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ABSTRACT

The relationship between crime and incarceration is growing in interest in the United States. The United States incarceration rate is often double or triple the rate of other Organization for Economic Co-operation and Development (OECD) countries. The hardline approach the United States has taken on crime has many citizens and academics questioning its effectiveness on achieving safer communities. Traditional theory suggests incarcerating individuals for deviant behavior reduces the crime rate through the mechanisms of incapacitation, deterrence, rehabilitation, and retribution. However, some scholars believe concentration of incarceration in neighborhoods disrupts the social fabric of the neighborhood and produces the opposite of its intended effect. There are numerous studies that test the relationship between crime and incarceration using datasets aggregated at the national, state, and county level. These studies support the theory of a negative relationship between crime and incarceration. A limited number of studies have been conducted at the neighborhood level, however, because data at this scale is harder to obtain. The few studies that have been conducted at the neighborhood level indicate the relationship may be positive and/or non-linear. They depict a scenario in which an increase in incarceration results in a decrease in crime, but only to a certain point. Once this inflection point is reached, further incarceration will destabilize the neighborhood and crime will increase. This paper examines this incarceration-crime relationship using a newly constructed panel dataset of neighborhood-level data from McLean County, Illinois for the period of 2013-2017. The results of this research indicate a significant positive and non-linear relationship between crime and incarceration. Understanding the "true" relationship between crime and incarceration could have major impacts on how local governments approach policing and incarceration.

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I. INTRODUCTION

Incarceration is a growing concern in the United States. Since the 1970s the incarceration rate has steadily been increasing. Currently, the United States is the world leader in the number of incarcerated persons. In 2013, the United States incarcerated 700 of every 100,000 residents. That means approximately 1 in 36 people in the United States were incarcerated at some point in year 2013 (BJS). This incarceration rate is often double or triple the rate of other Organization for Economic Co-operation and Development (OECD) countries. By the end of 2015, the United States had incarcerated 6,851,000 people (Bureau of Justice Statistics). Much of the increase in incarceration is attributed to the Crime Bill signed into law in 1994. To solve the country's "gang and drug" problem, the law imposed tougher prison sentences and provided prisons with more money (Johnson, 2014). Others suggested that the increase in incarceration started in the 1960s with the "Rockefeller Drug Laws" which effectively created stricter penalties for drug offenders. Decades later, the consequences of the bills have sparked the debate (Mann, 2013). The astounding increase in prison populations has raised two important points of discussion: 1) The increase in the number of inmates has placed a financial strain on many local and state governments. Some jails or prisons facing capacity must consider spending money on expanding their facilities or sending inmates to other facilities where they are charged a premium. For example, housing inmates in neighboring jails cost the McLean County Jail of Illinois over $750,000 in 2008 (Pantagraph). 2) There is uncertainty about the benefits of incarceration. It is unclear if higher incarceration rates results in fewer crimes or if incarceration negatively impacts individuals, families, and communities such that it increases crime. The cost of incarceration, which has been exacerbated by lack of jail and prison space, has given rise to the questioning of the effectiveness of incarceration. Although the financial aspect of this issue is important and provides support for its relevance, this paper will focus on the relationship between crime and incarceration. Understanding this relationship would help determine if the current penal system is achieving the goal of safer communities or in fact doing more harm. If the latter is true, then policymakers must consider making changes to the current penal system and develop alternative methods of reducing crime. The following section explores this question in detail. It analyzes the theoretically relationship between incarceration and crime as well as presents what some of the empirical data tells us.

II. LITERATURE REVIEW

Theoretical Relationship Between Crime and Incarceration: Why a Negative Relationship?

Incarceration is generally viewed as a necessary tool in order to reduce the deviant behavior of criminals; thus, protecting society. The desired expectation of incarceration can be broken-down into four effects: incapacitation, deterrence, rehabilitation, and retribution. The first effect, incapacitation, refers to removing deviant individuals from society so they are unable to commit future crimes, thus reducing the crime rate (Levitt, 2004). Secondly, incarceration is used as a deterrent mechanism. Incarceration is perceived as a cost to committing a crime given its negative impact on an individual's income, social status, and time. Therefore, if the cost of committing a crime is higher, for example tougher incarceration policies, fewer individuals will participate in criminal activities resulting in fewer crimes being committed (Becker 1968). The third effect is rehabilitation. Some theorists suggest that incarceration is also a tool used to rehabilitate deviant individuals (Rothman 1995). For example, incarceration can provide time for an individual to increase education or seek drug/alcohol treatment. If the individual is truly rehabilitated, there is less likelihood of recidivism; therefore, the function of incarceration has succeeded, and the individual will not commit more crimes post-release. The last effect, retribution, establishes a moral code for society. The idea is that people that have received punishment via incarceration post-incarceration will have gained the understanding that their actions were not in accordance with society's set of rules (Golash 2005). This understanding resultes in those individuals committing fewer crimes.

These four effects of incarceration listed above all predict that increasing incarceration will result in a lower crime rate and increased public safety. Intuitively these effects make sense and society wants to believe this system is working. However, to determine if a higher incarceration rate produces a lower crime rate, empirical evidence must be considered.

Level of Aggregation of Data Matters

Numerous studies have examined if incapacitation, deterrence, rehabilitation, and retribution have the desired effect of reducing crime. Results differ depending on the aggregation level of data; therefore, the remaining sections are broadly divided into two components. The next section discusses overall findings from models with highly aggregated data sets (those that use national, state and county level data sets). Later sections provide a theoretical explanation of why incarceration may increase crime and presents empirical models that implore micro-level data sets (models that use neighborhood-level data sets).

Empirical Data at the National, State, and County Level

Before any regression analysis is conducted simply looking at the trends between incarceration and crime can be somewhat insightful. Graph 1, in the appendix, shows the behavior of both changes in prisoner population (prisoners per 100,000 residents) and the number of homicides (per 100,000 people) in the United States from years 1934 to 1990. It shows there seems to be an inverse relationship between the homicides and prisoners. Graph 1 (Marvell 1997), found in the Appendix, suggests that as incarceration increases, homicides decreases. This supports the theories of incapacitation, deterrence, rehabilitation, and retribution. Of course, correlation does not imply causation. Regression analysis is needed to support causation.

Examining the regression analysis at the national level upholds the negative relationship in which the increase of incarceration leads to the decrease in crime. Using time series data covering 64 years, Marvell and Moody (1997) show strong evidence that higher prison populations reduced the number of homicides. They predicted that 10% increase in the prison population resulted in a 13% decrease in homicides. They also found similar relationship for robbery and assault, although they were weakly significant. Other studies have found similar results when uses national level data sets. Devine (1988) using time series data from 1948-1985 found a statically significant relationship between various crime types (homicide, robbery, and burglary) and the changes in prison population rate. Cohen and Land (1987) found a negative relationship between motor vehicle theft and incarceration. Both of these empirical works are consistent with the findings of Marvell and Moody and the public's opinion that more incarceration produces less crime. However, all these studies have had negative critique due to their lack accounting for a simultaneity bias in the model. In the general model, crime rate is the independent variable and the dependent variable is a measure of incarceration (the incarceration variable is typically prison population or admissions to prison). The simultaneity bias is present given that increases to crime increases incarceration. However, at the same time theory suggests that increases in incarceration should decrease crime rate. This simultaneity bias should be taken into account in order to avoid biased estimators. This is typically solved by incorporating an instrumental variables technique. Using the instrumental variables technique requires finding a new variable that has two qualities: 1) it is uncorrelated with the error term of the structural equation and 2) it is highly correlated with the endogenous right-hand-side variable. The fitted values obtained by regressing the right-hand-side endogenous variable on the instruments can then replace the original endogenous variable in the regression. As long as the two conditions hold, the instrumental variable estimator is consistent, thus the regression analysis is valid.

To test the directional relationship between incarceration and crime, Levitt (1996) made use of overcrowding litigations' status in various states as an instrumental variable. Levitt use a data set aggregated at the state level and found that for each prisoner released early due to overcrowding litigation, the total number of crimes increased by approximately 15 per year. Levitt estimated the social costs of these crimes to be approximately $45,000. Spelman (2005) turned Texas counties into a panel data set stretching from years 1990-2010. Spelman was also able to incorporate a series of instrument variable (such as sworn officers per capita, civilian police employees per capita, and police expenditure per capita). Spelman found that the elasticity of crime with respect to admissions was the highest when jail and prison populations were high. He therefore concluded that high incarcerations were a significant influence on the lower crime rates in Texas during the 1990s.

