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Crime, Income Inequality, and Density at the Neighborhood Level

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CRIME, INCOME INEQUALITY, AND DENSITY AT THE NEIGHBORHOOD LEVEL

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Abstract

An economic model of crime gives policymakers a basis to understand how income inequality and population density relate to crime at the neighborhood level. This study reveals a negative and significant relationship between population density in Census tracts and both property and violent crime rates. It finds ambiguous results that vary by city for income inequality. This cross-sectional analysis of Census tracts in Chicago, Los Angeles, Houston, and Dallas uses crime and demographic data from the National Neighborhood Crime Study. This study also yields interesting results about the importance of residential stability for crime prevention and comments on possible urban design tools for crime reduction.

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I. Introduction

Crime is a form of blight on communities throughout the world. It causes individuals and organizations to have lower confidence in their safety and hence devote resources for their security. It is a disruption to normal commerce and life, and it is often influenced by economic factors. Individuals or groups who commit crime often knowingly choose to do so, and hence these economic factors become important in understanding how to mitigate crime.

Crime is often used as an indicator of the overall health and vitality of a community. More specifically, economists are concerned with how public policies and other factors of economic health influence the occurrence of crime. Studies of crime through an economic lens began most notably with Nobel-prize winning economist Gary Becker's (1968) description of the ecological theories of crime. More recently, *Freakonomics* author and economist Steven Levitt (2001, 2009) has studied determinants of crime ranging from increased incarceration for drug-related crime to the effects of *Roe v. Wade*. Edward Glaeser's studies in urban economics frequently include examinations of crime as an indicator of city health (1998; 2010). Policy scholar and economist Phillip Cook (2009) looks closely at different public and private measures for preventing crime, starting from a regression analysis at the county level. These findings are a starting point for this paper.

Understanding the determinants and deterrents of crime at the neighborhood level helps local government officials formulate policies to combat crime. While the economics literature has a wide array of studies on crime, there are some gaps in addressing crime-related economic questions at a granular level. This study examines factors that influence individuals' decisions to supply crime. In particular, the relationships between income inequality and crime rates and between population density and crime rates are central points of examination. Understanding these relationships can help identify policies to reduce the supply of crime.

This study finds a negative association between the population density of a Census tract and the rates of both property and violent crimes. It finds ambiguous relationships between income inequality and crime rates in three of the four cities observed, contrary to most previous findings. The rate of housing vacancy in Census tracts stands out as a significant, positive descriptor of crime rates. The conclusion is that certain urban development policies focused on creating safe spaces and lively communities can help to reduce crime. However, more specific study of neighborhoods and generalization to more cities would help to make the findings of this study more relevant to policymakers. The regression model utilized fits the variation in violent crime better than for property crime, suggesting that further study on the different motivations for each of these crimes can help pinpoint different models for different crimes' supply functions.

This paper analyzes crime and its determinants at the Census tract level. Reference to "neighborhoods" in this paper hereafter refers to Census tracts. Neighborhoods, as organic units of community, do not follow Census tract lines, and that interaction among neighbors is a continuous spectrum rather than distinctly cut-off at tract boundaries. Nonetheless, this is the smallest observational unit for which many of the data are readily available.

The next section discusses an economic model of crime to provide an understanding of individuals' motivations to commit crime and the process by which society reaches an equilibrium level of crime. Section III reviews the relevant literature on this topic. Section IV describes the quantitative methodology for empirically testing the hypotheses and calculations particular to some of the variables. Section V describes the data for this analysis, and Section VI discusses the results of the regression analysis. The last two sections conclude with a summary of the findings of this study, their importance to policymakers, and topics future researchers can pursue to improve on this study.

II. Understanding the Economics of Crime

Understanding the occurrence of crime in a given area requires an examination of both the motivations of individuals to commit crime and the ability of citizens to prevent crime. An economic model of crime can help reveal these motivations. Becker (1968) and Cook (1986) have done important work in illustrating the market interaction between victims and offenders. This section illustrates a model that involves a market for criminal opportunities where society supplies criminal opportunities and where potential criminals consume these opportunities. This pairs with a market for criminal offenses in which any potential criminal is a supplier of crime and society is a "buyer." Central to this model are the costs to committing crime, the payoff to crime, and the probability and penalties of being caught.

Becker's (1968) paper focuses mostly on optimal levels of deterrence and crime allowed based on the total social welfare gains or losses due to crime. His discussion is important to understanding how society supplies criminal opportunities. Society supplies criminal opportunities based on the costs of prevention, deterrence, and apprehension to reduce crime. On the level of individual motivation, he points out the basic economic reasoning that an individual will choose to commit crime when the expected benefits outweigh the expected costs. This and other factors that influence the expected benefits to crime affect the willingness of individuals to supply criminal offenses.

Cook (1986) connects the supply of crime with a market for criminal opportunities. It can be difficult to think of how or why potential victims "supply" criminal opportunities. Just as Becker describes the socially optimal supply of criminal opportunities, Cook explains this supply as deriving from individuals' actions to mitigate the potential for crime to occur or to reduce the harm of crime to the victims. The opportunities supplied are those that cannot be prevented. Criminals have more demand for those opportunities that have higher payoff, and "tend to be somewhat selective in choosing a crime target and are most attracted to targets that appear to offer a *high payoff* with *little effort* or *risk of legal consequences"* (emphasis added) (Cook 1986, 2). It is to the benefit of society to find ways to 1) reduce the payoff to the criminal, 2) increase the effort for the criminal, or 3) increase the risk of consequences for the criminal. The following model for this study focuses on understanding these concepts and how policymakers can use this as a framework to reduce crime.

If individuals are rational agents who seek to maximize the net benefits from their actions, then any individual is a potential criminal. It is important to keep in mind that potential criminals almost always lack perfect information about the payoff from their criminal activities. So the decisions to commit crime are based on *expected* returns. Therefore, the decision to commit a crime involves weighing the expected costs and benefits. In this model, the costs of committing a crime by an individual are a function of the probability of apprehension and punishment (ρ_i) multiplied by the expected severity of punishment (r_i) for each crime. Punishment may be a cost in time served in prison or fines paid. This term can be considered a probability-punishment profile. For each crime committed by individual i this cost is expressed as:

$$C_i = (\rho_i(q) * r_i(q)) \,. \tag{2.1}$$

Note that ρ_i and r_i are functions of q where q is the number of crimes committed. Therefore, $\rho'_i(q)$ and $\rho''_i(q)$ are both positive. It implies that as the number of crime increases the probability of apprehension and punishment increases at an increasing rate. Similarly, $r'_i(q)$ and

$r''_i(q)$ are both positive implying that the severity of punishment increases at an increasing rate with each crime committed.

The commission of each crime will also have costs related to the planning and action of the crime. This can be thought of as the opportunity cost in capital and labor investment in the production of a crime, expressed as K. For some crimes, such as a premeditated murder, this cost might be very high, requiring meticulous planning and high capital investment in a weapon or other tools. Others, such as a spontaneous assault, may have little to no cost in terms of planning time or capital investment. The marginal costs to crime will in some cases be constant, but in other cases be related to the number of crimes not only of the same type but also to crimes of different types. For instance, a criminal who has committed a number of burglaries and is arrested for a motor-vehicle theft must include in her punishment function the probability-punishment profile of the previous burglaries given arrest for the motor-vehicle theft. The probability of arrest from previous crimes continues to be a factor with each additional new crime, creating a compounding effect. This suggests that there may be increasing marginal costs to supplying crimes. Therefore, the total cost of committing crime is:

$$\rho_i(q) * r_i(q) + Kq \; . \tag{2.2}$$

The marginal benefit an individual receives when committing a crime is represented as P. Cook (1986) terms this the "payoff" to each crime. This can be thought of as the price received by a supplier in a transaction. The marginal returns to crime will almost certainly be diminishing. Together, this creates a net benefit (Π) as a function of the number of crimes (q). This is analogous to a firm's profit function where profit is equivalent to the difference in total revenue and total cost. For each individual crime, any time Π exceeds zero, the individual will commit the crime. Each individual will attempt to maximize their own net benefit with respect to the number of crimes. To maximize $\Pi(q)$ with respect to q, one finds the first derivative of the net benefit function (2.3) with respect to q and sets it equal to zero, and solves for the optimal q. A second-derivative test confirms that the optimization point found in the first step is indeed a maximum when the second derivative of $\Pi(q)$ with respect to q is negative. The maximization process is as follows:

$$Max\ \Pi_i(q) = P_i(q) * q - (\rho_i(q) r_i(q) + Kq) \; . \tag{2.3}$$

$$Maximization\ Condition\colon\ \Pi'(q) = 0;\ \ \Pi'' < 0 \; . \tag{2.4}$$

Solving for q yields the net benefit maximizing level of crime for an individual to commit. Without knowing more about the functional forms of P, ρ, or r, one cannot derive an explicit optimal level of crime, q^*. Given equation (2.3), we can state the optimal amount of q as:

$$q_i^* = \frac{\rho'_i(q) r_i(q) + \rho_i(q) r'_i(q) + K - P(q)}{P'(q)} \quad . \tag{2.5}$$

This is still an implicit solution but provides a clearer look at how to solve for q. The costs are expressed as positive and the payoff function $P(q)$ is positive. For crime to occur in the first place $P(q)$ is greater than the first derivative of the cost function, making the numerator negative. Since the demand curve for offenses—that is, the crimes that society is unable to abate—is negatively sloped, $P'(q)$ is negative. Therefore, q^* is a positive value.

From this framework, one can conceptualize the potential to commit multiple crimes and understand how crime occurs in a geographic area, rather than on an individual basis. A strong assumption here is that all individuals are homogenous in nature, so one can sum up the behavior of all individuals in a neighborhood to discuss the neighborhood effects. This yields an overall expected quantity of crime for a particular observation unit of:

$$Q^* = \sum_{i=1}^{n} q_i^* \, . \tag{2.6}$$

As individuals commit more crimes, it is reasonable to expect that the payoff to each additional crime decreases. The costs on the other hand, will likely tend to increase. Consider the individual from the earlier example who has committed a number of serial burglaries. If she is apprehended for one of the crimes, prosecutors will be more likely to find evidence to convict her for her previous crimes as well, thereby raising the severity of punishment. Thus, in decisions to commit crime, individuals experience increasing marginal costs and decreasing marginal revenue. It is important to keep in mind that most individuals find the costs of supplying crime to be so great as to prevent them from entering most crime markets. While any given individual may find exceeding the speed limit to be an overall profitable activity, society has erected structures to cause the costs to burglary to be high enough that most individuals will not supply burglaries.

