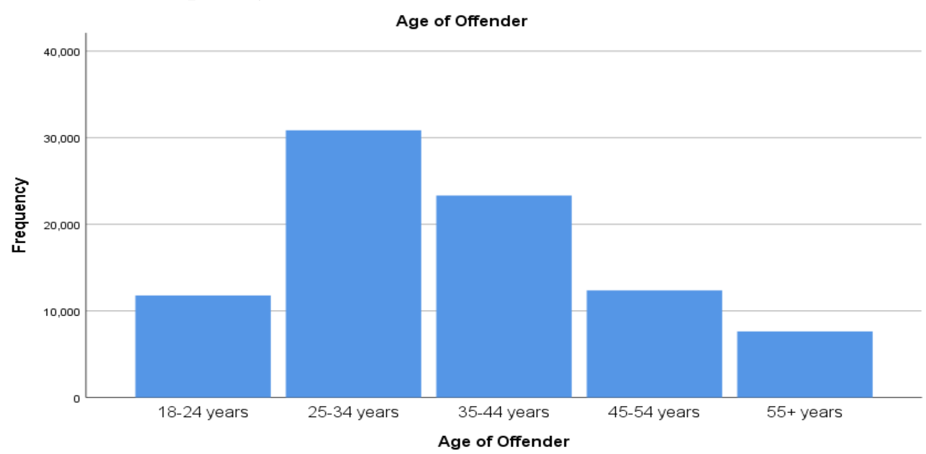


Table A14: Crime Frequency and RACE

Race of Offender

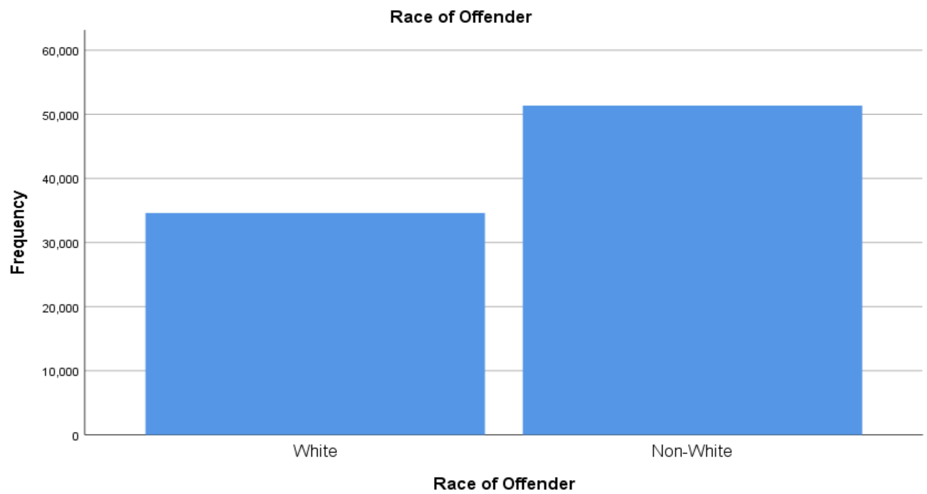
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	White	34606	40.3	40.3	40.3
	Non-White	51348	59.7	59.7	100.0
	Total	85954	100.0	100.0	