Models that used national, state, and county level dataset all seem to indicate that incarceration has the effect of reducing crime. Although, from these studies two important points must be discussed. First, with the increasing costs to housing inmate, is a high incarceration rate worth the money it would cost to keep crime rate low? In order to draw conclusions, an extensive cost analysis must be carried out. Spelman (2005) explains that incarceration in Texas may have decreased the crime rate but it may not have been worth the cost of building the new prisons, housing inmates, and the welfare benefits given to the inmates' families. Secondly, the estimates between national to county level data sets seem to be trending downward. In other words, national level studies find strong support for the negative relationship between incarceration and crime while at the state level results are weaker and nearly disappear at the county level (Dhondt, 2012). This event is a consequence of using aggregated data that does not take into account the high amount of variation of certain neighborhood characteristics. Dhondt's interpretation suggest that further analysis should be conducted at the neighborhood level where neighborhood characteristics that could influence a positive relationship between incarceration and crime can be accounted for in the data. These characteristics and a more in-depth explanation are discussed in the next section.

Theoretical Relationship between Crime and Incarceration: Why a positive relationship?

The section provides an alternative explanation of the negative relationship between incarceration and crime. First, we explore how it is theoretically feasible to have a positive relationship between incarceration and crime. Secondly, it is important to consider why results of empirical models might differ on the level of aggregation.

Incarceration can have devastating effects on the incarcerated individual. Reintegrating back into society post-incarceration has proven difficult for many individuals. In order to provide for themselves, ex-offenders must find employment. However, one study that followed 1,200 individuals post-release from state prisons across three different states found that after eight months 35% of them still had not found employment (Visher, 2011). There are a number of reasons for this, including the negative stigma towards ex-offenders. Oftentimes employers immediately discount individuals with a criminal record (Morenoff, 2014). Furthermore, many ex-offenders claim that even if they found a job, they need to provide personal documents that they did not have; such as a social security card or driver's license (Luther, 2011). Obtaining these documents can be challenging for any individual but for an ex-offender with a low level of education, no income and no means of transportation the task becomes closer to impossible. This stigma towards ex-offenders doesn't stop at employment as housing options are limited as well. Oftentimes ex-felons are ineligible to live in public housing or landlords are unwilling to rent to someone that has a criminal background (Luther, 2011). Employment and housing are essential for all individuals and not being able to meet those needs may influence an individual to resort back to previous criminal behaviors. One study concluded that a one dollar increase from legal employment lead to a seven cent decrease in income generated from illegal activity (Uggen and Thompson 2003). This shows that employment is a good way to combat an ex-offender's return to criminal behavior. Therefore, it can be argued that due to difficulty of finding employment and housing ex-offenders are more likely to recidivate, thus the relationship between incarceration and crime may be negative.

Family and other relationships can also have a large influence on the success of incarcerated persons returning to the community. On some occasions incarcerated persons are shunned from their family. This can be devastating not only due to the loss of financial or tangible assistance but also from the loss of emotional support. Loss of family or friends can lead to the incarcerated individual being left without guidance. If an individual doesn't have family and friends to influence them positively, they may not feel pressure to be obedient members of society. Likewise, the individual doesn't feel the stigma associated with crime and is at risk for recidivism (Lynch & Saboi, 2004). Incarceration can impact the family members of incarcerated persons as well, children in particular. One study found that parental imprisonment predicted the children's delinquent outcomes later in life (Murray, 2005). These consequences may result in a negative relationship between incarceration and crime which would be contradictory to the mainstream view.

Some experts have discussed a weakened effect where crime and incarceration are concentrated in a few neighborhoods within a city. The high number of population inflows and outflows due to imprisonment within these neighborhoods may result in the normalization of crime in the area. This normalization is reflected in a reduced stigma toward incarceration within that community. In other words, residents in the area don't perceive crime as a malevolent act. The removal of stigma has the effect of diminishing the deterrence effect argued from those that believe the relationship between incarceration and crime is positive (Zimring & Hawkins, 1973).

Another argument that provides support for the negative relationship between incarceration and crime is the connection of offenders to each other. The argument suggests that offenders being sent to prison are able to network with other criminals and are exposed to other schools of crime. Therefore, offenders learn more criminal skills in prison and are better equipped to participate in criminal activity post release. This may result in an increase in crime due to the incarceration experienced by the individuals (Justice & Meares, 2014). Another study suggests that the adverse psychological effects due to imprisonment can result in unstable social behavior that results in future crime (Tittle & Patternoster, 2000). Oftentimes, criminals have substance abuse issues with no proper method of dealing with them. One study reported, "approximately 80% of prisons and jail inmates have serious substance abuse problems. Returning prisoners are at high risk of substance abuse relapse, largely due to the fact that this period is characterized by the stress of major life changes" (Luther, 2011). Obviously, being released back into society is a major life change as offenders deal with problems such as lack of housing, unemployment and no transportation. If the stress is too much to overcome, offenders are at risk of relapsing thereby increasingly their chance of returning to prison. Another theory explains that removal of men from a community increases the amount of unsupervised youth in the community, thereby opening up the possibility for youth to participate in deviant behavior (Lynch & Sabol, 2002). Additionally, another relevant theory, Coercive Mobility, is discussed in depth in a later section.

Collectively, all these factors give reason to believe that the relationship between incarceration and crime may actually be positive. However, why don't the models with highly aggregated data sets support the theory of a positive relationship between incarceration and crime? This understanding starts with recognizing that incarceration is disproportionately distributed in a multitude of ways. Incarceration tends to affect some people more than others based mainly on four factors. One, men are 15 times more likely to be incarcerated than women. Two, black individuals are 7 times more likely to be incarcerated than white individuals. Three, people that fail to finish high school are 3 times more likely to be incarcerated. Four, young individuals (ages 18-24) of fill the majority of prisoners. Clear (2008) explains how these four concentrated group come together and produce a fifth crucial sphere of concentration: place. Due to the racial and socioeconomic segregation of housing in the United States, incarceration seems to be much more prevalent in some communities in comparison to others. This clustering is evident in a study by Lynch and Sabol (2004), where 5% of the neighborhoods in Baltimore accounted for 25% of admissions to prison in that year and 10% of the neighborhoods accounted for 40% of admissions to prison in that year. This spatial concentration is important because models that used aggregated data sets did not capture this phenomenon. In a highly aggregated dataset, the high incarceration rates of a few communities are pooled together with neighborhoods having low incarceration rates. In order to capture the effects of high incarceration, the places that experience the highest incarceration must be accounted for individually.

Empirical Models at the Neighborhood level

Several studied have attempted to address the impact of high incarceration on communities. The aim of these studies is to determine whether the theoretical positive relationship between incarceration and crime holds when using data sets at the neighborhood level. They do not specifically address the individual effects but rather test whether on the community level there is a non-linear or positive relationship between incarceration and crime. The general methodology that is followed by most scholars is as follows:

$$crime_i = \beta_0 + \beta_1 I_i + \beta_2 I_i^2 + \beta_3 I_i^3 + \beta_4 Z_i + \beta_5 X_i + u_i$$

Here, crime rate is a non-linear function of the incarceration rate (I). Studies with highly aggregated data set use prison population as the dependent variable for incarceration. At the neighborhood level, prison population is no longer a suitable variable as prisons hold inmates from across different communities. Therefore, at the neighborhood level, scholars have used admissions and releases from prison. Thus I_i is an estimator that represents either the number of admissions to prison or leases from prison for neighborhood i. Some models make use of squared and cubic terms in order to predict a non-linear relationship. Due to the endogeneity of I some studies have employed an instrumental variable technique. Therefore, instrumental variables parameter estimates are obtained in a two-stage process. First, by regressing the incarceration variable on the instrumental variable and obtaining the fitted values. In the second stage the obtained fitted values are then placed in the original equation and serve as an unbiased and consistent estimator of the incarceration variable. Some models make use of squared and cubic terms of the incarceration variable in order to account for the possibility of a non-linear relationship; these variables are labeled as I2 and I3. The crime t-1 variable is one period lag of the dependent variable. Most models include this variable because it accounts for the criminal history of the neighborhood. Some authors claim that including this variable also solves the endogeneity problem; this is discussed later. The variable X is a place holder for a number of control variables. Typical control variables are: employment, past neighborhood crime rate, and population. It is important to note that because of data limitations there have not been many studies that have tested for this relationship between incarceration and crime at the neighborhood level. The following studies are presented because they are believed to be the most insightful in this specific issue.