Rather than attempt to model the net benefit gained from crimes or probability-punishment profiles accepted by criminals, this study focuses on neighborhood characteristics that affect either the payoffs to crime or the probability of apprehension. The literature review fills out the theoretical framework by determining what social and economic factors may be at play in the net benefit equation for crime. It also identifies some existing policies that target reduction in the supply of crime through reducing criminal opportunities or the net benefit for criminals.

III. Literature Review & Theoretical Grounding

The theoretical model requires identifying quantifiable factors that contribute to crime. One can build an understanding of these factors by drawing on economic intuition and the contributions of previous work in economics, criminology, sociology, and urban studies. Table 3.1 gives insight into each of the variables included in the regression analysis and how they are included in the theoretical model.

Table 3.1: Theoretical Basis of Variables

Variable	*Theoretical Relationship with Crime*	*Parameter Affected*	*Expected Sign*
Population Density	Decreases probability of arrest	ρ	-
Gini Coefficient	Increases expected returns	P	+
Per Capita Income	Expected returns and opportunity cost	P, K	?
Poverty Rate	Decreases opportunity cost or increases expected returns	K, P	+
Unemployment Rate	Decreases opportunity cost	K	+
Housing Value	Increases expected returns	P	?
High School Graduation Rate	Increases social cohesion	P	-
Female-headed-Households	Decreases social cohesion	P	+
New Immigrants	Severity of punishment, social cohesion	r, P	+
Percent White	Severity of punishment , opportunity cost	r, K	-
Percent Black	Severity of punishment , opportunity cost	r, K	+
Percent Hispanic	Severity of punishment , opportunity cost	r, K	+
Percent Asian	Severity of punishment , opportunity cost	r, K	-
Racial Diversity Index	Social cohesion	K	-
Vacancy Rate	Probability of arrest, social cohesion	ρ, P	+
Percent of Movers	Probability of arrest, social cohesion	ρ, P	+
Percent Renters	Probability of arrest, social cohesion, expected returns	ρ, P	+

Studies examining Census tracts are often more difficult to find. Kreager, Lyons, and Hays (2011) provide a helpful study of the relationship between gentrification and crime at the Census tract level. Krivo and Peterson's (2009) study on racial composition and crime in Census tracts also provides insight. As Kelly (2000) explains, income inequality is a source of social angst and can also make crime more rational from an economic standpoint. Highly unequal areas provide more incentive to target those at the upper end of the income distribution. The relationship between population density and crime is a matter of incentives to commit or avoid crime based on the density of targets and deterrents. Harvard urban economists Edward Glaeser and Bruce Sacerdote (1999) explain the impact of population density on the probability of success or failure of a criminal act. The literature identifies many other factors of urban neighborhood life as important to crime rates. The following sub-sections provide a closer look at these other factors that determine crime rates. The concluding sub-section includes a brief review of policies that draw together urban planning and crime prevention.

a. Variables of Interest

Income inequality's influence on the returns to crime is widely discussed in the literature. The social distress caused by inequality might increase expected benefit to committing a crime for lower income individuals. With potential victims of a higher income in the same vicinity, one should expect the monetary payoff to property crime to be higher. Kelly (2000) shows a significant, positive relationship between violent crime and inequality but does not find a significant result for property crime on the county level. Jesse Brush's (2007) similar study shows a positive relationship between inequality and both property and violent crime.

Only a few studies have confronted the relationship between crime and income inequality at the neighborhood level. Most studies observe counties (Morgan 2000; Brush 2007). Kreager, Lyons, and Hays (2011) study gentrification from 1990 to 2000 in Seattle Census tracts. They found that as neighborhoods first began to gentrify, as measured by property values, racial composition, and mean household income, crime increased. Once a gentrification transition became more complete and neighborhoods became more homogenous in wealth and demographic composition, crime rates subsided. This suggests that the introduction of inequalities and other heterogeneities places stress on a neighborhood that is manifested in crime.

Whitworth (2013) provides insight into why the inequality-crime relationship behaves differently at different geographical levels and densities. His study shows how the relationship between income inequality and crime varies as one extends the area of observation. He begins by looking at each middle layer super output area (MSOA)[1] in London and South Yorkshire, United

[1] MSOAs have an average population of 7,200, making them somewhat more populous than an urban U.S. Census tract.

Kingdom. He assesses the elasticity of crime with respect to inequality between MSOAs by averaging the inequality of a central observation MSOA compared to those first within one contiguous ring, then two layers of contiguity around it, and so on for 10 layers. Whitworth finds that for the dense city of London, the relationship between the inequality and crime becomes more positive as the observation size grows. For the less dense city of South Yorkshire, the relationship becomes less negative as the observation size grows, even becoming negative after eight layers are included in the observation. This variation in the relationship with different observation sizes may be apparent in the findings for this study at the Census tract level.

One expects a positive relationship between income inequality and both property and violent crime. Inequalities in income motivate people to seek more income if they are in the lower portion of the income distribution. Some individuals may be driven to property crime as an alternative source of income. Violent crime, with the exception of robbery, is less rational in this regard because it does not have financial benefit except when it is either done for pay or is an externality of a property crime. Dissatisfaction and frustration resulting from inequalities seem more likely to influence an individual to commit violent crimes than prospects of financial gain.

The relationship of population density and crime is a difficult one to predict because of the differing effects of population density on the probability of apprehension and supply of criminal opportunities. Journalist and urban theorist Jane Jacobs' (1961) theory on the health of cities centers on the importance of density, defensible space, and diversity in economic and social use of spaces. Studies like Craglia et al (2001) and Watts (1931) find a positive association between crime and density, contrary to Jacobs' idea that more "eyes upon the street" deter crime (1961, 44). Glaeser and Sacerdote (1999) suggest that a higher concentration of potential targets and low probability of recognition increases the likelihood of criminal incidents. However, despite her lack of empirical support, Jacobs's eyes on the street idea is also a viable economic idea. In a residential neighborhood, individuals who interact frequently have more incentive to prevent crime from occurring in their neighborhood because it detracts from the standard-of-living of the neighborhood and individual neighbors. Thus, with more individuals to be potential witnesses to crime in a densely populated neighborhood, a criminal has a higher probability of being held accountable for his or her actions.

Criminologist Dennis Roncek (1981) finds some evidence to support that smaller units of observation show negative relationships between density and crime. He studied the cities of

Cleveland (relatively high density) and San Diego (relatively low density) and found that population density had negative and significant relationship with property crime among city blocks. The relationship is negative and significant for violent crime in Cleveland, but not in San Diego. Although Cleveland is a more dense city and has an overall higher crime rate than San Diego, the elasticity of property crime with respect to density for Cleveland is -0.331 compared to only -0.063 for San Diego. A stronger negative relationship between density and crime is present for the denser city. This certainly warrants further investigation.

The literature on public housing shows that density corresponding with a high concentration of poverty or disadvantage is more concerning for crime (see, e.g. Popkin et al. (2012)). This may be due to a social divide that changes the economic motivations of individuals in poorer neighborhoods compared to wealthier ones. Disadvantaged individuals may be less likely to report crime or prevent it as bystanders for a number of reasons. First, an individual may fear that the obligations of being a witness interfere with earnings and employment activities. Second, a fear of retaliation might be greater in a poorer neighborhood than in a wealthier one, regardless of population density. Third, since poorer individuals are in general more likely to commit crime, they may shy away from interference or reporting for fear of having their own criminal activities discovered. The current study predicts a negative relationship between population density and crime rates. It may become evident that as lower incomes are paired with higher density, crimes become higher than in denser, high income areas. This opens up discussion for other factors that may contribute to the supply of crime.

b. Background Literature on Other Variables

Many other factors are expected to have effects on the supply of different types of crime and have been reliably shown to have significant relationships in previous studies. Each of these factors has some influence on the probability of apprehension, the input costs, or the expected return to crime.

Socioeconomic Characteristics

Income and poverty are two important characteristics to examine. Their places in the theoretical model are difficult to parse because they can impact opportunity costs and expected benefits simultaneously. Lower income individuals will have a greater expected benefit to crime, both explicitly from property crime and through the implicit benefit of violent crime. Relative opportunity costs to incarceration will be lower for these individuals, while opportunity costs to fines will be higher relative to their incomes. This would cause one to expect income to have a negative relationship with violent crime rates. The case is less obvious for property crime, since higher income tracts are more attractive targets for crime. So for property crime, higher income raises the expected benefit of the crime but also raises the opportunity cost for criminals. Similarly, poverty can be expected to relate positively with violent crime rates, but the hypothesized association with property crimes is unclear. Since poverty indicates both financial and social marginalization, this positive relationship should be expected for both property and violent crime rates.

Housing value can serve as a very visible indicator of financial well-being. Neighborhoods with higher housing value would tend to have more incentive to protect their homes and the means to do so. On the other hand, a higher-valued home may attract more burglars because they expect the return to their crime to be higher. The unemployment rate also stands out as an important control variable. Levitt (2004) shows that the unemployment rate is positively related to crime rates. The opportunity costs to crime decrease if an individual is unemployed because they will have more time to plan and commit the crime. The relative expected benefit is also higher because the individual may lack legitimate sources of income.

The socioeconomic standing of a neighborhood can be indicated not only by explicit indicators of financial well-being like income, housing value, or unemployment rate, but also factors like education and the percent of female-headed households. Greater levels of education not only open up individuals' possibilities for legitimate earning activities, but also may be a proxy for a greater level of social cohesion or willingness of an individual to conform to social rules and expectations. The high school graduation rate serves as this proxy and one expects it to have a negative relationship with crime rates. Other studies have included this as a control variable, finding a negative relationship, including Cook (2009) and Krivo and Peterson (2011). Another commonly used control variable is a measure of social disorganization as proxied by the percent of female-headed households. In addition to being more likely to be in poverty, female-headed households indicate a lack of adult male engagement with family and community. This also suggests a lack of male role models for young men in a neighborhood. Cook (2009) shows positive relationships between the percent of female-headed households and both robbery and murder. Glaeser and Sacerdote (1999) show that individuals from a female-headed household are more likely to be victims of crime and those areas with more female-headed households have higher rates of crime.

Racial Characteristics

Other important population control variables are those to do with race and ethnicity. Most major crime studies control for race, and some go as far as to examine racial diversity. Criminologists Krivo and Peterson (2011) study how interactions among different races relate with crime as a measure of social tension. Cook (2009) uses the percent of Hispanics and blacks as a control in his regression analysis of crime rates across U.S. counties. Building on these ideas, this study includes the percent composition of white, black, Hispanic, and Asian as defined by the U.S. Census and additionally measures the racial diversity of these tracts with a specially constructed index described in more detail in Section IV. This study also adds the percent of new immigrants to understand whether immigrant populations experience or impact crime differently. New immigrants may have less connection to their surrounding community and thus less incentive to protect it, suggesting a positive relationship with crimes. Asians and whites are expected to have a negative relationship with crime, and Hispanics and blacks are expected to have a positive relationship. The latter races are historically more marginalized than Asians and whites and are thus expected to have more reason to commit property crimes. Another important factor to consider is the probability of apprehension and conviction as well as the severity of conviction. New immigrants and non-whites tend to experience the criminal justice system differently than native-born, white citizens.