Race of Offender * Community Service/Parole Crosstabulation

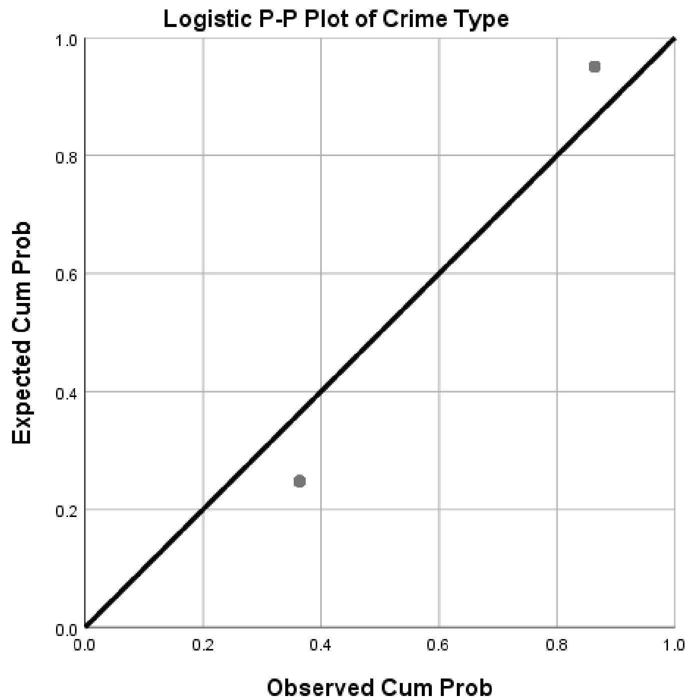
Count

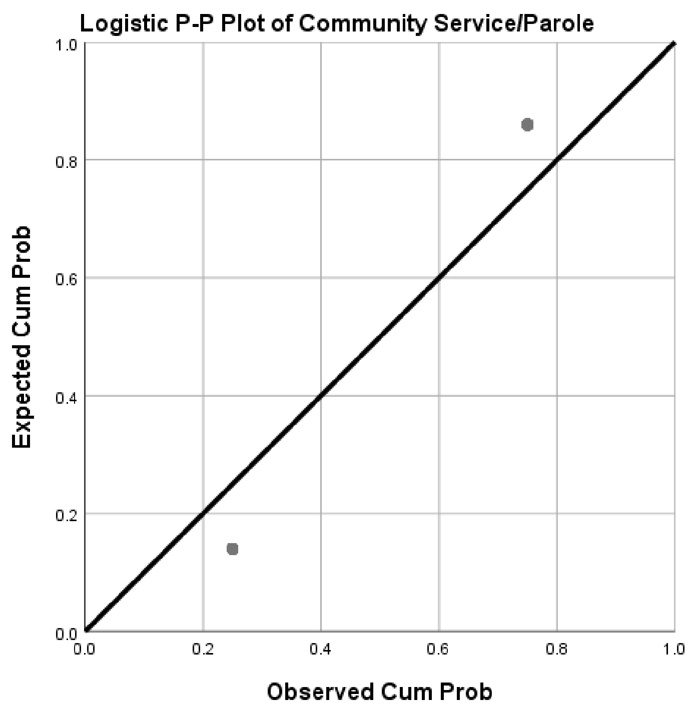
		Community Service/Parole Non-Parole Participant	Community Service/Parole Parole Participant	Total
Race of Offender	White	17750	16856	34606
	Non-White	25227	26121	51348
Total		42977	42977	85954