Clear (2003) conducted the first empirical study that explicitly tested for a non-linear or a positive relationship between incarceration and crime on the neighborhood level. Clear broke down the city of Tallahassee, Florida into 80 different neighborhoods and used them to form a cross sectional data set. The regression analysis showed that the relationship between crime (dependent variable) and admissions and releases (independent variables) from the previous year had a positive relationship; where admissions are the number of offenders admitted to prison and releases are the number of offenders released back into the community post incarceration. Clear used the generalized linear model with a negative binomial response function to conduct the regression analysis. Clear claims that this model is appropriate for prediction of positive integers and it can be applied to crime rates as long as logged population is incorporated in the model as an explanatory variable. Osgood (2000) also indicates that it is better than OLS because of its ability to constraint predicted values to positive numbers. Furthermore, by squaring and cubing the admission's variable Clear showed that the relationship between crime and admissions was non-linear. This suggests that there is a tipping point in which incarceration decreased the crime rate until a certain point is reached and further incarceration results in an increase in crime. Graphically, this appears as a U-shape. Clear accredited this outcome to the theory of Coercive Mobility. The theory claims that the effects of admissions and releases into prison can be modeled after Residential Mobility Theory; where high levels of voluntary inward and outward flows of residents can cause reduced formal social efficacy, which ultimately leads to an increase in crime. Social efficacy can be interpreted as a measure of social cohesion among neighbors combined with their willingness to be involved in the specific community issues (Bursik, 1994). Coercive Mobility suggests a similar occurrence from the effect of admissions to and releases from prison. These results are the opposite effect predicted by the models where national and state level data sets were utilized. Clear does add that future research should be conducted with a larger data set and data from multiple time points. It is also important to note that Clear's most convincing model was with the downtown area removed from the sample where there is low residential population and high crime of downtown. Clear acknowledges that this could be seen as "cooking the books" however defends this practice by claiming that the downtown isn't a true residential area. Clear's work suggests that further research should consider incorporating non-linearity tests and the need to investigate the issue of outliers.

Though Clear's findings shined new light on the relationship between incarceration and crime, other authors have noted a problem with his model. Clear did include an instrumental variable in his regression making it difficult to draw inferences about the direction of causality between incarceration and crime (Lynch & Sabol, 2004). In other words, there is the problem of simultaneity bias, where it is unclear if incarceration levels influence crime or vice versa. Lynch & Sabol (2204) used monthly panel data from 30 neighborhoods in Baltimore, Maryland to revamp Clear's model. This time however Lynch and Sabol included the discretionary portion of drug arrests (or the drug arrest rate not explained by the index crime rate) as an instrumental variable for prison admissions. Their analysis showed a negative relationship between incarceration and crime which was consistent with the theories regarding deterrence, incapacitation, rehabilitation, and retribution. As an experiment Lynch and Sabol tested their model again without the instrumental variable and found that the positive relationship similar to the findings of Clear. This indicates that future research should take into account the endogeneity issue, doing so is crucial in order to produce valid estimators.

Dhondt (2012) has produced the most recent comprehensive model that has tested the non-linear or positive relationship between incarceration are crime. Dhondt uses the same data set as Clear but expands it into a panel by incorporating six more years of data. The panel data set improves the Clear's model in two ways. First, it increases the low number of observations of 80 in Clear's model to 560. Secondly, Clear's cross-sectional approach only explains the effect of incarceration of the current year on crime on the following year. One would expect that effects of incarceration accrue over time; therefore, Dhondt's data set captures a long-run effect. To deal with the endogeneity problem, Dhondt includes the lag of the incarceration variable as a dependent variable. Dhondt decided to use a fixed effects model instead of random effects model because of the large differences across crime, admissions, and releases across neighborhoods.

Dhondt (2012) finds a positive relationship between admissions and crime, which is in support of Clear's Coercive Mobility Theory. However, his test for non-linearity leads to insignificant results. Dhondt's analysis also includes the creation of a new variable call "prison cycling", which is the number of admissions plus the number of releases in a given community. Clear discusses this possibility however discounts it, claiming that he wanted to capture both effects separately. Admissions and releases are both circumstances of incarceration and events that are constantly occurring in a community. By using "prison cycling" Dhondt demonstrates that he doesn't care about their individual effects. The "prison cycling" variable only captures the total effect of incarceration (the sum of admission and releases). By doing so, Dhondt finds the relationship with "lagged prison cycling" and crime is positive and a non-linear relationship at a statistically significant level. Both of these results are consistent with the Coercive Mobility Theory. From Dhondt's work there is a new variable to consider, prison cycling. Additionally, Dhondt provides a new way of addressing the endogeneity issue by simply including the lag of the crime rate as a right-hand side variable in the model.

Renauer (2006) tests the Coercive Mobility Theory using a new cross-sectional data set from the neighborhoods of Portland, Oregon. Renauer finds a potential issue with the estimation technique used in Clear's original model in the use of the negative binomial regression which transforms the dependent variable in logs. As suggested by Hannon and Kapp (2003) this may create misleading results when testing for non-linear relationships. For instance, the results may show a non-linear relationship even when the true relationship is linear. To account for this possibility, Renauer includes three models each with a different estimation technique: Ordinary Least Squares, Heteroscedasticity Consistent Covariance Matrix (HC3) and the Negative Binomial Regression. The HC3 technique was suggested by Hannon and Kapp (2003) as it is more suitable for determining non-linear relationships because it does not transform the dependent variable. A problem with the HC3 technique is that it is sensitive outliers, therefore Cook's D test utilized to identify the outliers and was run with and without them. Due to issues of multi-collinearity the releases variable was not included in the analysis. The results overalls for Renauer's analysis were consistent with the Coercive Mobility Thoery. When removing Cook D's top outliers all three estimator techniques produced significant results that suggested a curvilinear relationship between crime and admissions to prison. This was indicated by a positive and significant coefficient of the cubed admissions variable. Therefore, Renauer concludes that even when considering other estimation techniques there is a tipping point where incarceration starts to cause an increase in violent crimes rather than the decrease as predicted by deterrence, incapacitation, rehabilitation, and retribution. In order to deal with the issue of endogeneity, Renauer includes violent crime of the previous year as control variable. He argues that including this variable leaves little variation to be explained with other covariates, this is due to the high correlation between the violent crime of the current year and the previous year. By doing so, Renauer claims he effectively deals with the endogeneity issue. From this research it is evident that multiple estimate techniques should be considered when testing for non-linear relationships between crime and incarceration. It is also important to note that Ranauer does not include an instrumental variable suggested Lynch and Sabol (2004).

There are two additional empirical works that focus solely on the individual effect of releases. The general consensus is that a neighborhood with higher a number of people returning from prison will increase crime in the neighborhood. This relationship is theoretically supported by the idea that ex-offends find themselves in a position of no employment and are often times placed in a criminal environment. Others believe that offenders returning to a community can have the opposite effect, in which an influx in ex-offenders into a community decreases the crime rate. This is supported by the theory that returning offenders will mend broke-homes and increase informal and parochial social controls. Hipp and Yates (2009) set out to test the relationship between the number of parolees in a neighborhood the crime rate of that respective neighborhood. They used a panel data from Sacramento at monthly intervals which was design to capture the short term effect the parolees had on the community. The authors utilized a fixed effects model with a negative binominal and tests four different functional forms. The logarithmic form was determined to be the most valid and produced results that showed a positive relationship between changes the number of parolees (via releases) and crime rate. It was unclear whether this positive relationship existence because of a direct impact where parolees commit the crimes themselves or the returning parolees effected on crime in an indirect matter. An indirect impact suggests that returning parolees may disrupt the social fabric of communities which leads to the increase in crime. This hypothesis of an indirect impact is in line with the Coercive Mobility Theory put forth by Clear.

The indirect impact was looked at by Drakulich who's model test the relationship between incarceration and violent crime; and specifically addresses whether the positive relationship is due to indirect effects by including social variables which were "collective efficacy" and "criminogenic situations" in the model. In this case, "collective efficacy" is the ability of the community to achieve goals pertaining to public safety and "criminogenic situations" are the number of social situations conducive to criminal behavior. Data for both variables were gathered by surveying the respective communities. The results show that low "collective efficacy" and high "criminogenic situation" resulted in a higher crime rate. This analysis suggests that the effect of incarceration on crime is more than just a direct impact (criminals/parolees reoffending in their respective communities) but that indirect effects are also occurring. In other words, high levels of incarceration lead to reduced "collective efficacy" and an increase in "social situations conducive to criminal behavior" which ultimately lead to an increase in violent crimes. This analysis is important because it contributes to the idea that high concentrations of ex-offenders make changes to the fabric of the community such that it suppresses social control and prevents improvers.