As racial diversity increases, the ties and relationships between members of a neighborhood may diminish, creating a higher level of social disconnect and thus a higher expected return to violent crime. For this reason, one can expect the strength of a negative relationship between the Racial Diversity Index and crime to be greater for violent crime than property crime.[2] Racial composition variables give an indication of the social status of a neighborhood.

Housing Characteristics

In addition to all these indicators, attributes relating to stability and housing can reveal a lot about a neighborhood population's behavior toward the space in which they live. Vacancy rates are used as a proxy for neighborhood decay indicating social disorganization and lack of

[2] The Racial Diversity Index used here has lower values for more diverse tracts. See Section IV.

care. Ellen, Lacoe, and Sharygin (2013) find that foreclosed properties tend to indicate residential instability or decay and positively correspond with crime rates. Ciu (2010) finds that high vacancy rates as a result of foreclosed homes relate with increased violent crime. The percent of recent movers is also used to indicate whether residents of an area are likely to be unfamiliar to that area or less attentive to activity within it. The lack of care for a neighborhood and fewer neighbors attending to crimes would decrease the probability of apprehension in a neighborhood, allowing the crime rate to rise. Similarly, rental rates (or, inversely, ownership rates) indicate a lower incentive to monitor crimes and prevent them. Again, this lowers the probability of apprehension, leading to a positive association with crime rates. Concerns about endogeneity can arise with variables like the percent of recent movers and the vacancy rate. People are less likely to want to move to neighborhoods with high crime rates, so vacancy rates might increase, and the neighborhood may be more transient, causing an increase the percent of recent movers.

With background on the factors that influence the supply of crime, one can turn to understanding some of the policy tools that exist to target crime. This study takes a particular focus on how space can be planned to raise the costs to committing crime.

c. Policy Background

Criminologist and urban planner Derek Paulsen (2013) points out that many planners see the importance of finding ways to combat crime and that many police departments see the importance of the built environment to crime. However, studies to combine the two are limited. Jane Jacobs introduced the discussion with her 1961 book and many ideas of how the built environment creates social control have blossomed since. One of the foremost theories of planning to reduce crime is "defensible space." Oscar Newman (1973) based this theory on the principle that giving residents control and a sense of ownership over their neighborhoods through private partition creates incentive for them to surveil it. Paulsen (2013) explains a different set of principles based on well-moderated diversity of uses and connectivity of streets.

Defensible space principles aim to divide spaces among residents to encourage them to protect their individual space. Newman (1996) shows in a policy memo that developers can create this sense of ownership through dividing up space through fences, constructing row houses instead of towers, or separating high-traffic arterial roads from residential access avenues. Former Secretary of Housing and Urban Development Henry Cisneros (1996) points out that many components of defensible space design can be implemented inexpensively and easily. The overarching theme of defensible space is clear articulation of spaces and their ownership.

Rather than the separation and division policies of defensible space, Paulsen (2013) points to theorists that suggest more connectivity among streets and neighborhoods as ways to increase interaction. One model even discourages cul-de-sacs in street design, directly contradicting Newman's (1973, 1996) support for cul-de-sacs as a means of assigning ownership. Paulsen discusses ways to increase social control and natural surveillance through urban planning. Much of this is based on Jacobs' (1961) ideas to increase the "eyes on the street" by encouraging walking and social interaction. Zoning policies, mixed-use development, and connectivity are all relevant issues for crime prevention. Paulsen illustrates that there are complex nuances in how diversity or intensity of uses can impact crime.[3] This makes studying these policies' effectiveness very difficult without closely studying individual street blocks over time.

Although comprehensive study of the impacts of crime prevention-oriented planning is difficult, one can draw some direction from previous studies. Paulsen (2013) indicates that property crimes are more likely to occur in areas of mixed-use diversity. Usage intensity, on the other hand, does not seem to have the same effect. This is logical since property crime can be expected to concentrate around commercial areas where people are more likely to walk. Murder and rape, however, tend to occur in residences between a perpetrator and victim who know one another. These crimes are less impacted by the built environment. These trends are important to keep in mind for understanding how crime differs across neighborhoods due to usage.

With this background from the literature, the methods for quantitative analysis come into question. The rest of this study comprises of an examination of the relationships among the socioeconomic factors that influence the supply of crime and their relationships to observed crime rates. Section IV describes the quantitative methodology for this analysis and Section V provides a quantitatively descriptive look at each of the variables discussed in the literature review.

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[3] Usage *diversity* refers to differences in use such as commercial versus residential. Usage *intensity* refers to the differences and depth in one type of use, for instance, the presence of apartment towers, row homes, and single-family units all as residential use in a space.

IV. Methodology

In order to provide a robust study of the variables and relevant policy, this study includes descriptive statistics, correlation analysis, spatial lag regression analysis and negative binomial regression analysis. The original analysis is performed for the city of Chicago, Illinois. This is supplemented with a comparison to results for Los Angeles, California, and Houston and Dallas, Texas. These cities together are four of the seven most populous cities in the United States. New York City, Philadelphia, and Phoenix are among the seven largest as well, but this study does not use them due to many missing observations in the National Neighborhood Crime Study.

This explanation of methodology first describes the regression models used in this study based on an understanding of the probability distributions of the variables. It also discusses the problem of spatial autocorrelation in geographically interrelated data. Finally, it explains the process for constructing the Gini coefficient used in this analysis and the Racial Diversity Index.

a. Regression Models

The variables described in Section IIIa are the variables of interest in the study and those in Section IIIb are the additional control variables. With all of these variables, the final model takes the form:

$$\begin{aligned} E(Y_t|\boldsymbol{X_t}) = \exp(\beta_0 & \\ & + \boldsymbol{\beta_i}\, log(\boldsymbol{X}_{it}) + \lambda\, log(DENSITY) + \gamma \log(GINI) + \theta \log(DENSITY) \\ & * \log(Poverty) + \log(N) + \varepsilon_t)\,. \end{aligned} \tag{4.1}$$

In (4.1), Y_t is the crime rate for each tract t, β_0 is a constant intercept, $\boldsymbol{\beta}_i$ is the coefficient vector for the ith control variable in the vector of variables X_{it}, λ is the coefficient on the log of population density, γ is the coefficient on the log of the Gini coefficient, θ is the coefficient on the interaction term between density and poverty, N is the population, and ε is the error term. Hereafter, the density term, Gini coefficient term, and the interaction term are implied to be included in X_{it}.

Descriptive statistics and histograms show that most of the variables are not normally distributed, but appear closer to normally distributed after a natural log transformation. This provides the motivation for log-transforming the independent variables. Some Census tracts have observations of 0 for variables like the poverty rate or unemployment rate. These variables are transformed by taking $log(X + 1)$ for all observations of the variable X. Since crime counts are count variables bounded at zero, Poisson or negative binomial models are more appropriate than simple linear regression. Osgood (2000) explains in detail how the counting process of a Poisson works well for crime rates, especially when counts and population sizes are relatively low. Other studies such as Kelly (2000) use a Poisson process to model crime rates. Osgood also explains the use of a negative binomial regression model. These are useful when there is overdispersion in the model. A χ^2 for overdispersion indicates that negative binomial models are appropriate for the data in this study. Both Osgood (2000) and Kelly (2000) also use an exposure term as a means of accounting for population differences among observations. This is accomplished simply by adding the log of population to the right-hand side of the equation with the assumed coefficient of one.

The negative binomial model is a generalization of the Poisson where the error terms can be heterogeneous (Greene 2008). Using the same symbols as the model in (4.1), the negative binomial is:

$$E(Y_t|\boldsymbol{X_t}) = \exp(\beta_0 + \beta_i \, log(\boldsymbol{X}_{it}) + log\,(N) + \varepsilon_t)\,. \tag{4.2}$$

b. Spatial Autocorrelation

With this foundation for regression models, one can turn to an issue that arises in analyzing crime patterns. In cross-sectional datasets where the analysis is over relatively small geographical regions, it is important to consider that each observation affects all others. Many methods exist for correcting spatial autocorrelation. Luc Anselin (1996; 2003) has developed an extensive literature on spatial econometrics. This is especially a concern when trends in data do not fall exactly within the spatial constraints of each observation. Anselin and Bera (1998) explain that a "mismatch between the spatial unit of observation and the spatial extent of the economic phenomena under consideration" will result in spatial autocorrelation among the errors in the variable observed (Anselin and Bera 1998, 239). Assuming those observations farther from the central observation have proportionally lower impact on that central observation than those closer, one can construct a matrix of weights based on inverse distance of one observation to any other. Spatial autocorrelation can be measured using Moran's I. Moran's I measures the correlation among variables in a given space. Reported Z-scores indicate the level of autocorrelation with negative numbers indicating more uncorrelated and positive numbers indicating more correlated (Moran 1948).

To build an understanding of this model, it is easiest to start with the Ordinary Least Squares (OLS) model. This foundation is also important for understanding a spatial-lag regression. A log-log OLS model is represented as:

$$log(E(\psi_t|\boldsymbol{X})) = \beta_0 + \beta_i log(\boldsymbol{X}_{it}) + \varepsilon_t \,. \tag{4.3}$$

All the symbols on the right-hand side match that of equation 4.2. However, there is no exposure term. Instead, ψ on the left side represents the crime rate—simply the crime count adjusted by population. Anselin (2003) and Pisati (2012) explain a method for correcting autocorrelation in regression that includes the spatial weight matrix in a regression equation to account for spatial lag. The spatial lag model adds in a factor to a typical regression equation where the vector of all the dependent variable values over the observations is multiplied by the respective weights in the matrix. A log-log OLS form with a spatial lag term is represented as:

$$log(E(\psi_t|\boldsymbol{X})) = \beta_0 + \beta_i \, log(\boldsymbol{X}_{it}) + \Phi log(\boldsymbol{\psi}_m) + \varepsilon_t \tag{4.4}$$

The spatial weights term is represented as $\Phi log(\boldsymbol{\psi}_m)$, where Φ represents the spatial weights matrix and $\boldsymbol{\psi}_m$ on the right hand side is the vector of the crime rates for each tract m. Each element in this vector is multiplied by its corresponding weight in square matrix Φ.[4,5]

c. Construction of the Gini Coefficient and Racial Diversity Index

With the details of the regression models determined, it is also useful to consider that not all of the variables in this study are directly observed from existing datasets. The Gini coefficient and the Racial Diversity Index are both variables in this study that the researcher constructs before analysis.