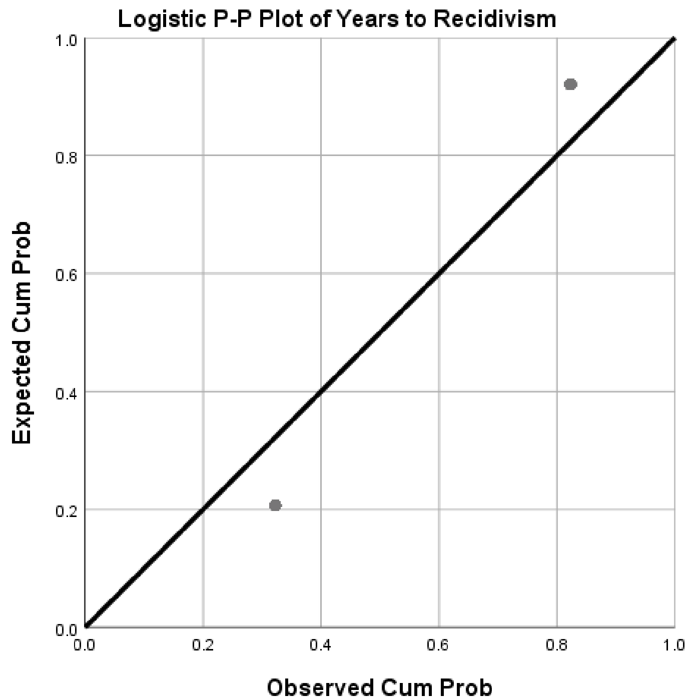
Figure A14: Crime Frequency and RACE

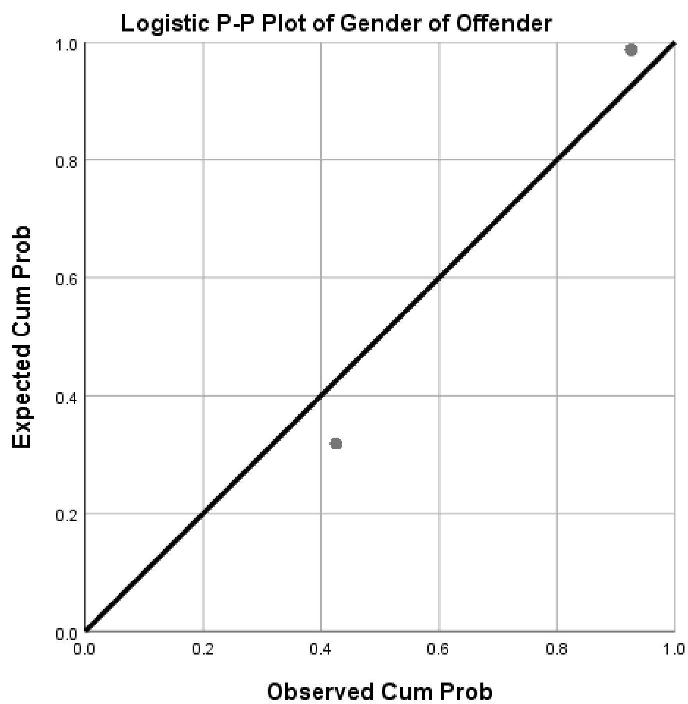


H2 Data Distribution Tests using Logistic P-P Plots


Logistic P-P Plot of Crime Type
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Community Service/Parole
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Years to Recidivism
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Gender of Offender
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Age of Offender
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Logistic P-P Plot of Race of Offender
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0

APPENDIX B

DESCRIPTIVE STATISTICS

Descriptive Statistics for H1 Dataset

Table B1: Pearson Correlation

Correlations

		Gender of Offender	Year Crime Occurred	Level of Education	Financial Crime	Race of Offender	Age of Offender	Unemployment Rate	Average Income
Gender of Offender	Pearson Correlation	1	.000	.023**	.105**	-.078**	.035**	-.001	.001
	Sig. (2-tailed)		.776	.000	.000	.000	.000	.430	.103
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792
Year Crime Occurred	Pearson Correlation	.000	1	.040**	-.012**	.010**	.003**	.871**	-.967**
	Sig. (2-tailed)	.776		.000	.000	.000	.001	.000	.000
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792
Level of Education	Pearson Correlation	.023**	.040**	1	-.002*	-.096**	.146**	.033**	-.038**
	Sig. (2-tailed)	.000	.000		.019	.000	.000	.000	.000
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792
Financial Crime	Pearson Correlation	.105**	-.012**	-.002*	1	-.095**	-.022**	-.011**	.012**
	Sig. (2-tailed)	.000	.000	.019		.000	.000	.000	.000
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792
Race of Offender	Pearson Correlation	-.078**	.010**	-.096**	-.095**	1	-.077**	.009**	-.010**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792
Age of Offender	Pearson Correlation	.035**	.003**	.146**	-.022**	-.077**	1	-.002**	-.004**
	Sig. (2-tailed)	.000	.001	.000	.000	.000		.003	.000
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792
Unemployment Rate	Pearson Correlation	-.001	.871**	.033**	-.011**	.009**	-.002**	1	-.828**
	Sig. (2-tailed)	.430	.000	.000	.000	.000	.003		.000
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792