Summary of Major Findings

Although there are theoretical arguments for both a positive and negative relationship between incarceration and crime, based on the empirical evidence the "true" relationship is still unclear. Models using highly aggregated data sets suggest a negative relationship showing incarceration reducing crime rates, while results from models using neighborhood level data sets are mixed. To draw a more definitive conclusion, further empirical analysis must be conducted. Future analyses should include the following aspects in their research. First, empirical models should use data sets at the neighborhood level. Due to the difficulty of obtaining neighborhood crime data, there is a limited amount of studies which have utilized this level of aggregation. Secondly, datasets should be constructed such that there are more observations. This can be accomplished by constructing panel datasets which provides information across neighborhoods and time. Third, future studies should address the issue of simultaneous bias between crime and incarceration to prevent biased estimators. Previous works have addressed this by incorporating instrumental variables or including a lag of the incarceration variable as a dependent variable. Future empirical models which undertake these methods will help society better understand the "true" relationship between crime and incarceration.

III. DATA & MEASURES

Sources of Data

The raw data utilized in this analysis comes from two sources. All criminal incidents reported in McLean County, Illinois and all admissions to the McLean County Jail were provided by McLean County, Illinois. Demographic and neighborhood social characteristics data was collected from the United States Census Bureau. This dataset was newly constructed for the sole propose of this analysis. Extensive work was dedicated to geocoding locations of incidents and admissions to jail.

Data Summary

This is a balanced panel dataset where the cross-section data is neighborhoods and time is years 2013 -2017. There is a total of 205 observations before outliers are removed, and 195 observations after outliers are removed. The minimum and maximum neighborhood crime rate per 100 residents was .002 and .264 respectively and a mean of .4. The minimum and maximum admissions rate per 100 residents was .003 and .219, respectively and a mean of .4. The summary statistics for all variables are included in the Appendix: Figure 1.

Neighborhood Districts

This is a neighborhood-level dataset. For the proposes of this analysis a neighborhood is considered a census tract within McClean County, Illinois. This parameter was determined because the vast amount of readily available data that is collected from the United States Census Bureau. McLean County has a total of 41 census tracts.

Variable list

Independent Variable	
Area Crime Rate	The number of incidents were totaled for each neighborhood. The Area Crime Rate was then calculated by summing the total number of incidents from the subject neighborhood and all the adjacent neighborhoods and then dividing by the total population of those respective neighborhoods. This variable is considered to be the crime rate of the subject neighborhood and adjacent neighborhoods. Including the adjacent neighborhoods was implemented to account for crime spilling over from one neighborhood to its adjacent neighborhoods.
Dependent Variables	
Admission Rate	The number of admissions to the McLean County jail per 100 residents from the year prior. The total number of admissions from a neighborhood was summed and divide by the neighborhood population. For certain models, the admissions rate variable is centered and transformed into a second-order polynomial. To center, the variable mean was subtracted from every value of the variable. Centering prior to the construction of the polynomial terms alleviates issues of multicollinearity.
Median Earning	The annually median earning of individuals over the age of 25 in the given year. The unit of measurement is in dollars.
Education Attainment	The percentage of individuals over the age of 25 with a high school diploma or equivalent in a given year.
Employment Rate	The percentage of individuals over the age of 16 employed in a given year.
Residential Stability	The percentage of residents within a neighborhood which lived in the same neighborhood the year prior.
Black Population	The percentage of black residents within a neighborhood in a given year.

Instrumental Variable	
Area Violent/Drug Admissions Rate	The number of violent- and drug-related admissions to the McLean County jail per 100 residents from the year prior. Due to the simultaneous bias between crime and admissions certain models make use of an instrumental variable. Lynch and Sabol (2004) used drug arrests as an instrument in their analysis. I use both violent and drug admission rate. It was calculated by summing the total number of violent- and drug-related admissions from the neighborhood and all the adjacent neighborhoods and then dividing by the total population of those respective neighborhoods. For certain models, the admissions rate variable is centered and transformed into a second-order polynomial. To center, the variable mean was subtracted from every value of the variable. Centering prior to the construction of the polynomial terms alleviates issues of multicollinearity.

IV. THEORETICAL FRAMEWORK

The theoretical hypothesis is that higher neighborhood incarceration rates to the McLean County Jail will result in higher crime rates within that neighborhood and its surrounding neighborhoods the following year. Incarceration is intended to lower crime rates however this not necessarily the result in disadvantaged neighborhoods where incarceration rates are high. The negative social impact of concentrated incarceration disrupts the social fabrics of neighborhoods and has the opposite effect of increasing the crime rate in the neighborhood and surrounding area.

My motivation is to contribution empirical data which will determine the “true” relationship between crime and incarceration at the neighborhood level. To determine the relationship, I utilize a panel dataset at the neighborhood level using data collected from McLean County, Illinois. A panel dataset will increase the number of observations compared to cross-sectional data previously utilized. Larger datasets provide more accurate results. Furthermore, the panel dataset will detect the long-term effect of incarceration, as its impact can be experienced across multiple years. This analysis includes four empirical models. All models employ a fixed-effect model, where crime rate is regressed on the incarceration variable. I use a fixed-effect model instead of random effects model because of the large differences across crime and admissions between neighborhoods. A random-effects model would also not be appropriate because this dataset does not represent a random selection of neighborhoods. Each model implements a technique to address endogeneity issues and two models tests for non-linearity by incorporating second-order polynomials of the incarceration variable. The incarceration variable in this analysis is admissions to the McLean County Jail. Other control variables are included in each model. The basic fixed-effects model is below:

$$Y_{it} = \beta_o + \beta_1 I_{it} + \beta_1 I^2_{it} + \beta_1 Z_{it} + \alpha_i + \gamma_t + \mathcal{E}_{it}$$

where subscript *i* corresponds to neighborhoods, and subscript *t* represents index years. *Y* is the dependent variable, crime rate. *I* is the variable of interest, admission rate from the prior year. I^2 is squared variable of *I*. *Z* represents control variables to account for demographics, social characteristics, and socioeconomic status.

Influential Observations

In small samples, outliers are often a concern as a few extreme influential observations can substantially alter the results of a regression analysis. Given the models of this study utilize a relatively small sample size, an extensive analysis of influential observations using Cook's Distance (D) method was conducted. A cross-sectional model for each year was regressed with crime rate as the independent variable and admissions rate, median earning, education attainment, employment rate and residential stability as dependent variables. A Cook's D predictor was then created to determine D-values. For the purpose of the study, a D value over 4/N was determined to be an outlier. Given the cross-sectional data sets have an N =41, a D-value over .0976 was determined to be an outlier.

There were two census tracts that were consistently found to have high D-values over the determined threshold of .0976 each year. The census tracts were number 2 and number 13.02. This is not surprising as both census tracts are unique in nature. Census Tract number 2 is entirely Illinois State University and Census Tract 13.02 is primarily Illinois Wesleyan University. With most of the population being students', numerous variables were very different from the average of the other census tracts. Employment rate for both tracts were approximately 40 percent, whereas the entire dataset reflected an employment rate of 64 percent. Other variables such as admission rates, residential stability, and median earning were all much lower than the dataset mean. Crime that occurred in each census tract varied. Census tract 4 (Illinois State University) experienced crime rates above the dataset average. Meanwhile census tract 13.02 (Illinois Wesleyan University) experienced crime rates well below the dataset average.

Given, the results of the Cook's D testing and the unique nature of the census tract 2 and 13.02, the models for this study remove these observations as they are considered outliers that do not have qualities of a typical neighborhood. The Cook's D values for the census tracts 2 and 13.02 can be seen in Figure 2 in the Appendix and the summary statistics for these census tracts can be viewed in Figure 3.

Multicollinearity

Before models could be determined there was concern regarding multicollinearity issues with the right-hand side variables. Several variables can be derived from community level census data to predict crime rate in any given year. Including too many similar predicting variables may lead to high correlation between variables and redundant information in explaining variation of the crime rate. Multicollinearity in dependent variables results in small t-statistics, wide confidence intervals, and imprecise coefficient estimates. In order, to check for multicollinearity a correlation table of dependent variables was generated and can be view in Figure 4 the Appendix. The correlation table is used to identify any red flags of multicollinearity by evaluating correlations between each variable.

The correlation table shows high correlation between the second-order polynomials of the admissions variable. This is expected as the higher order polynomials variable are derived from the first order variable. This is solved by centering prior to the calculation of the polynomials to alleviate the difficulties created by multicollinearity.

I was also concerned that a correlation between education attainment and employment rate may lead to multicollinearity issues. Theoretically, a higher education translates into higher levels of employment, thus a neighborhood with highly educated individuals will have a strongly positive relationship with employment rates of the neighborhood. The correlation table shows a correlation of .5107, which does not indicate a high level of correlation. Furthermore, OLS variance inflation factors (VIF) were analyzed, both education attainment and employment rate had VIF values less than 1.84, signifying an acceptable amount of correlation. VIF results are found on Figure 5 of the Appendix. After analyzing correlation tables and variance inflations factors all multicollinearity concerns were deem absent or solvable by variable transformation.