A Gini coefficient is a commonly used measure of income inequality for social scientists. Gini coefficients are typically calculated from an estimation of a Lorenz Curve using quintile data. Since this type of data is unavailable for the year 2000 at the Census tract level, this paper uses grouped data. The method for calculation of the Gini coefficient used in this paper is described in detail in Abounoori and McCloughan (2003) a similar method is described in Gastwirth (1972). These papers illustrate how this method differs from other methods using grouped data and results from traditionally calculated Gini coefficients using a Lorenz Curve, indicating that this method yields results very near the traditional method (Abounoori and

[4] The weight in Φ is 0 where ψ_m is observed for the same tract as ψ_t. That is, the diagonal of matrix Φ is all zeroes.
[5] Limitations of the software for this analysis prevented using spatial negative binomial or other generalized linear models.

McCloughan 2003). The generalized form of the Gini originally used by Milanovic (1994) is the following:

$$Milanovic\ Gini = C\sum_{k=1}^{K} w_k \left(1 - \frac{\bar{y}_k}{\bar{y}}\right) \tag{4.5}$$

There is a constructed Gini coefficient for each Census tract from grouped household income data. This Gini is calculated assuming the median of each group to be the group mean y_k. For instance, the group of incomes between $15,000 and $19,999 has an assumed group mean of $17,500. The category for those with less than $10,000 household income is assumed to have a group mean of $5000, and the group of above $200,000 assumes $750,000 as the mean. As shown in the descriptive statistics, this produces Gini coefficients similar to those for counties used in Kelly (2000) and Cook (2009). A sensitivity analysis changing the assumed means on the upper and lower groups is provided in the Appendix. This shows that the assumed group means for the upper and lower groups of $5,000 and $750,000 provide a point in the middle of the possibilities when the bounds are arranged as combinations of $0 or $9,999 and $200,000 or $1,500,000. Interpretation of the Gini coefficient is simple: a Gini coefficient ranges between 0 and 1 with higher values indicating more inequality. While 1 represents perfect inequality where one party receives all the income, 0 represents perfect parity where all parties have equal income.

In regards to race, it is important to measure not only the percentages of each race in a neighborhood, but also the heterogeneity or homogeneity of races in a given tract. The scope of possible diversity indices is large and draws from many fields. This study measures racial diversity using a sum of squares index very similar to the Herfindahl-Hirschman Index (HHI) that is used by economists to measure the market concentration of competing firms. Qian (2013) uses this index to measure ethnic diversity in U.S. metropolitan areas. Weiss and Sommers (2008) also use this method to measure the racial diversity of basketball teams in a study measuring the relationship between team performance and racial diversity. Racial heterogeneity is the sum of the proportional shares of each race squared for each tract. The formula for the Racial Diversity Index in each tract is as follows:

$$Racial\ Diversity = \sum_{j}^{n} X_i^2 \tag{4.6}$$

In equation (4.6) j is the race-ethnic category, and X is the proportional share of that race-ethnic group in a tract. With four race-ethnic groups included (white, black, Hispanic, and Asian or

Pacific Islander), this value ranges from 2,500 to 10,000.[6] The minimum case indicates that each of the race-ethnic groups is evenly distributed. The maximum indicates perfect homogeneity for one group.

All this methodology makes progress towards modeling the equilibrium quantity of crime in a neighborhood. It is not enough to simply theorize on these variables. The rigorous econometric procedures outlined in this section show how a researcher can use statistical tools to apply the economic theory of crime to observations of real life. Section V explains the specific nature of the data used for these models and transformations in more detail. It provides descriptive statistics to help the reader understand the peculiarities of each variable and their economic meaning.

V. Data & Variable Descriptions

a. Data Descriptions

This section describes the variables used in this study first by noting their measurement, then by explaining descriptive statistics. It also gives a look at the geographic distribution of the variables of interest. Table 5.1 provides a brief description of each of these variables and lists their respective sources. All variables are specified at the Census tract level unless otherwise noted. Most of the data for this study come from the National Neighborhood Crime Study (NNCS), a dataset assembled by Krivo and Peterson providing Census tract level data on crime rates and many other variables. For this study, all variables are transformed using a natural logarithm except the crime counts.

In addition to the variables listed in Table 5.1, an interaction term gauges the importance of the effect of density and poverty together. Crime rates in the dataset are all expressed as crimes reported per 1,000 people in each Census tract as an average over three years from 1998 to 2000.

[6] Because the racial category of "Other" was not included, some values for this actually range lower to about 2,400.

Table 5.1: Variable Descriptions		
Variable	*Description*	*Symbol*
DEPENDENT VARIABLES		
Violent Crime Rate	Number of violent crimes per 1,000 people per year	VIOLRT
Property Crime Rate	Number of property crimes per 1,000 people per year	PROPRT
Violent Crime Count	Number of violent crimes over three years	VIOL
Property Crime Count	Number of property crimes over three years	PROP
INDEPENDENT VARIABLES		
Per Capita Income	Average income per person in real 2000 US$.	PCINC
Unemployment Rate	Number of unemployed persons as a percent of the labor force.	UNEMP
New Immigrants	The percent of newly immigrated residents.	NEWIMM
Area	Area of a Census tract in square kilometers.	AREA
Population	Total tract population in the 2000 Census.	POP
Population Density	Tract population divided by tract area. Expressed as persons per square kilometer.	DENSITY
Percent [Race]	Proportion present of white, black, Asian, and Hispanic by U.S. Census reporting.	PCWHT, PCBLK, PCASN, PCHISP
Racial Diversity Index	An index measuring the sum of squared proportions of major race-ethnic groups.	RDI
Female-headed Households	Percent of female-headed households.	FHH
Males 15-24	Percent of males aged 15-24.	YMALE
High School Graduates	Percent of tract population who are high school graduates.	HSGRAD
Percent Renters	Percent of tracts households who rent their housing.	PCRENT
Vacant Housing	Percent of vacant housing units.	VACANT
Housing Value	Value of housing in US $.	HSVALU
Recent Movers	Percent of residents who have moved in the last 5 years.	MOVER
Poverty Rate	Percent of population below the poverty line.	POVERTY
Gini Coefficient	Gini index of income inequality.	GINI

b. Descriptive Statistics

Table 5.2 shows descriptive statistics for the variables in Chicago Census tracts. A typical Chicago Census tract has a population (POP) of just over 3,500 residents, but these can range from as few as 302 to as high as over 15,000. With an average area of 0.63 square kilometers and population density (DENSITY) of 7,130, Chicago is fairly dense.

The neighborhoods of Chicago take on many different patterns of characteristics throughout the 800 Census tracts observed in this study. While the average poverty rate (POVERTY), the percentage of people below the poverty line, is 22.45 percent, some tracts have no residents in poverty, while others have as many as 92.7 percent in poverty. The median per capita annual income (PCINC) of $15,585 and average of $20,055 were below the U.S. per capita income of approximately $30,000 at the time. In some cases, tracts ranged as high as $110,000 for per capita income but as low as $2,500. Income inequality, as measured by the Gini coefficient, varies widely across tracts but has a median and mean of 0.43 and a standard deviation of 0.07, showing that 95 percent of these tracts have Ginis (GINI) between 0.29 and 0.57. These are on par with the estimates from Cook (1986) and Kelly (2000) for U.S. counties. Housing value (HSVALU) in Chicago has a median value of $140,000 and a mean of $160,000, but in a handful of outlying tracts, the average housing value is over half a million U.S. dollars.

While about 69 percent of the adult population are high school graduates (HSGRAD) in each tract on average, as few as a quarter have graduated in some cases. Fifty-two of the 800 tracts have greater than 50 percent female-headed households (FHH) while there are 79 with less than 5 percent female-headed households. The mean is about 23 percent.

Racial composition in Chicago shows that a typical Census tract has about 29 percent white (PCWHT), 42.8 percent black (PCBLK), 3.7 Asian (PCASN), and 22.8 percent Hispanic (PCHISP) population. Racial disparity seems to exist more across tracts than within them. The minimum and maximum statistics for each race show that tracts can be highly homogenous with at least one tract being all black and another being greater than 99 percent Hispanic. A Racial Diversity Index (RDI) of 10,000 indicates perfect homogeneity while values of 2,500 would suggest an even 25 percent split across the races.[7] Over 250 of the tracts have RDI values over 9,000 (implying at least 94.5 percent of one race) while 212 are fewer than 5,000 (where two races each make up half the population). The average value is 6,988.93. The proportion of new immigrants is also an important factor for race-ethnic composition. While the median tract has only 4.6 percent new immigrants (NEWIMM), and the average has 8 percent, 314 of the tracts have fewer than 2 percent. Only one tract has greater than 50 percent new immigrants.

Housing characteristics in Chicago are widely varied with vacancy rates ranging from 0.0 to 71 percent with a standard deviation of 8 percent, even though the average tract has a vacancy rate (VACANT) of approximately 9 percent. The typical Census tract has about 45 percent of its population who have moved there in the last five years (MOVER) and a rental rate with a

[7] Note in Table 2 that there are values below 2500. This is a result of the exclusion of the “other races” category from the calculation of this index.

median and mean close to 60 percent. In some areas, less than 5 percent of the population rents their homes, while the maximum is 100 percent renters (PCRENT).

Descriptive statistics for the crime rates show that there is not a great deal of consistency in crime across tracts in Chicago. Each of these crime rates is expressed as the number of crimes per 1,000 people averaged over a three-year period. While some tracts have almost no violent crime, others are much higher, with the maximum violent crime rate reaching over 145 crimes per 1,000 people each year. While the median murder rate is just 0.07 per year—fewer than 1 murder per 10,000 people in a year—55 of the 800 tracts observed more than one murder per 1,000 people per year. Aggravated assault is the most frequently occurring violent crime with a median rate of 7.77 and average of 11.73. The mean property crime rate was 69.49 and the median was 49.75. Larcenies are the most common property crimes at a rate of 46.60 on average. However, larcenies also have a large standard deviation of 82.17 because they range as high as a rate of 1609.

Property crimes tend to occur more frequently than violent crimes. Only 14 Census tracts in Chicago experienced higher rates of violent crime than of property crime. Most of these tracts had especially high rates of assault and comparatively low rates of larceny. All but two of these tracts also had poverty rates greater than 50 percent, and low rates of racial diversity (high RDI scores), suggesting that social and financial conditions influence violence, but the level of deprivation makes committing property crimes less rewarding.

With this context for the magnitudes of variables and understanding of the city of Chicago, proceeding to correlations gives insight into how the variables relate to one another.