Average Income	Pearson Correlation	.001	-.967**	-.038**	.012**	-.010**	-.004**	-.828**	1
	Sig. (2-tailed)	.103	.000	.000	.000	.000	.000	.000	
	N	1403792	1403792	1403792	1403792	1403792	1403792	1403792	1403792

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table B2: Descriptive Statistics for All Crime Types

Descriptive Statistics

	N	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Gender of Offender	1403792	1	2	1.11	.000	.314	.099
Year Crime Occurred	1403792	2005	2010	2007.56	.001	1.703	2.900
Level of Education	1403792	1	2	1.49	.000	.500	.250
Financial Crime	1403792	0	1	.42	.000	.493	.243
Race of Offender	1403792	1	2	1.53	.000	.499	.249
Age of Offender	1403792	1	5	2.31	.001	1.045	1.093
Unemployment Rate	1403792	4.60	9.60	6.5551	.00181	2.14050	4.582
Average Income	1403792	73178	78167	75297.36	1.539	1823.078	3323613.284
Valid N (listwise)	1403792						

Table B3: Descriptive Statistics for Financial Crimes

Statistics

		Gender of Offender	Year Crime Occurred	Level of Education	Race of Offender	Age of Offender	Unemployment Rate	Average Income
N	Valid	582758	582758	582758	582758	582758	582758	582758
	Missing	0	0	0	0	0	0	0
Mean		1.15	2007.53	1.49	1.47	2.28	6.5263	75323.69
Median		1.00	2008.00	1.00	1.00	2.00	5.8000	75007.00
Std. Deviation		.357	1.703	.500	.499	1.031	2.13253	1825.501

Table B4: Descriptive Statistics for Non-Financial Crimes

Statistics

	Gender of Offender	Year Crime Occurred	Level of Education	Race of Offender	Age of Offender	Unemployment Rate	Average Income

N	Valid	821034	821034	821034	821034	821034	821034	821034
	Missing	0	0	0	0	0	0	0
Mean		1.08	2007.58	1.49	1.57	2.33	6.5756	75278.67
Median		1.00	2008.00	1.00	2.00	2.00	5.8000	75007.00
Std. Deviation		.276	1.703	.500	.495	1.055	2.14591	1821.126

Descriptive Statistics for H2 Dataset

Table B5: Pearson Correlation

Correlations

		Financial Crime	Community Service/Parole	Years to Recidivism	Gender of Offender	Age of Offender	Race of Offender
Financial Crime	Pearson Correlation	1	.071**	.360**	-.155**	-.344**	-.378**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	85954	85954	85954	85954	85954	85954
Community Service/Parole	Pearson Correlation	.071**	1	-.052**	-.150**	-.164**	.021**
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	85954	85954	85954	85954	85954	85954
Years to Recidivism	Pearson Correlation	.360**	-.052**	1	-.219**	-.403**	-.475**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	85954	85954	85954	85954	85954	85954
Gender of Offender	Pearson Correlation	-.155**	-.150**	-.219**	1	.506**	.186**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	85954	85954	85954	85954	85954	85954
Age of Offender	Pearson Correlation	-.344**	-.164**	-.403**	.506**	1	.416**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	85954	85954	85954	85954	85954	85954
Race of Offender	Pearson Correlation	-.378**	.021**	-.475**	.186**	.416**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	85954	85954	85954	85954	85954	85954