Endogeneity

The simultaneous bias between crime rate and incarceration leads to biased estimators. The endogenous variable in this study is admission rate. I solve this issue by incorporating two methods in my model, both methods were utilized in previous works:

1) I follow a similar approach to Lynch and Sabol (2004) in Baltimore, Maryland who used drug arrests as an instrument variable in their analysis. I use area violent/drug admissions rate. Some Mclean County neighborhoods had very few drug admissions, thus a small spike or one incident involving multiple persons could inflate the true depiction of a neighborhood. By also including violent admissions I decrease variability in the statistic and reduce the risk of outliers. A series of tests were conducted to determine if there was endogeneity between area crime rate and admission rate. Area crime rate was regressed on admission rate for each year, thus using a cross sectional dataset. From each regression a Durbin and Wu-Hausman test was conducted. The

results of the Durbin and Wu-Hausman tests show significant p-values indicating the presence of endogeneity, see Figure 6 in the Appendix. First-stage regression summary statistics show high F-stats relative to critical values and moderately high partial R-square values signifying violent/drug admissions rate is an adequate instrument for admission rate.

2) I also use a method developed by Dhondt (2012) which utilizes the lag of the incarceration variable as an dependent variable. I incorporate this technique into my models by taking the previous year's admission rate and including it as an additional dependent variable. This effectively solves the endogeneity issue by accounting for a neighborhood's past criminal history.

I. ECONOMETRIC MODELS AND ESTIMATION METHODS

I am interested in determining the relationship between crime rate and admissions rate using data aggregated at the neighborhood level. I designed four econometric models, which all use a fixed-effects model to regress crime rate and admission rate. The difference between each model is 1) method of accounting for the simultaneous bias between crime rate and admissions rate and 2) testing for non-linearity of the variable of interest, admission rate.

$$(1) \quad Y_{it} = \beta_o + \beta_1 \hat{I}_i + \beta Z_{it} + \alpha_i + \gamma_t + \mathcal{E}_{it}$$

In Equation (1) the independent variable is Area Crime Rate. $\hat{I}$ represents Admission Rate however an instrumental variable, Area Violent/Drug Crime Admissions Rate, is employed signified by the hat symbol. The instrumental variable alleviates the simultaneous bias between Area Crime Rate and Admissions Rate. The expected sign of the coefficient is positive, which would indicate an increase to admissions rate would result in a higher Area Crime Rate. Graphically, this would be represented by an upward sloping line. Z represents the control variables Median Earning, Education Attainment, Employment Rate, Residential Stability, and Black Population.

$$(2) \quad Y_{it} = \beta_o + \beta_1 \hat{I}_{it} + {}_t + \beta_2 \hat{I}^2{}_{it\ it} + \beta_1 Z_{it} + \alpha_i + \gamma_t + \mathcal{E}_{it}$$

In Equation (2) the independent variable is Area Crime Rate. $\hat{I}$ represents Admission Rate however using Area Violent/Drug Crime Admissions Rate as an instrumental variable. This is signified by the hat symbol. $\hat{I}^2$ represents the squared Admission Rate variable, where Area Violent/Drug Crime Admissions Rate is employed as an instrumental variable. The Admission Rate variable has been centered prior to squaring to alleviate multicollinearity issues. The expected sign of $\hat{I}$ is negative and the expected sign of $\hat{I}^2$ is positive. This outcome would indicate a negative relationship between Area Crime Rate until an inflection point where the relationship reverses and becomes positive. Graphically, this would be represented by a U-shaped curve. This result would confirm the hypothesis that higher levels of incarceration could lead to higher Area Crime Rates. Z represents the control variables Median Earning, Education Attainment, Employment Rate, Residential Stability, and Black Population.

$$(3) \quad Y_{it} = \beta_o + \beta_1 I_{it} + \beta_2 X_{it-1} + \beta_1 Z_{it} + \alpha_i + \gamma_t + \mathcal{E}_{it}$$

In Equation (3) the independent variable is Area Crime Rate. I represents Admission Rate. The expected sign of the coefficient is positive. A positive coefficient would indicate the same outcome as Equation (1), an increase to Admissions Rate would result in a higher Area Crime Rate. Graphically, this would be represented by an upward sloping line. X represents the lag of the admissions rate; this variable is incorporated to alleviate the simultaneous bias between Area Crime Rate and Admissions Rate. Z represents the control variables Median Earning, Education Attainment, Employment Rate, Residential Stability, and Black Population.

$$(4) \quad Y_{it} = \beta_o + \beta_1 I_{it} + \beta_1 I^2_{it} + \beta Z_{it} + \alpha_i + \gamma_t + \mathcal{E}_{it}$$

In Equation (4) the independent variable is Area Crime Rate. I represents Admission Rate and I^2 represents the Admission Rate variable squared. The Admissions Rate term was centered prior to being squared to alleviate multicollinearity issues. The expected sign of I is negative and the expected sign of I^2 is positive. This outcome would indicate the same outcome as Equation (2), a downward sloping relationship until an inflection point where the relationship reverses and becomes positive. Graphically, this would be represented by a U-shaped curve. This result would confirm the theory that higher levels of incarceration can increase the Area Crime Rate instead of decreasing it. X represents the lag of the Admissions Rate, this variable is incorporated to alleviate the simultaneous bias between Area Crime Rate and the Admissions Rate. Z represents the control variables Median Earning, Education Attainment, Employment Rate, Residential Stability, and Black Population.

Expected Coefficient Signs of Control Variables

<u>Median Earnings</u>*:* The expected relationship between Area Crime Rate and Median Earning is negative. As Median Earnings increase the need to commit crimes decrease and the benefit to committing crimes decrease. This would be represented by a negative coefficient.

<u>Education Attainment</u>*:* The expected relationship between Area Crime Rate and Education Attainment is negative. As Education Attainment increases, jobs prospects increase, and the need to engage in criminal activity decreases. This would be represented by a negative coefficient.

<u>Employment Rate</u>*:* The expected relationship between Area Crime Rate and Employment Rate is negative. As residents of the neighborhood have more jobs opportunities the need to commit crimes decrease. This would be represented by a negative coefficient.

__Residential Stability__: The expected relationship between Residential Stability and Area Crime Rate is negative. As residents live in a neighborhood for longer periods it is an indication of neighborhood cohesion and collective efficacy, where residents are more willing to intervene on behalf of a neighborhood (Dhondt 2012). This would be represented by a negative coefficient.

__Black Population__: The expected relationship between Black Population and Area Crime Rate is positive. Strong evidence suggests that percentage of Black Population in a neighborhood has a strong correlation with crime and incarceration variables (Dhondt 2012). This would be represented by negative coefficient.

II. RESULTS

The four models produce evidence that indicate a positive relationship between Area Crime Rate and Admissions Rate to the Mclean County Jail. Model (1) and (3) were both restricted to a linear regression. The difference in the models was the technique employed to solve the endogeneity issue. The coefficients for the incarceration variable, Admissions Rate, in both models were positive and highly significant. For Model (1), a one percent point increase in the Admissions Rate in the previous year is associated with an increase the Area Crime Rate of .572 percent. For Model (3) a one percent point increase in the Admissions Rate resulted in a .161 percent increase in the Area Crime Rate. The size of the coefficients are relatively small however even low increases in crime rate can lead to major challenges for a neighborhood and determine how local governments react to neighborhood's criminal activity. The findings of model (1) and (3) are very consist with previous works that used neighborhood level datasets. Dhondt (2012) found a 1 percent point increase in admissions rate from the previous year resulted in 1.4% increase in crime rate. Clear (2003) ran three models which found a one percent increases in admissions rate to jail was associated with increases in the crime rate ranging from .307 to .879.

Models (2) and (4) were largely similar to Models (1) and (3), however include a centered squared Admissions Rate variable. Model (2) and (4) differ by the technique in resolving endogeneity issues. In both models, the squared Admissions Rate variable was negative and significant. For both models the first order terms of Admission Rate were positive. This outcome is represented by inverted U-shape curve suggesting that increasing the Admissions Rate will increase the Area Crime Rate to a point and then decrease as Admissions Rate continue to increase. This result is not consistent with the finding of Clear (2003), who found a U-shaped curved. While these results imply increasing Admissions Rate may drive the Area Crime Rate higher, it may also imply that relationship is not a parabola shape. The results from each model are summarize in the table below. The full output statistics of the regression analysis can be viewed in the Appendix as Figure 7.