Table 5.2: Chicago Descriptive Statistics

Variable	*Mean*	*S.D.*	*Median*	*Min*	*Max*
Crimes					
VIOL (count)	187.85	150.38	154.00	6.00	954.00
PROP (count)	61.42	45.15	52.38	8.50	474.84
VIOLRT (rate)	20.50	18.44	14.58	0.52	145.28
PROPRT (rate)	69.49	92.18	49.75	9.10	1717.39
Tract Characteristics					
POP	3504.28	2558.71	2769.50	302.00	15359.00
DENSITY	7130.84	4500.71	6332.11	395.07	35042.82
AREA	0.63	0.68	0.45	0.04	8.65
Economic & Social Characteristics					
GINI	0.44	0.07	0.43	0.25	0.76
POVERTY	22.45	16.13	18.98	0.00	92.69
PCINC	20055.24	14742.36	15585.50	2465.00	110000.00
UNEMP	13.08	10.38	10.22	0.00	57.45
HSVALU (000s)	160.00	91.65	140.00	0.00	680.00
HSGRAD	68.98	16.91	69.79	24.22	100.00
NEWIMM	8.02	9.20	4.63	0.00	61.68
YMALE	7.31	2.51	7.15	0.00	17.33
FHH	23.00	16.47	17.74	0.00	80.93
VACANT	9.34	8.18	7.05	0.00	71.15
MOVER	45.53	14.60	44.37	9.58	93.20
PCRENT	58.02	22.33	62.07	2.91	100.00
Racial Composition					
PCWHT	28.96	31.44	14.79	0.00	95.55
PCBLK	42.76	43.64	16.17	0.00	100.00
PCASN	3.74	8.26	0.83	0.00	84.93
PCHISP	22.82	28.73	7.50	0.00	99.35
RDI	6988.93	2260.14	7093.02	2390.36*	10000.00

**This value is lower than the expected minimum of 2500 because the racial category "Other" was not included.*

c. Spatial Inference

A look at maps of Chicago colored by crime rate or other variables can give an understanding of some of the expected trends for crime rates, crime hotspots, or relationships among variables in a more visual sense. Figure 5.1 shows the property crime rate in Chicago with tracts colored by the number of standard deviations of the property crime rate from the mean. Figure 5.2 shows the violent crime rate colored the same way. Figure 5.3 shows population density, and Figure 5.4 shows the Gini coefficient by Census tract. All of these figures are colored according to the number of standard deviations by which the observation varies from the mean.

An immediately noticeable difference between the two crime rate maps is the difference in the concentration of high violent crimes rates compared to high property crime rates. Figure 5.1 shows a clustering of high property crime on the northeast side of Chicago. The Census tracts in this area make up a large, defined neighborhood known as Near Northside, just south of the Lincoln Park neighborhood. Near Northside includes the Cabrini-Green public housing project, an area rife with crime. Figure 5.2 shows that violent crime is more concentrated on the south side in the Wagner and Sherman Park neighborhoods, as well as on the northwest side in the Garfield Park neighborhood. Examining Figure 5.3, the densest areas of Chicago are on the far northeast side along the lake and the west central portion. Comparing this to the crime maps, it is apparent that most of the tracts with density of greater than 1.5 standard deviations from the mean have crime rates that are near or at least 0.5 standard deviations below the mean. Finally, looking at Figure 5.4 for the Gini coefficient shows that high and low rates of income inequality are generally scattered throughout the city without any clear clustering.

It is useful to look at the levels of spatial correlation among tracts' crime measures. Moran's I is the selected measure of spatial autocorrelation. Both the violent crime rate and the property crime rate have significant levels of spatial correlation as measured by Moran's I.[8] The negative values actually indicate that the variables are more dispersed than expected.

Descriptive statistics provide a snapshot of the city of Chicago. The look at spatial relationships gives a visualization of the variables as well as a basis for understanding spatial autocorrelation. A regression analysis will help to better discern the role of each variable in the supply of crime.

Table 5.5: Spatial Diagnostics for Chicago

VARIABLE	*Moran's I*	*Z-score*
VIOLRT	-0.004	-2.985**
PROPRT	-0.006	-6.34**

**Significant at 5% level, **Significant at 1% level*

[8] Moran's I ranges from -1 to 1 where -1 indicates perfect dispersion and 1 indicates perfect concentration. The correlation among different measures of crime rates can best be assessed by looking at the Z-score for Moran's I.

Figure 5.1

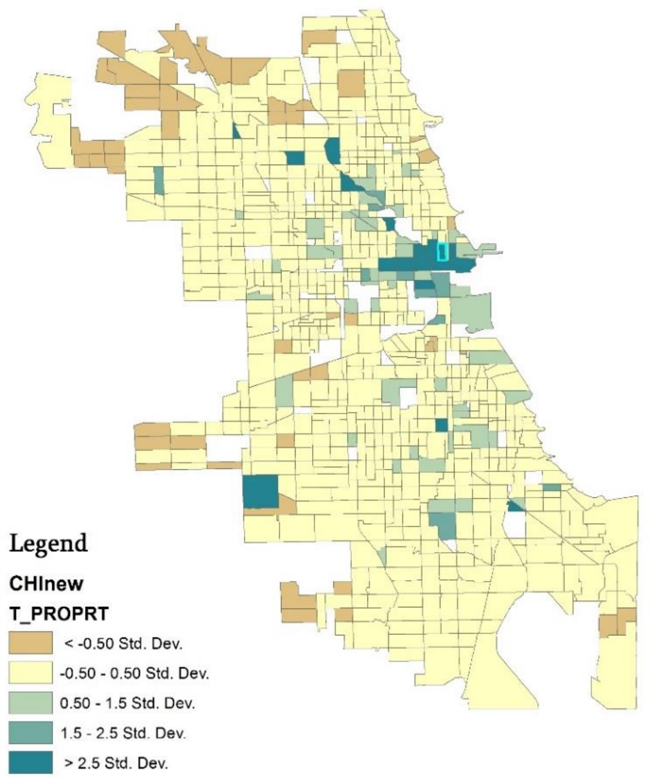


Figure 5.2

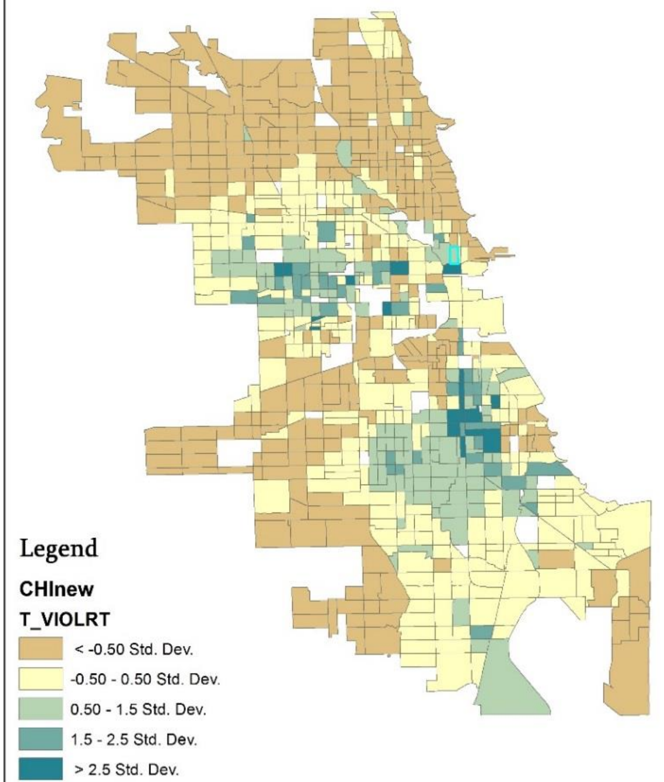


Figure 5.3

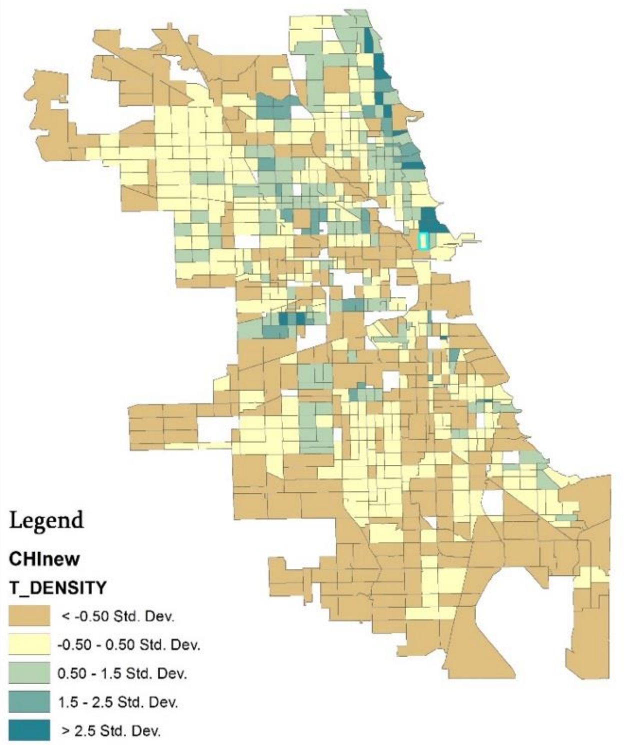
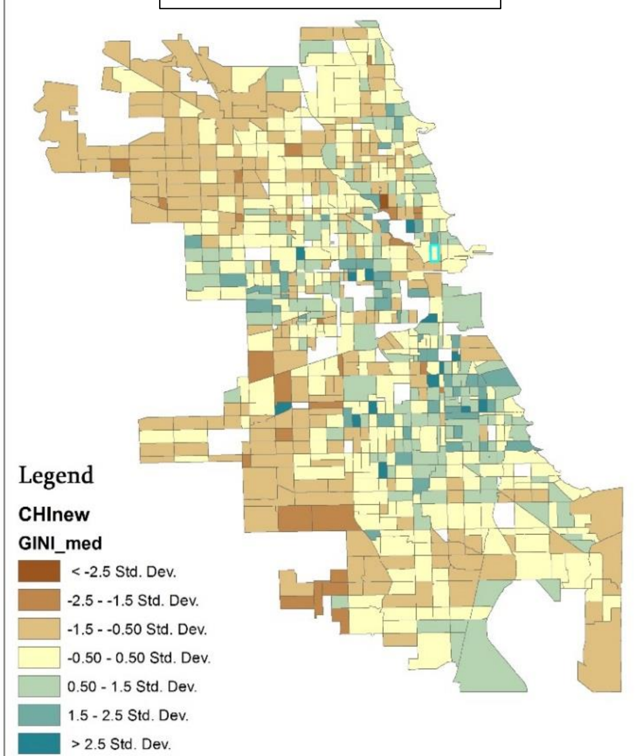


Figure 5.4



VI. Empirical Results

The findings from the models analyzed generally support the hypothesis about population density, showing a negative relationship between the density and crime rates. There is not a statistically significant relationship between the Gini coefficient and crime rates for Chicago. This section first addresses some of the econometric concerns raised in the model and goes through a correlation analysis. It then presents the violent and property crime results for spatial regressions from Chicago. These are followed by results for violent and property crime negative binomial regressions from Chicago. The regressions results from Chicago are the focus of this paper, but these are supported and compared with results for the variables of interest from negative binomial regression results for Dallas, Houston, and Los Angeles.