**. Correlation is significant at the 0.01 level (2-tailed).

Table B6: Descriptive Statistics for Parole and Non-Parole Recidivism

Descriptive Statistics

	N	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Financial Crime Type	85954	0	1	.27	.002	.445	.198
Community Service/Parole	85954	0	1	.50	.002	.500	.250
Years to Recidivism	85954	0	1	.36	.002	.479	.229
Gender of Offender	85954	1	2	1.15	.001	.357	.127
Age of Offender	85954	1	5	2.69	.004	1.144	1.309
Race of Offender	85954	1	2	1.60	.002	.490	.241
Valid N (listwise)	85954						

Table B7: Descriptive Statistics for Parole Recidivism

Statistics

		Financial Crime Type	Years to Recidivism	Gender of Offender	Age of Offender	Race of Offender
N	Valid	42977	42977	42977	42977	42977
	Missing	0	0	0	0	0
Mean		.30	.33	1.10	2.50	1.61
Std. Error of Mean		.002	.002	.001	.005	.002
Median		.00	.00	1.00	2.00	2.00
Std. Deviation		.460	.470	.294	1.005	.488
Variance		.212	.221	.087	1.010	.238

Table B8: Descriptive Statistics for Non-Parole Recidivism

Statistics

		Financial Crime Type	Years to Recidivism	Gender of Offender	Age of Offender	Race of Offender
N	Valid	42977	42977	42977	42977	42977
	Missing	0	0	0	0	0
Mean		.24	.38	1.20	2.88	1.59
Std. Error of Mean		.002	.002	.002	.006	.002
Median		.00	.00	1.00	3.00	2.00
Std. Deviation		.428	.485	.402	1.240	.492
Variance		.183	.236	.162	1.538	.242

APPENDIX C

LOGISTIC REGRESSION FOR H1 AND H2

H1 Logistic Regression – All Variables

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	1403792	100.0
	Missing Cases	0	.0
	Total	1403792	100.0
Unselected Cases		0	.0
Total		1403792	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Non-Property	0
Property	1

Block 0: Beginning Block

Classification Table[a,b]

			Predicted		
			Financial Crime		Percentage Correct
	Observed		Non-Property	Property	
Step 0	Financial Crime	Non-Property	821034	0	100.0
		Property	582758	0	.0
	Overall Percentage				58.5

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.343	.002	40050.624	1	.000	.710

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Gender of Offender	15483.939	1	.000
		Year Crime Occurred	214.720	1	.000
		Level of Education	5.531	1	.019
		Race of Offender	12705.046	1	.000
		Age of Offender	690.278	1	.000
		Unemployment Rate	181.155	1	.000
		Average Income	207.863	1	.000
	Overall Statistics		27925.245	7	.000

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	27821.291	7	.000
	Block	27821.291	7	.000
	Model	27821.291	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1877606.816[a]	.020	.026

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	12709.843	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Financial Crime = Non-Property		Financial Crime = Property		
		Observed	Expected	Observed	Expected	Total
Step 1	1	84633	95022.063	57838	47448.937	142471
	2	83427	87340.356	50666	46752.644	134093
	3	100578	95093.775	47915	53399.225	148493
	4	95648	90107.043	47365	52905.957	143013
	5	92474	84687.335	45576	53362.665	138050
	6	90771	84077.952	55365	62058.048	146136
	7	80965	79251.501	60746	62459.499	141711
	8	70845	74459.596	65377	61762.404	136222
	9	63323	74140.033	76952	66134.967	140275
	10	58370	56854.346	74958	76473.654	133328

Classification Table[a]

			Predicted		
			Financial Crime		Percentage
	Observed		Non-Property	Property	Correct
Step 1	Financial Crime	Non-Property	760891	60143	92.7
		Property	505607	77151	13.2
	Overall Percentage				59.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B) Lower	Upper
Step 1[a]	Gender of Offender	.635	.005	13502.795	1	.000	1.886	1.860	1.913
	Year Crime Occurred	-.008	.005	3.241	1	.072	.992	.980	1.004