Model Results

Variables	Equation (1)	Equation (2)	Equation (3)	Equation (4)
Admission Rate -IV	0.572***	1.209***		
	(0.124)	(0.28)		
Admission Rate -squared - IV		-7.722***		
		(2.419)		
Admission Rate			.161***	.332***
			(.035)	(.06)
Admission Rate -squared				-1.34***
				(.394)
Median Earning	3.08e-08	-6.7e-08	-2.70e-07	-3.05e-07*
	(-1.71e-07)	(1.94e-07)	(1.91e-07)	(1.83e-07)
Education Attainment	-0.009	-0.023	-.006	-.007
	(-0.043)	(0.0477)	(.033)	(.032)
Employment Rate	-0.003	-0.0249	-.009	-.012
	(-0.023)	(0.026)	(.017)	(.016)
Residential Stability	0.028**	0.001	-.004	-.002
	(-0.126)	(0.016)	(.008)	(.008)
Black Population	.027*	0.049***	.024***	.0278***
	(.016)	(0.018)	(.011)	
Admission t-1			-.099	-.079
			(.076)	(.073)

Other Finding in the Models

An interesting observation from the four models is the findings of the Black Population variable. The coefficients for each model were significant and positive. The coefficients of the Black Population varied from .024, in year 2015, to .049 in year 2014. For 2014, this indicates a one percent point increase in black population in a neighborhood would result in a .049 increase the Area Crime Rate. Dhondt (2012) also found neighborhoods with higher Black Populations tended to have crime rates. Dhondt also noted that there were higher rates of admissions from black neighborhoods even though underlying crime rates were not very different from non-black neighborhoods.

III. CONCLUSION

This paper estimates the effect of incarceration on crime rate at the neighborhood level. Previous studies using highly aggregated datasets (at the Country, State, or County level) have illustrated a trend that suggests a negative relationship between crime rate and incarceration. However, many of these analyses have failed to incorporate data at the neighborhood level, thereby excluding significant information needed to capture the full effect of incarceration on specific neighborhoods. The analysis employed in this paper utilizes a neighborhood-level panel dataset in order to study the effects of incarceration on the neighborhoods of McLean County, Illinois. To my knowledge, this analysis is only the second study to use a neighborhood-level panel dataset to test the relationship between crime rate and incarceration.

By utilizing a neighborhood-level dataset, I provide evidence that increasing the admissions rate to jail has a positive relationship with the area crime rate. This suggests that incarcerating at high levels leads to the opposite of its intended effect and actually increases crime. The positive relationship is found in two empirical models and are consistent with previous analyses that employ datasets aggregated at the neighborhood-level. Dhondt (2012) found that a 1% increase in admissions from the previous year resulted in a 1.4% increase in crime rate. Clear (2003) also found a positive relationship between crime rate and incarceration, however our results differ in the sign of the quadratic coefficient.

Understanding the “true” relationship between crime and incarceration could have major impacts on how local governments approach policing and incarceration. If higher incarceration rates result in increased crime, local governments should consider implementing criminal justice reform programs or other alternatives. Allocating less funds to policing and more funds towards community development programs may be more effective in reducing crime and achieving safer communities.

Further research on this topic is still needed. The analysis conducted in this paper should be employed in other localities to test if the results of this paper can be replicated. I recommend future scholars conduct their research in geographic areas that have a higher population and more neighborhoods to increase the number of observations. While this study incorporates more observations than previous works, it was still a relatively small dataset. Additionally, future studies can integrate more variables in the model. There are several predictors of crime rate that census data does not capture such as neighborhood cohesion or social efficacy. To build on the existing body of work, researchers should consider surveying neighborhoods to collect these hidden social variables and incorporating them into the model. Future empirical models should also explore other non-linear relationships between crime rate and admissions. While this study found a positive relationship between crime rate and admissions rate, which is consistent with other previous works, the shape of the non-linear relationship differed. Further research building on the findings of this paper will help identify the “true” relationship between crime and incarceration and could lead to an alternative to the traditional theory that deviant behavior is best corrected through incapacitation, deterrence, rehabilitation, and retribution.

IV. REFERENCES

Becker, Gary S. ,"Crime and Punishment: An Economic Approach."Economic Analysis of the Law: 255-65. Doi:10.1002/9780470752135.ch25.

Brady-Lunny, Edith. "Overflow Forces McLean County to House Inmates Elsewhere." Pantagraph, February 24, 2015.

Bursik, Robert J., Jr., and Harold G. Grasmick." Neighborhood and Crime: The Dimensions of Effective Community Control." American Journal of Sociology 99, no. 5 (1994): 1387-1389.

"Bureau of Justice Statistics (BJS). "Bureau of Justice Statistics (BJS). Accessed April 20, 2016. http://www.bjs.gov/.

Clear, Todd R., Dina Rosa, Elin Waring, and Kristin Scully. "Coercive Mobility and Crime: A Preliminary Examination of Concentrated Incarceration and Social Disorganization." Justice Quarterly 20, no. 1 (2003):33-64.doi:10.1080/07418820300095451.

Clear, Todd R. " The Effects of High Imprisonment Rates on Communities. "Crime and Justice 37, no. 1 (2008): 97-132. Doi:10.1086/522360.

Cohen, Lawrence E., and Kenneth C. Land. "Age Structure and Crime:Symmetry Vensus Asymmetry and the Projection of Crime Rates Through the 1990s." American Sociological Review 52, no. 2 (1987): 170. Doi:10.2307/2095446.

Devine, Joel A., Joseph F. Sheley, and M. Dwayne Smith. "Macroeconomic and Social-Control Policy Influences on CrimeRate Changes, 1948-1985." American Sociological Review 53, no. 3 (1987): 407. Doi:10.2307/2095648.

Dhondt, Geert. "The Bluntness of Incarceration: Crime and Punishment in Tallahesse Neighborhoods, 1995 to 2002." Crime Law Soc Change Crime, Law and Social Change 57, no 5 (2012): 521-38. Doi:10:1007/s10611-012-9376-z.

Drakulich, Kevin M., Robert D. Crutchfield, Ross L. Matsueda, and Kristin Rose. "Instability, Informal Control, and Criminogenic Situations: Community Effects of Returning Prisoners. " Crime Law Soc Change Crime, Law and Social Change 57, no. 5 (2012): 493-519. doi: 10.1007/s10611-012-9375-0.

Golash, Deirdre. The Case against Punishment: Retribution, Crime Prevention, and the Law. New York: New York University Press, 2005.

Hannon, Lance and Peter Knapp. "Reassessing Nonlinearity in the Urban Disadvantage/Violent Crime Relationship: An Example of Methodological Bias from Log Transformation*." Criminology 41, no. 4 (2003): 1427-448. Doi 10.1111/j.1745-9125.2003.tb010126.x.

Hipp, John R., and Daniel K. Yates. "Do Returning Parolees Affect Neighborhood Crime? A Case Study of Sacramento." Criminology 47, no.3 (2009)619-56. Doi:10.1111/j.1745-9125.2009.00166.x.

Levitt, S.D. "The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation." The Quarterly Journal of Economics 111, no. 2 (1996): 319-51. doi: 10.2307/2946681.

Levitt, Steven D. “Understanding Why Crime Fell in the 1990s:Four Factors That Explain the Decline and Six That Do Not.” Journal of Economic Perspectives 18, no. 1 (2004): 163-90. Doi:10.1257/089533004773563485.

Luther,James B., Erica S.Reichert, Evan D. Holloway, Alexis M. Roth, and Matthew C. Aalsma. “an Exploration of Community Reentry Needs and Services for Prisoners: A Focus on Care to Limit Return to High-Risk Behavior.” AIDS Patient Care and STDs 25, no 8 (2011): 475-81.doi:10.1089/apc.2010.0372.

Lynch, James P., and William J. Sabol. “Effects of Arrests and Incarceration on Informal Social Control in Baltimore, Maryland, Neighborhoods, 1980-1994.” ICPSR Data Holdings. Doi:10.3886/icpsr03796

Marvell, T.B., and C.E. Moody. “The Impact of Prison Growth on Homicide.” Homicide Studies 1, no. 3 (1997): 205-33. Doi:10.1177/1088767997001003002.

Meares, Tracey L. “Law of Community Policing and Public Order Policing.” Encyclopedia of Criminology and Criminal Justice, 2014 2823-827. Doi:10.1007/978-1-4614-5690-2_543.

Morenoff, Jeffery D., and David J. Harding. “Incarceration, Prisoner Reentry, And Communities.” Annu. Rev. Sociol. Annual Review of Sociology 40, no. 1 (2014): 411-29. Doi: 10.1146/annurev-soc-071811-145511.