All of the variables shown in the correlation analysis are included in the regression except the area of a tract and the percent composition of whites. The area is provided purely for descriptive reference. The percent of whites is not included in the regression because to prevent multicollinearity with the other racial variables. There is one interaction term in the model that multiplies the log of population density by the log of poverty. The interaction between density and poverty gives some idea of how the effects of density vary depending on the financial well-being of a tract's population.

Multicollinearity and heteroskedasticity are two econometric issues coming from the models in this study. Robust standard errors were generated to alleviate any concerns of heteroskedasticity.[9] Multicollinearity is an issue that occurs when variables are related. The correlation analysis in Section V indicates some of the variables that may be concerning in the model. A Variance Inflation Factor test of the variables indicates that while multicollinearity is a concern for the variables involved in the interaction term, as would be expected given their mathematical relatedness, multicollinearity does not confound the model overall.[10] Furthermore, any theoretical considerations for including variables outweigh any econometric issues.

a. Correlation Analysis

This section describes the correlation coefficients of some of the variables of interest, and to that end, this section provides two correlation tables. Table 6.1 shows the relationships between the dependent variables and the set of independent variables. The second set of tables,

[9] The results of Breusch-Pagan tests for OLS regressions of property and violent crime are reported in the appendix.
[10] The full results of this test are given in the appendix.

Tables 6.2a and 6.2b, supports the Variance Inflation Factor test and directs the researcher to understand sources of collinearity in the model.

Correlates of Crime

Correlations among the dependent variables and the independent variables provide preliminary insight into the relationships that may emerge from a regression model. Both the rates of violent and property crime and the counts of violent and property crime are shown. The lack of control for population in the count variable certainly causes differences between the two, as evidenced by the difference in direction of correlations for the population between counts and rates. The focus here is on the relationships with crime rates rather than crime counts since. This section first discusses the variables of interest, discusses the poverty rate and per capita income in more detail, and then highlights correlations from the remaining control variables.

Population density correlates at -0.166 with the violent crime rate, -0.056 with the property crime rate. However, it correlates positively with the counts at 0.217 for the violent count and 0.304 with the property count. The Gini coefficient has strong positive correlations with the violent crime rate and count at 0.676 and 0.415, respectively. It was negative correlations of -0.003 and -0.121 with the property rate and count, respectively.

The poverty rate correlates positively for both rates and counts, and more strongly with violent crime than property crime at 0.361 and 0.264 for the violent rate and count, respectively, compared to 0.054 and 0.021 for the property rate and count, respectively. Similarly, per capita income correlates at 0.681 and 0.423 with the violent crime rate and violent crime count, but at only 0.022 and -0.109 with the property rate and count, respectively. Note that intuitively a high poverty rate would suggest a low per capita income. One would expect that if poverty relates positively with a variable, income should related negatively. However, differences in these variables' contributions to the theoretical model outlined in Section II may lend to their differences in empirical results.

The unemployment rate correlates negatively with the violent crime rate at -0.378 but positively with the property crime rate at 0.206. The relationships are similar for the counts of crime. Housing value has strong relationships with violent crime than property crime. While it has a correlation coefficient of 0.528 with the violent crime rate, it has a coefficient not statistically different from 0 for the property crime rate. This is surprising given that one might associate higher value homes with a higher expected return for a crime like burglary. The high school graduation rate has negative correlations with violent crimes at -0.370 with the violent rate but positively with the property crime rate at 0.106. The percentage of female-headed households correlates negatively with both of the crime rates at -0.355 with the violent crime rate and -0.255 with the property crime rate. Note that these relationships are positive for the crime counts, but once controlled for population, this relationship changes. The percentage of new immigrants has a correlation of -0.341 with the violent crime rate and 0.131 with the property crime rate.

Table 6.1: Correlations between Crime rates and Independent Variables

	VIOLRT	PROPRT	VIOL	PROP
POP	-0.355	-0.255	0.452	0.497
AREA	-0.237	-0.242	0.118	0.096
DENSITY	-0.166	-0.056	0.217	0.304
GINI	0.676	-0.003	0.415	-0.121
POVERTY	0.361	0.054	0.264	0.021
PCINC	0.681	0.022	0.423	-0.109
UNEMP	-0.378	0.206	-0.348	0.255
HSVALU	0.528	0.006	0.337	-0.081
HSGRAD	-0.370	0.106	-0.377	0.019
FHH	-0.355	-0.255	0.452	0.497
NEWIMM	-0.341	0.131	-0.257	0.193
PCWHT	0.691	-0.059	0.501	-0.110
PCBLK	-0.405	-0.079	-0.194	0.029
PCASAN	-0.571	0.038	-0.519	0.044
PCHISP	0.676	0.043	0.507	0.003
RDI	-0.243	0.009	-0.206	0.019
VACANT	0.619	0.155	0.258	-0.037
MOVER	-0.191	0.207	-0.201	0.170
PCRENT	0.387	0.062	0.226	-0.028

The racial composition variables indicate differences among the races for relationships with crime. While the percent composition of whites correlates negatively at 0.691 with the violent crime rate, an unexpected result, it correlates negatively with the property crime rate. The percent composition of blacks correlates negatively with both the violent and property crime rates. The percent composition of Asians correlates negatively with violent crimes and trivially with property crimes. The percent of Hispanics correlates positively with both crimes. The Racial Diversity index has a negative correlation with the violent crime rate, indicating more heterogeneity corresponds with higher crime, but has a very small positive relationship with property crimes.

As anticipated, the vacancy rate correlates positively with both the violent crime rate and property crime rate. This is also true of the percent of renters. However, the percent of recent movers correlates negatively with the violent crime rate but positively with the property crime rate.

Independent Variable Correlations

Correlations among independent variables (Table 5.4a and 5.4b) are important to understanding sources of collinearity in the model. In the matrices below, an asterisk indicates that a coefficient has an absolute value greater than 0.500. The greatest correlation among the independent variables is a coefficient of 0.782 between the unemployment rate and the poverty rate. There is a correlation between the per capita income and housing value of 0.709. Per capita income is also highly correlated with the percent of whites at 0.732.

The variables of interest, population density and the Gini coefficient, have a correlation coefficient of 0.090. This is one of the lowest in the model. This is good for the analysis because these variables are not closely related to one another. Density corresponds most strongly with the percent of renters at 0.377. This is not surprising since rental apartments can be developed more densely than single-family homes. The Gini coefficient correlates most strongly with the poverty rate at 0.534.

The poverty rate is one of the most highly correlated variables across the matrix with a coefficient of -0.553 with the high school graduation rate and of -0.651 with the percent of whites. It also has a positive correlation of 0.658 with the percent of new immigrants. The percent of female-headed households has a coefficient of 0.765 with the unemployment rate, a correlation of 0.734 with the poverty rate, and a correlation of -0.400 with the high school graduation rate. This indicates levels of high poverty, low employment, and low education for female-headed households.

High correlations also turn up for per capita income. Housing value correlates with the high school graduation rate at 0.719. Along with some of the other correlations present here, there may be some issues with multicollinearity resulting from the inclusion of these variables together. However, it is important to consider that each of these variables has a unique theoretical reason for inclusion. For instance, while high school graduation and income are highly correlated, the inclusion of both helps to separate out the effect of the high school graduation rate on social expectations rather than purely based on its boost to income.

b. A Note on Interpreting Results

For all the regressions displayed, a coefficient on a scalar variable can be interpreted as an elasticity. That is, a one-percent change in the value of the independent variable results in a percentage change in the dependent variable equal to the coefficient on the independent variable. Multiplicative interaction terms and their components must be treated all together. The elasticity of a dependent variable with respect to an independent variable is the partial derivative of the natural log of dependent variable Y with respect to the natural log of independent variable X. To discern the total effect of the variables that are components of the interaction term, consider the following equation:

$$log(Y) = \beta_1 \, log(A) + \beta_2 \, log(B) + \beta_3[log(A) * log(B)] + u \qquad (6.1)$$

Where Y is the dependent variable, and A and B are two independent variables being multiplicatively interacted. The elasticity of Y with respect to A is the partial derivative of the natural log of Y with respect to the natural log of A giving the equation:

$$\frac{\delta log(Y)}{\delta log(A)} = \varepsilon_A^Y = \beta_1 + \beta_3 log(\bar{B}) \qquad (6.2)$$

To find the elasticity, the right hand side of this expression is evaluated using the estimated coefficients β_1 and β_3 and the sample mean of B. The same can be done for the elasticity of Y with respect to B, by taking the partial derivative of (6.1) with respect to *log(B)*, effectively substituting β_2 for β_1 and A for B in (6.2). This method can be applied to all models in this analysis.

Table 6.2a: Correlation Matrix for Independent Variables

	POP	AREA	DENSITY	GINI	POVERTY	PCINC	UNEMP	HSVALU	HSGRAD
POP	1.000								
AREA	0.472	1.000							
DENSITY	0.378	-0.333	1.000						
GINI	-0.096	-0.151	0.082	1.000					
POVERTY	-0.227	-0.203	0.037	0.510*	1.000				
PCINC	0.015	-0.029	0.149	-0.129	-0.552*	1.000			
UNEMP	-0.210	-0.111	-0.116	0.393	0.789*	-0.528*	1.000		
HSVALU	-0.086	-0.159	0.178	-0.037	-0.386	0.709*	-0.442	1.000	
HSGRAD	0.043	0.104	-0.047	-0.187	-0.557*	0.710*	-0.449	0.488	1.000
FHH	-0.187	-0.056	-0.178	0.297	0.744*	-0.613*	0.772*	-0.539*	-0.409
NEWIMM	0.312	-0.003	0.322	-0.202	-0.213	-0.079	-0.392	0.046	-0.257
PCWHT	0.086	0.080	0.074	-0.322	-0.643*	0.733*	-0.657*	0.636*	0.620*
PCBLK	-0.197	-0.036	-0.232	0.382	0.588*	-0.420	0.716*	-0.474	-0.132
PCASN	0.088	-0.030	0.111	0.023	-0.146	0.143	-0.272	0.147	0.173
PCHISP	0.168	-0.025	0.230	-0.232	-0.132	-0.216	-0.269	-0.032	-0.543*
RDI	-0.209	-0.032	-0.187	0.184	0.430	-0.244	0.544*	-0.341	-0.215
VACANT	-0.273	-0.191	-0.041	0.307	0.595*	-0.256	0.503*	-0.181	-0.316
MOVER	-0.009	-0.227	0.352	0.012	-0.145	0.508*	-0.321	0.531*	0.291
PCRENT	-0.163	-0.383	0.369	0.459	0.609*	-0.181	0.372	0.089	-0.260