	Level of Education	-.033	.004	88.613	1	.000	.967	.959	.976
	Race of Offender	-.373	.003	11385.276	1	.000	.689	.683	.695
	Age of Offender	-.062	.002	1378.507	1	.000	.939	.935	.944
	Unemployment Rate	-.003	.002	3.469	1	.063	.997	.993	1.001
	Average Income	.000	.000	.214	1	.644	1.000	1.000	1.000
	Constant	16.086	9.403	2.926	1	.087	9679537.409		

a. Variable(s) entered on step 1: Gender of Offender, Year Crime Occurred, Level of Education, Race of Offender, Age of Offender, Unemployment Rate, Average Income.

Correlation Matrix

		Constant	Gender of Offender	Year Crime Occurred	Level of Education	Race of Offender	Age of Offender	Unemployment Rate	Average Income
Step 1	Constant	1.000	.004	-1.000	.012	.003	-.002	.479	-.898
	Gender of Offender	.004	1.000	-.005	-.014	.056	-.034	.001	-.005
	Year Crime Occurred	-1.000	-.005	1.000	-.013	-.004	.001	-.489	.892
	Level of Education	.012	-.014	-.013	1.000	.087	-.139	.002	-.004
	Race of Offender	.003	.056	-.004	.087	1.000	.068	.002	.000
	Age of Offender	-.002	-.034	.001	-.139	.068	1.000	.009	.005
	Unemployment Rate	.479	.001	-.489	.002	.002	.009	1.000	-.110
	Average Income	-.898	-.005	.892	-.004	.000	.005	-.110	1.000

H1 Logistic Regression – Restricted to variables with significant p values in first regression

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	1403792	100.0
	Missing Cases	0	.0
	Total	1403792	100.0
Unselected Cases		0	.0
Total		1403792	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Non-Property	0
Property	1

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted		
			Financial Crime		Percentage Correct
			Non-Property	Property	
Step 0	Financial Crime	Non-Property	821034	0	100.0
		Property	582758	0	.0
	Overall Percentage				58.5

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.343	.002	40050.624	1	.000	.710

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Gender of Offender	15483.939	1	.000
		Level of Education	5.531	1	.019
		Race of Offender	12705.046	1	.000
		Age of Offender	690.278	1	.000
	Overall Statistics		27752.194	4	.000

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	27644.950	4	.000
	Block	27644.950	4	.000
	Model	27644.950	4	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1877783.157[a]	.020	.026

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	14239.767	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Financial Crime = Non-Property		Financial Crime = Property		
		Observed	Expected	Observed	Expected	Total
Step 1	1	105564	119475.602	74355	60443.398	179919

	2	111287	109751.369	58420	59955.631	169707
	3	83266	77043.629	37887	44109.371	121153
	4	135491	128276.783	70054	77268.217	205545
	5	65921	56905.983	31604	40619.017	97525
	6	89652	86119.941	62383	65915.059	152035
	7	55219	55511.157	44868	44575.843	100087
	8	73950	79403.572	72206	66752.428	146156
	9	63309	72231.581	77726	68803.419	141035
	10	37375	36314.383	53255	54315.617	90630

Classification Table[a]

Observed			Predicted		
			Financial Crime		Percentage Correct
			Non-Property	Property	
Step 1	Financial Crime	Non-Property	760837	60197	92.7
		Property	506219	76539	13.1
	Overall Percentage				59.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B) Lower	Upper
Step 1[a]	Gender of Offender	.634	.005	13502.295	1	.000	1.886	1.860	1.913
	Level of Education	-.035	.004	99.156	1	.000	.966	.957	.974
	Race of Offender	-.373	.003	11424.630	1	.000	.688	.682	.695
	Age of Offender	-.062	.002	1375.642	1	.000	.940	.935	.944
	Constant	-.286	.011	720.756	1	.000	.751		

a. Variable(s) entered on step 1: Gender of Offender, Level of Education, Race of Offender, Age of Offender.