Morris, Norval, and David J. Rothman. The Oxford History of the Prison: The Practice of Punishment in Western Society. Nw York: Oxford University Press, 1995.

Murray, Joseph, and David P. Farrington. “Parental Imprisonment: Effects on Boys’ Antisocial Behavior and Delinquency through the Life-course.” J Child Psychol & Psychiat Journal of Chikd Psychology and Psychiatry 46, no. 12 (2005): 1269-278. Doi:10.1111/j.1469-7610.2005.01433.x.

Brian, Mann. “ The Drug Laws That Changed How We Punish.” NPR, February 14, 2013. http://www.npr.org/2013/02/14/171822608/the-drug-laws-that-changed-how-we-punish.

Carrie Johnson. “20 years Later, Parts Of Major Crime Bill Viewed As Terrible Mistake.” NPR, September 13, 2014. http://www.npr.org/2014/09/12/347736999/20-years-later-major-crime-bill-viewed-asterrible-mistake.

Renauer, B/C. “Tipping the Scales of Justice: The Effect of Overincarceration on Neighborhood Violence.” Criminal Justice Policy Review 17, no. 3 (2006): 362-79. doi.10.1177/0887403406286488.

Sherman, Lawrence W., Robert J. Bursik, and Harold G. Grasmick. “Neighborhoods and Crime: The Dimensions of Effective Community Control.” Contemporary Sociology 23, no. 1 (1994):112.doi10.2307/2074915.

Spelman, William. “Jobs or Jails? The Crime Drop in Texas.” J.Pol. Annual.Manage.Journal of Policy Analysis and Management 24, no. 1 (2004): 133-65.doi:10.1002/pam.20073.

Tittle, Charles, R,. and Raymond Paternoster, Social Deviance and Crime: An Organizational and Theoretical Approach. Los Angeles, CA: Roxbury., 2000.

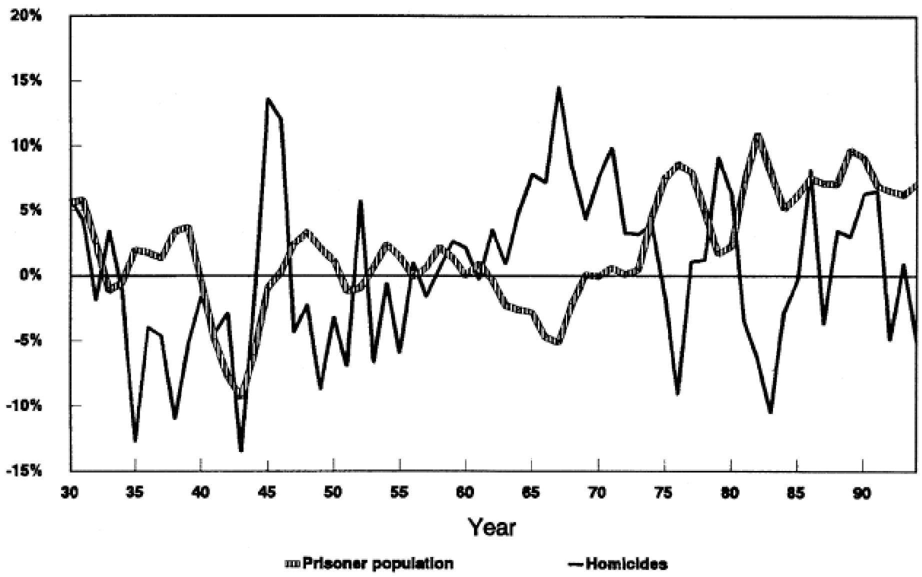
Uggen, Christopher, and Melissa Thompson. “The Socioeconomic Determinants of Ill-Gotten Gains: Within-Person Changes in Drugs Ise and Illegal Earnings1. “American Journal of Sociology 109, no. 1 (2003): 146-85. Doi:10.1086/378036.

Visher, Christy A., Sara A. Debus-Sherrill, and Jennifer Yahner. "Employment After Prison: A Longitudinal Study of Former Prisoners." Justice Quarterly28, no. 5 (2011): 698-718. Doi:10.1080/07418825.2010.535553.

Zimring, Franklin, and Gordon Hawkins. "Deterrence: The Legal Threat in Crime Control." Stanford Law Review 25, no. 4 (1973): 6577. doi: 10.2307/1227719.

V. APPENDIX

<u>Graph 1</u>: Annual Changes in Homicide and Prison Population Rates, 1930- 1994



*Provided by (Marvell 1997)

***Figure 1**: Data Summary*

	Mean	Std. Dev.	Min.	Max.
Total Number of Incidents in a Neighborhood	136.89	119.86	5	604
Total Number of Incidents in a Neighborhood and Adjacent Neighborhood	931.00	444.69	151	2166
Neighborhood Crime Rate	0.04	0.04	0.002	0.264
Adjacent Area Crime Rate	0.04	0.02	0.009	0.093
Neighborhood (Census Tract) Population	4210.87	2351.34	1123	12446
Total Admissions from a Neighborhood	124.41	104.29	9	480
Admissions Rate for a Neighborhood	0.04	0.04	0.003	0.219
Neighborhood Violent/Drug Crime Admissions Rate	13.87	13.73	0	64
Total Number of Area Violent/Drug Crime Admissions	92.10	57.65	8	273
Total Number of Area Violent/Drug Crime Rate	0.00	0.00	0.000	0.014
Median Earning (25+ year of age)	$ 41,478	$ 11,981	$ 11,786	$77,409
Education Attainment (25+ year of age)	0.94	0.04	0.720	0.998
Employment Rate	0.64	0.08	0.329	0.814
Residential Stability	0.79	0.14	0.226	0.951
Percent Black	0.09	0.09	0.000	0.384

Figure 2: Cook's D Values

Census Tract 2 (Illinois State University)	
Year	**Cooks D Predictor**
2013	**0.531**
2014	**0.229**
2015	**0.331**
2016	**1.196**
2017	**0.769**

Census Tract 13.02 (Illinois Wesleyan University)	
Year	**Cooks D Predictor**
2013	**0.190**
2014	**0.309**
2015	**0.115**
2016	**0.077**
2017	**0.146**

Figure 3: **Data Summary of Removed Outlier Observations**

Census Tract 2 (Illinois State University)	Mean	Std. Dev	Min	Max
Total Number of Incidents in a Neighborhood	228.2	111.0032	142	417
Total Number of Incidents in a Neighborhood and Adjacent Neighborhood	1699.6	277.15	1431	2166
Neighborhood Crime Rate	0.049	0.024	0.027	0.089
Adjacent Area Crime Rate	0.048	0.009	0.039	0.058
Neighborhood (Census Tract) Population	4783	1242	3679	6896
Total Admissions from a Neighborhood	150.40	33.86	112	196
Admissions Rate for a Neighborhood	0.032	0.008	0.025	0.047
Neighorhood Violent/Drug Crime Admissions Rate	12.2	6.942622	1	20
Total Number of Area Violent/Drug Crime Admissions	121	12.51	101	132
Total Number of Area Violent/Drug Crime Rate	0.003	0.001	0.003	0.004
Median Earning (25+ year of age)	$27,508	$9,190	$11,786	$32,989
Education Attainment (25+ year of age)	0.844	0.085	0.72	0.94
Employment Rate	0.409	0.126	0.329	0.629
Residential Stability	0.392	0.286	0.226	0.901
Percent Black	0.091	0.054	0.013	0.159

Census Tract 13.02 (Illinois Wesleyan University)	Mean	Std. Dev	Min	Max
Total Number of Incidents in a Neighborhood	54.4	12.19836	45	75
Total Number of Incidents in a Neighborhood and Adjacent Neighborhood	918	89.42874	852	1073
Neighborhood Crime Rate	0.02	0.007	0.011	0.031
Adjacent Area Crime Rate	0.058	0.020	0.023	0.079
Neighborhood (Census Tract) Population	2772.8	772.8653	2371	4150
Total Admissions from a Neighborhood	42	9.974969	33	58
Admissions Rate for a Neighborhood	0.016	0.005	0.011	0.024
Neighorhood Violent/Drug Crime Admissions Rate	8.4	2.302173	6	12
Total Number of Area Violent/Drug Crime Admissions	136.8	11.7983	119	147
Total Number of Area Violent/Drug Crime Rate	0.009	0.003	0.004	0.01
Median Earning (25+ year of age)	\$34,470	\$5,118	\$2,8125	\$41,000
Education Attainment (25+ year of age)	0.966	0.013	0.945	0.978
Employment Rate	0.468	0.08	0.427	0.611
Residential Stability	0.516	0.184	0.404	0.842
Percent Black	0.062	0.03	0.012	0.095