*Coefficient has absolute value greater than 0.500

Table 6.2b: Correlation Matrix for Independent Variables

	FHH	NEWIMM	PCWHT	PCBLK	PCASN	PCHISP	RDI	VACANT	MOVER	PCRENT
FHH	1.000									
NEWIMM	-0.468	1.000								
PCWHT	-0.737*	0.155	1.000							
PCBLK	0.818*	-0.646*	-0.732*	1.000						
PCASN	-0.321	0.466	0.205	-0.314	1.000					
PCHISP	-0.320	0.657*	-0.061	-0.606*	-0.056	1.000				
RDI	0.633*	-0.540*	-0.494	0.703*	-0.439	-0.366	1.000			
VACANT	0.511*	-0.253	-0.391	0.426	-0.128	-0.171	0.324	1.000		
MOVER	-0.443	0.273	0.397	-0.395	0.253	0.075	-0.379	-0.026	1.000	
PCRENT	0.293	0.042	-0.322	0.230	0.057	-0.018	0.077	0.432	0.400	1.000

*Coefficient has absolute value greater than 0.500

c. Spatial Regression Results

This section presents the results for the linear spatial regression. This section acts as a basis for understanding the empirical relationships between the control variables, variables of interest, and the crime rates. It is necessary to use these spatial regressions to understand the influence of spatially-related crime rates. As the ρ parameters of these regressions show, one can safely move on and ignore spatial autocorrelation.[11] The results for violent crime and property crime are explained side-by-side here. First the relationships between the crime rate and variables of interest are explained. Relationships between the crime rate and different economic, social, racial, and housing characteristics are then explained in order.

Table 6.3: Spatial Regressions for Chicago

	Violent Rate (log)		Property Rate (log)	
VARIABLE	β	*SE*	β	*SE*
log.DENSITY	-0.369	0.193	-0.535	0.151**
log.DENSITY * log.POVERTY	0.053	0.057	0.045	0.043
log.POVERTY	-0.191	0.493	-0.187	0.366
log.GINI	-0.171	0.159	-0.255	0.139
log.PCINC	-0.044	0.102	0.344	0.098**
log.POP	-0.155	0.033**	-0.167	0.029**
log.UNEMP	0.020	0.049	0.064	0.045
log.HSVALU	0.015	0.018	0.002	0.011
log.HSGRAD	-0.444	0.130**	0.039	0.118
log.FHH	-0.019	0.064	-0.192	0.067**
log.NEWIMM	-0.036	0.038	0.019	0.033
log.PCBLK	0.258	0.027**	0.126	0.024**
log.PCHISP	0.046	0.030	0.031	0.028
log.PCASN	-0.089	0.034**	-0.049	0.030
log.RDI	0.149	0.113	0.163	0.100
log.VACANT	0.116	0.031**	0.073	0.028**
log.MOVER	0.114	0.090	0.318	0.083**
log.PCRENT	0.267	0.065**	0.203	0.059**
Constant	4.538	2.025*	1.930	1.823
**Significant at the 5% level, **Significant at the 1% level*				
ρ	0.000	0.000	0.000	0.000
Variance Ratio	0.765		0.541	

[11] The additional ρ term is the coefficient on the spatial lag vector of the spatial weights multiplied by the vector of the dependent variable. The measures of ρ here are very near 0 and insignificant, indicating that the impact of the spatial lag on the regression was almost nothing.

Table 6.3a: Total Marginal Effect of Density and Poverty for Spatial Regression

	Violent Crime	*Property Crime*	*Sample Mean*
Density	-0.089	-0.103	7130.840
Poverty	0.120	0.055	22.450

The spatial lag model indicates an elasticity of the violent crime rate with respect to density of -0.089 and of the property crime rate with respect to density of -0.103. That is, an increase in population density of 1 percent would correspond with a 0.089 percent drop in the violent crime rate and a 0.103 percent drop in the property crime rate. These negative results are consistent with the hypothesis and findings of all other models in this study. The results for the Gini coefficient are statistically insignificant. The poverty rate does not have a significant relationship with either aggregate crime rate in this model. Per capita income does not have a significant relationship with the violent crime rate, the property crime rate has an elasticity of 0.344 with respect to per capita income, meaning a 1 percent increase in per capita income corresponds with a 0.344 percent increase in the property crime rate. This supports the theoretical expectation that expected returns are higher in a wealthier neighborhood, thus making crime more profitable.

The violent crime rate and property crime rate have elasticities with respect to population of -0.155 and -0.167, respectively. Both housing value and the unemployment rate do not have statistically significant relationships with the crime rates. The lack of significant relationship for the unemployment rate is particularly surprising given findings of previous studies. The high school graduation rate has a negative relationship with an elasticity of -0.444 with violent crime, but no significant relationship with the property crime rate. The opposite is true of the percent of female-headed households. Property crime has an elasticity of -0.192 with respect to the percent of female-headed households. The proportion of new immigrants does not have a significant relationship with either crime rate.

The variables dealing with racial composition indicate that the percentage of residents who are black corresponds positively and significantly with both crime rates, returning the hypothesized relationshipThe racial diversity index has a negative and significant result for the violent crime rate. The negative relationship suggests that more diversity indicates more crime. This is the expected result.

Finally, all three housing characteristics have positive relationships with both crime ratesthat are significant at the 1 percent level. The violent crime rate and property crime rate have elasticities with respect to the percent of recent movers of 0.114 and 0.318, respectively. A 1 percent increase in the vacancy rate corresponds with a 0.073 percent increase in property crimes and a 0.116 percent increase in violent crimes. The rental rate has elasticities of 0.267 for the violent crime rate and 0.203 for the property crime rate. In terms of actual crimes per 1,000 people, these numbers all mean very small changes, but the consistency and direction of the relationship are important.

d. Negative Binomial Results

The standard in the literature is to use a Poisson or negative binomial regression to model crime counts with an exposure term (Kelly 2000, Osgood 2000). The models presented here have robust standard errors, and a χ^2 test of the likelihood ratios indicates that the negative binomial model is statistically preferred to the Poisson. This section first goes through the results of the violent crime regression and then the property crime regression for Chicago Census tracts. The variables of interest, poverty rate, and per capita income are explained first, followed by economic variables, then racial composition variables, then housing variables. The results can be found in Table 6.4.

Violent Crimes

The regression for the violent crime count supports the main hypothesis about population density, while not rejecting the null hypothesis for the Gini coefficient, and leaving an understanding of poverty and income's effects ambiguous. The violent crime count has an elasticity with respect to population density of -0.238, indicating that a 1 percent increase in population density from one tract to another means a 0.238 percent drop in the violent crime count. The Gini coefficient does not have a statistically significant relationship with the violent crime count. The violent crime count has an elasticity with respect to the poverty rate of 0.284 while having an insignificant relationship with per capita income. Population has a total marginal effect of 0.809 after allowing for an additional population parameter with the exposure.

Similarly to the spatial regressions, the unemployment rate, housing value, percentage of new immigrants, and proportion of female-headed households do not have significant relationships with the violent crime count. Again, this is surprising given their expected contributions to the theoretical model. The high school graduation rate has a total marginal effect of -0.358 and is significant at the 1 percent level. This follows the same result from the spatial regressions. Since there are many other variables in the model that capture income and economic well-being, the value of education towards socially-accepted behavior may be the major contribution of this factor to the theoretical model.

The results from this model indicate a positive relationship between the percent of blacks and the violent crime count. This follows the theoretical expectations and previous empirical results in the literature. The percent of Hispanics does not have a statistically significant relationship, and the percent of Asians has a negative and significant relationship with the violent crime count. In general, these are the expected relationships. The Racial Diversity Index has a positive and signficant relationship with the violent crime count, indicating that more racial concentration corresponds with a higher crime rate. An increase of 1 percent in the Racial Diversity Index corresponds with a 0.260 percent increase in the number of violent crimes.

The vacancy rate and rental rate both have positive and statistically significant relationships with the violent crime count. The violent crime count has an elasticity of 0.133 with respect to vacancy and 0.261 with respect to the percent of renters. These both follow the expected results from the theoretical model.The percent of recent movers, on the other hand, does not have a statistically significant relationship with the count of violent crimes.

Property Crimes

The regression for the property crime count reflects many of the same results as the violent crime. The number of property crimes has an elasticity with respect to population density of -0.461, following the hypothesized negative relationship. There is no significant relationship between the Gini coefficient and the property crime count. Like the violent crime count regression, this value is negative, but is statistically insignificant. Poverty has a positive total marginal effect of 0.250 on the property crime count and per capita income has a total marginal effect of 0.346. A positive relationship for both of these variables with the property crime count indicates that each of them are important to the theoretical model, but possibly for different reasons. That is, while income may contribute to the expected returns to crime, the poverty rate also may indicate a level of deprivation that may drive persons to crime. Population has a total marginal effect of 0.807 after adding the exposure parameter to the equation.

The unemployment rate, housing value, high school graduation rate, and percent of new immigrants all do not have significant relationships with the property crime count. These social and economic variables, while important to the theoretical model, do not have consistent relationships in the data observed. The property crime count has an elasticity with respect to the percent of female-headed households of -0.256.This is an unexpected result given the previous findings of Cook (2009) and others, as well as the theoretical expectation that the percent of female-headed households indicates deprivation and lower social cohesion.

The variables dealing with racial composition have similar results to their relationships with the violent crime count. The percent composition of blacks corresponds positively with the count of property crimes. Neither the percent composition of Hispanics nor the percent composition of Asians has a statistically significant elasticity. The property crime count has an elasticity with respect to the Racial Diversity Index of 0.301 and is statistically significant. This again indicates that more homogeneity corresponds with more crime.

The property crime count has an elasticity with respect to the vacancy rate of 0.105, following expected positive theoretical relationship. There is also an elasticity with respect to the percent of recent movers of 0.321, indicating that a 1 percent increase in the percent of recent movers from one area to another relates with a 0.321 percent drop in the number of property crimes. The percent of renters does not have a significant relationship with the property crime count, unlike for the violent crime count.

Together, the results for violent crime and property crimes in Chicago show that density negatively and significantly influences crime rates. This suggests that density positively influences the probability of apprehension, rather than decreasing it as Glaeser and Sacerdote (1999) showed in their city-level studies. This look at Census tracts is more revealing of density on a human scale. An important distinction between property crimes and violent crimes is the relationship with per capita income. Property crimes are positively related to income while violent crimes are negatively related. This indicates that the positive influence of income on the benefits to crime outweighs its impact on the opportunity costs. This could be an issue arising from the fact that this measure of income simultaneously captures the income of victims and perpetrators.