Correlation Matrix

		Constant	Gender of Offender	Level of Education	Race of Offender	Age of Offender
Step 1	Constant	1.000	-.580	-.476	-.596	-.310
	Gender of Offender	-.580	1.000	-.014	.056	-.034
	Level of Education	-.476	-.014	1.000	.087	-.139
	Race of Offender	-.596	.056	.087	1.000	.068
	Age of Offender	-.310	-.034	-.139	.068	1.000

H2 Logistic Regression – All Variables

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	85954	100.0
	Missing Cases	0	.0
	Total	85954	100.0
Unselected Cases		0	.0
Total		85954	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Non-Property Crime	0
Property Crime	1

Block 0: Beginning Block

Classification Table[a,b]

Observed	Predicted		
	Financial Crime		Percentage Correct
	Non-Property Crime	Property Crime	

Step 0	Financial Crime	Non-Property Crime	62511	0	100.0
		Property Crime	23443	0	.0
	Overall Percentage				72.7

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.981	.008	16399.795	1	.000	.375

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Community Service/Parole	436.821	1	.000
		Years to Recidivism	11135.637	1	.000
		Gender of Offender	2064.012	1	.000
		Age of Offender	10147.056	1	.000
		Race of Offender	12271.193	1	.000
	Overall Statistics		18355.071	5	.000

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	20563.941	5	.000
	Block	20563.941	5	.000
	Model	20563.941	5	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	80167.963[a]	.213	.308

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	3041.630	8	.000

Contingency Table for Hosmer and Lemeshow Test

		Financial Crime = Non-Property Crime		Financial Crime = Property Crime		
		Observed	Expected	Observed	Expected	Total
Step 1	1	8724	8546.269	0	177.731	8724
	2	3334	3319.964	129	143.036	3463
	3	12179	11398.212	0	780.788	12179
	4	6768	7930.872	2064	901.128	8832
	5	6548	6880.422	1869	1536.578	8417
	6	6676	6674.387	2318	2319.613	8994
	7	5485	5023.653	2343	2804.347	7828
	8	2580	2351.936	1564	1792.064	4144
	9	5975	5698.859	5391	5667.141	11366
	10	4242	4686.426	7765	7320.574	12007

Classification Table[a]

	Observed		Predicted: Financial Crime: Non-Property Crime	Predicted: Financial Crime: Property Crime	Predicted: Percentage Correct
Step 1	Financial Crime	Non-Property Crime	58269	4242	93.2
		Property Crime	15678	7765	33.1
	Overall Percentage				76.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B) Lower	99% C.I.for EXP(B) Upper
Step 1[a]	Community Service/Parole	.704	.019	1315.103	1	.000	2.022	1.924	2.126
	Years to Recidivism	.993	.019	2662.935	1	.000	2.700	2.569	2.837

	Gender of Offender	-.296	.035	71.462	1	.000	.744	.680	.814
	Age of Offender	-.508	.010	2563.226	1	.000	.601	.586	.617
	Race of Offender	-1.174	.019	3670.933	1	.000	.309	.294	.325
	Constant	1.488	.052	829.046	1	.000	4.427		

a. Variable(s) entered on step 1: Community Service/Parole, Years to Recidivism, Gender of Offender, Age of Offender, Race of Offender.

Correlation Matrix

		Constant	Community Service/Parole	Years to Recidivism	Gender of Offender	Age of Offender	Race of Offender
Step 1	Constant	1.000	-.074	-.467	-.679	-.267	-.488
	Community Service/Parole	-.074	1.000	.252	-.085	-.035	-.232
	Years to Recidivism	-.467	.252	1.000	.065	.146	.196
	Gender of Offender	-.679	-.085	.065	1.000	-.153	.052
	Age of Offender	-.267	-.035	.146	-.153	1.000	-.141
	Race of Offender	-.488	-.232	.196	.052	-.141	1.000

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