<u>Figure 4</u>: Correlation Table (Tests for Multicollinearity)

	Admiss~e	Admiss~2	Admiss~3	Median~a	Educat~a	Employ~e	Reside~y	Percen~k
AdmissionR~e	1.0000							
AdmissionR~2	0.9345	1.0000						
AdmissionR~3	0.8358	0.9723	1.0000					
MedianEarn~a	-0.5399	-0.3909	-0.2969	1.0000				
EducationA~a	-0.4846	-0.4055	-0.3304	0.4623	1.0000			
EmployedRate	-0.2595	-0.2376	-0.2017	0.3526	0.5107	1.0000		
Residentia~y	-0.1272	-0.0448	-0.0082	0.3177	0.1127	0.3800	1.0000	
PercentBlack	0.5700	0.4885	0.4074	-0.4041	-0.2400	-0.1223	-0.2286	1.0000

Figure 5: Variance Inflations Factors (Tests for Multicollinearity)

Variable	VIF	1/VIF
TotalAdmis~s	2.45	0.407457
MedianEarn~a	1.86	0.536485
EducationA~a	1.83	0.547570
PercentBlack	1.73	0.576978
EmployedRate	1.64	0.611002
Residentia~y	1.32	0.758065
TractPopul~g	1.25	0.800861
Mean VIF	1.73	

Figure 6: Durbin and Wu-Hausman (Tests for Endogeneity)

	Durbin	Wu-Hausman	First-Stage Regression Summary Statistics	
	P-value	P-value	F Stat	Partial R-squared
2013	0.0012	0.0021	29	0.4821
2014	0.3571	0.4128	40	0.5607
2015	0.0031	0.0054	33	0.5092
2016	0.0377	0.0584	91	0.7403
2017	0.0377	0.0584	60	0.6525

Figure 7: Results

Equation (1)

```
Fixed-effects (within) IV regression            Number of obs     =        195
Group variable: CensusTract                     Number of groups  =         39

R-sq:                                           Obs per group:
     within  =      .                                         min =          5
     between = 0.5740                                         avg =        5.0
     overall = 0.4818                                         max =          5

                                                Wald chi2(6)      =    1886.15
corr(u_i, Xb)  = -0.6237                        Prob > chi2       =     0.0000
```

AdjacentAreaCrimeRate	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
AdmissionRate	.5720663	.1244618	4.60	0.000	.3281258	.8160069
MedianEarningover25yoa	3.08e-08	1.71e-07	0.18	0.857	-3.04e-07	3.66e-07
EducationAttainment25yoa	.00892	.0425275	0.21	0.834	-.0744324	.0922725
EmployedRate	-.0032228	.0226958	-0.14	0.887	-.0477057	.0412602
ResidentialStability	-.0281187	.012611	-2.23	0.026	-.0528359	-.0034015
PercentBlack	.0271597	.0155131	1.75	0.080	-.0032453	.0575648
_cons	.0261176	.0364201	0.72	0.473	-.0452645	.0974997
sigma_u	.01439833					
sigma_e	.01114683					
rho	.62525494	(fraction of variance due to u_i)				

```
F  test that all u_i=0:     F(38,150) =     4.12          Prob > F     = 0.0000

Instrumented:   AdmissionRate
Instruments:    MedianEarningover25yoa EducationAttainment25yoa EmployedRate
                ResidentialStability PercentBlack DrugViolentAdmissionAdjRate
```

Equation (2)

```
Fixed-effects (within) IV regression           Number of obs      =       195
Group variable: CensusTract                    Number of groups   =        39

R-sq:                                          Obs per group:
     within  =      .                                        min =          5
     between = 0.4889                                        avg =        5.0
     overall = 0.4187                                        max =          5

                                               Wald chi2(7)       =    1494.34
corr(u_i, Xb)  = -0.7880                       Prob > chi2        =     0.0000
```

AdjacentAreaCrimeRate	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
AdmissionRate_cen	1.209111	.280123	4.32	0.000	.6600801	1.758142
AdmissionRate_cen2	-7.721713	2.419357	-3.19	0.001	-12.46357	-2.979859
MedianEarningover25yoa	-6.70e-08	1.94e-07	-0.35	0.729	-4.46e-07	3.12e-07
EducationAttainment25yoa	-.0225559	.0476774	-0.47	0.636	-.1160019	.0708901
EmployedRate	-.024895	.0266235	-0.94	0.350	-.077076	.027286
ResidentialStability	.0014034	.0156979	0.09	0.929	-.0293639	.0321707
PercentBlack	.0485589	.0187028	2.60	0.009	.011902	.0852158
_cons	.0798705	.0398339	2.01	0.045	.0017975	.1579436
sigma_u	.02151907					
sigma_e	.01253858					
rho	.74654277	(fraction of variance due to u_i)				

```
F  test that all u_i=0:     F(38,149) =     3.41          Prob > F     = 0.0000

Instrumented:   AdmissionRate_cen AdmissionRate_cen2
Instruments:    MedianEarningover25yoa EducationAttainment25yoa EmployedRate
                ResidentialStability PercentBlack DrugViolentAdmissionAdjRate_cen
                DrugViolentAdmissionAdjRate_cen2
```

Equation (3)

```
. xtreg AdjacentAreaCrimeRate AdmissionRate MedianEarningover25yoa EducationAttainment25yoa EmployedRate Reside
> ntialStability PercentBlack Admissiont1, fe

Fixed-effects (within) regression               Number of obs     =        156
Group variable: CensusTract                     Number of groups  =         39

R-sq:                                           Obs per group:
     within  = 0.2318                                         min =          4
     between = 0.3831                                         avg =        4.0
     overall = 0.3536                                         max =          4

                                                F(7,110)          =       4.74
corr(u_i, Xb)  = 0.0412                         Prob > F          =     0.0001
```

AdjacentAreaCrimeRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
AdmissionRate	.1605294	.0335049	4.79	0.000	.0941304	.2269283
MedianEarningover25yoa	-2.70e-07	1.91e-07	-1.42	0.160	-6.49e-07	1.08e-07
EducationAttainment25yoa	-.0055814	.0332538	-0.17	0.867	-.0714827	.0603199
EmployedRate	-.0086969	.0167895	-0.52	0.606	-.0419697	.024576
ResidentialStability	-.0044191	.0082417	-0.54	0.593	-.0207522	.011914
PercentBlack	.0243983	.0107928	2.26	0.026	.0030095	.0457871
Admissiont1	-.0987208	.0759665	-1.30	0.196	-.2492687	.051827
_cons	.0543286	.0300939	1.81	0.074	-.0053106	.1139677
sigma_u	.01158618					
sigma_e	.00744609					
rho	.70770204	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(38, 110) = 3.20                     Prob > F = 0.0000
```

Equation (4)

```
. xtreg AdjacentAreaCrimeRate AdmissionRate_cen AdmissionRate_cen2 MedianEarningover25yoa EducationAttainment2
> yoa EmployedRate ResidentialStability PercentBlack Admissiont1, fe

Fixed-effects (within) regression               Number of obs     =        156
Group variable: CensusTract                     Number of groups  =         39

R-sq:                                           Obs per group:
     within  = 0.3057                                         min =          4
     between = 0.4271                                         avg =        4.0
     overall = 0.4013                                         max =          4

                                                F(8,109)          =       6.00
corr(u_i, Xb)  = -0.2112                        Prob > F          =     0.0000

------------------------------------------------------------------------------------------
 AdjacentAreaCrimeRate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
     AdmissionRate_cen |   .3321484   .0596735     5.57   0.000     .2138774    .4504194
    AdmissionRate_cen2 |  -1.341671   .3937756    -3.41   0.001    -2.122121   -.5612205
  MedianEarningover25yoa |  -3.05e-07   1.83e-07    -1.67   0.098    -6.67e-07    5.73e-08
EducationAttainment25yoa |  -.0072536   .0317614    -0.23   0.820    -.0702037    .0556965
          EmployedRate |  -.0116853   .0160581    -0.73   0.468    -.0435119    .0201413
  ResidentialStability |  -.0024428   .0078922    -0.31   0.758    -.0180849    .0131994
          PercentBlack |   .0277658   .0103545     2.68   0.008     .0072436    .0482881
           Admissiont1 |  -.0787303   .0727854    -1.08   0.282    -.2229887     .065528
                 _cons |   .0644304   .0286835     2.25   0.027     .0075807    .1212802
-----------------------+------------------------------------------------------------------
               sigma_u |  .01144022
               sigma_e |  .00711106
                   rho |  .72130957   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
F test that all u_i=0: F(38, 109) = 3.60                     Prob > F = 0.0000
```