These results make valuable contributions to an understanding of crime rates and the way the economic theory of crime works in Chicago neighborhoods. To generalize this model and comprehend the conclusions as robust, a comparison to results from other cities is valuable.

Table 6.4: Negative Binomial Regressions with Population Exposure for Chicago

N= 800	*Total Violent Crimes*		*Total Property Crimes*	
VARIABLE	*β*	*SE*	*β*	*SE*
log.DENSITY	-0.483	0.177**	-0.668	0.155**
log.DENSITY * log.POVERTY	0.084	0.051	0.071	0.044
log.POVERTY	-0.447	0.425	-0.365	0.367
log.GINI	-0.209	0.164	-0.330	0.160
log.PCINC	0.026	0.114	0.346	0.114**
log.POP	-0.191	0.029**	-0.193	0.030**
log.UNEMP	0.020	0.048	0.038	0.051
log.HSVALU	0.009	0.018	0.003	0.010
log.HSGRAD	-0.358	0.129**	0.183	0.129
log.FHH	-0.034	0.060	-0.256	0.069**
log.NEWIMM	-0.009	0.040	0.056	0.036
log.PCBLK	0.252	0.025**	0.151	0.025**
log.PCHISP	0.048	0.029	0.051	0.028
log.PCASN	-0.071	0.032*	-0.032	0.032
log.RDI	0.260	0.118*	0.301	0.108**
log.VACANT	0.133	0.032**	0.105	0.030**
log.MOVER	0.122	0.077	0.321	0.091**
log.PCRENT	0.261	0.061**	0.168	0.071
Constant	-1.974	1.853	-4.276	1.865*
α	0.184	0.014**	0.185	0.014**
Test of χ^2	1.3 E04**		8.8 E 04**	
**Significant at the 5% level, **Significant at the 1% level*				
Goodness-of-Fit Measures	*Total Violent Crimes*		*Total Property Crimes*	
Pseudo R^2	0.1202**		0.0739**	

Table 6.4a: Total Marginal Effects

	Violent Crime	*Property Crime*	*Sample Mean*
Density	-0.238**	-0.461**	7130.840
Poverty	0.284**	0.250**	22.450

e. Testing Against Other City Data for Robustness

This section presents a comparison of the negative binomial results from Dallas, Houston, and Los Angeles in table 6.5. The focus here is only on the two variables of interest and the poverty rate and per capita income. Overall, the expected negative relationship between density and the crime counts holds. The results for the Gini coefficient are ambiguous and may indicate that this relationship depends more on the individual city. The poverty rate and per capita income also have differing results. The discussion moves through each of the variables for all three cities at once, first focusing on violent crimes, then property crimes.

The violent crime count has a negative relationship with population density in Dallas and Los Angeles, but does not for Houston. The elasticity of the violent crime count with respect to population density for Houston is positive but not statistically significant. Dallas and Los Angeles both have negative relationships, but only Los Angeles has a statistically significant elasticity at -0.147.

The Gini coefficient has statistically significant relationships with the violent crime count for Los Angeles and Houston, but not for Dallas. Both Dallas and Chicago had negative but insignificant relationships between violent crimes and the Gini coefficient. However, the elasticities of the violent crime count with respect to the Gini coefficient for Los Angeles and Houston are 0.553 and 0.518, respectively. Not only are these relationships positive, as the theoretical model and previous empirical findings suggest, but they are also of large magnitude with both indicating that a 1 percent increase in the Gini coefficient corresponds with greater than a 0.5 percent increase in the violent crime count.

The poverty rate has positive relationships with the violent crime counts across all cities as expected. The relationship is significant for Dallas with an elasticity of 0.468 of the violent crime count with respect to the poverty rate and for Houston at 0.264. Per capita income, on the other hand, has more ambiguous results. Recall that the relationship between the violent crime count and per capita income for Chicago was positive but insignificant. This is also true for Dallas. Los Angeles, however has an elasticity of the violent crime count with respect to per capita income of -0.545. This is more in line with the theoretical expectation that lower per capita income indicates more deprivation and thus more crime than indicating a higher expected return to crime.

Turning to the results for property crime, the results from Dallas, Los Angeles, and Houston all indicate that population density and property crime relate negatively and significantly. This provides a firm rejection of the null hypothesis about the relationship between population density and property crime, suggesting the positive result from Glaeser and Sacerdote (1999) should be reconsidered.

The Gini coefficient generally maintains an insignificant relationship as it did for Chicago. However, in Los Angeles, the property crime count has an elasticity with respect to the Gini coefficient of 0.603. Los Angeles stands as the only city for which the relationship between the Gini coefficient and both property and violent crimes shows the expected positive relationship.

The results for the poverty rate indicate differences among cities as well. The relationship between the property crime count and poverty is positive everywhere, but only for Dallas is there a significant elasticity at 0.217. Per capita income also has ambiguous results for the other cities' property crime counts. Dallas has a significant elasticity of the property crime count with respect to per capita income of 0.473 while Los Angeles has a statistically significant elasticity of -0.535. Houston does not have a statistically significant result. Both the violent and property crime counts for Los Angeles have negative relationships with per capita income, but no significant relationships with poverty. However, for Chicago and Dallas in particular, the positive relationships for both variables with both crime counts shows there is both theoretical and statistical value to including both in the model because this suggests they do not act collinearly. Additionally, including both variables in the model improved the goodness-of-fit.

Table 6.5: **Total Marginal Effects from Other Cities' Negative Binomial Results**

	Dallas				*Los Angeles*				*Houston*			
	Violent		*Property*		*Violent*		*Property*		*Violent*		*Property*	
	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*	β	*S.E.*
log.DENSITY	-0.102	0.080	-0.149	0.071*	-0.147	0.037**	-0.408	0.043**	0.055	0.060	-0.264	0.068**
log.GINI	-0.252	0.354	-0.218	0.308	0.553	0.169**	0.603	0.187**	0.518	0.208**	0.277	0.231
log.POVERTY	0.468	0.132**	0.217	0.102*	0.088	0.083	0.095	0.088	0.264	0.115*	0.037	0.125
log.PCINC	0.267	0.246	0.473	0.208*	-0.545	0.123**	-0.535	0.115**	-0.043	0.119	0.029	0.135

**Significant at the 5% level, **Significant at the 1% level*

With an understanding of how the variables of interest relate in different cities and by different crime, one can draw conclusions about ways to combat crime and take the study of crime farther. While the results for population density are consistent and robust, the other results here indicate that a look at different cities individually is important to a study of crime before making broad-based policy prescriptions.

VII. Conclusions and Public Policy Implications

Tying all the theory and observations together, one can understand the greater potential applications and impact of this study. The models indicate that population density has a negative and significant relationship with crime rates. Residential stability appears to be an important factor in crime reduction based on the evidence from the vacancy rates, percent of recent movers, and rental rate results. It should be noted, however, that the vacancy rate might be endogenous with the crime rates. That is, as crime increases in a neighborhood, people will move away from that neighborhood, leaving vacant homes behind. Each of these variables can be heavily influenced by different local economic development and urban planning strategies.

From these results and inferences, one can look to the literature on crime reduction and urban planning to see how each of the determinants of crime can be controlled. While these are not all direct conclusions from the statistical results, it is important to consider the interrelatedness and nuances of factors in urban life. Statistical models and economic theory cannot tell us everything about crime reduction and merely point us in the right direction to identify policies that reduce crime and improve urban life.

Income Inequality

The lack of any significance in most cases for the Gini coefficient may offer some support to Whitworth's (2013) finding that measures for income inequality need to reach a larger geographical extent before they start to have significant relationships with crime rates. While a Census tract may be too small of an area to observe this inequality, grouping five or more together may show the differences. This confirmation is an important contribution to the literature that also warrants further study into how income inequality among tracts or other observational levels relates to crime as opposed to how income inequality within these observational units relates to crime.

Residential Stability

Vacancy rates as a measure of neighborhood decay signal a general need to revitalize a neighborhood. Drawing investment into housing and commercial development in neighborhoods plagued with high crime is a difficult task, but if cities can influence strategic investment in areas with high vacancy, they may be successful in reducing crime there as well. Ehrenhalt (2012) advocates the use of mixed-use zoning as a strategy for reducing vacancy. Euclidean zoning that separates businesses from residences may lead people to move away from residential areas that lack easily accessible commercial amenities. This conflicts with what Cisneros (1996) and Newman (1973, 1996) stress as the importance of distinguished space to defensible space creation. Paulsen (2013) advocates for planning that balances usage diversity with intensity to design safe spaces that encourage community engagement in safety and crime prevention.

Moderating the percent of recent movers and rental rate is a more difficult question. Redevelopment or revitalization of a neighborhood means new residents who are recent movers. On the other hand, there may be endogeneity involved with this variable that complicates the relationship. That is, people may be more likely to move in and out of high crime neighborhoods more quickly than other neighborhoods, rather than crime being influenced by the number of people who moved recently. Further study similar to Kreager, Lyons, and Hays (2010) examining the distinction between tracts that have a long-term trend of turnover versus those that are undergoing revitalization could be helpful to understanding this difference.

Paulsen (2013) and Newman (1996) both elaborate on the construction of tall apartment towers as problematic for crime. The defensible space principle of a sense of ownership does not necessarily require reduction in the rental rate. Instead, individuals could feel a sense of ownership over areas with more clearly delineated responsibility for space in arrangements that use more of the possible space in a lot rather than a tall tower and a large, open, public space with no particular custodian. Densely developed row houses are a commonly proposed alternative to apartment towers. Raising the incentive to watch over one's neighborhood will decrease the supply of criminal opportunities and also increase the probability of arrest, thereby overall decreasing the supply of criminal offenses.

Population Density

The negative relationships between density and the crime rates observed in the regression models of this study contradict the findings of numerous studies done at the city or county level such as Glaeser and Sacerdote (1999) and Cook (2009). The hypothesis about the impact of density on an individual's decision to commit crime also directly contradicts theirs. However, this does not mean these results are totally opposed. In fact, a simple look at descriptive statistics shows that Chicago is about three times as dense, on average, as Dallas and Houston. It also has higher average and median crime rates. The difference in the size of analysis unit matters. This study, performed at the Census tract level, discerns the relationship between population density and crime rates as it occurs on a human scale. Individuals have an incentive to look after their own neighborhood. More individuals looking after a neighborhood increases the number of eyes on the street and increases the probability of arrest. The other studies compare dense cities to less dense cities rather than dense and less dense areas within the same city. Since responsibility is more diffused on a city level, density might not have the same effect on the probability of arrest.

Housing and development laws can regulate population density. Dense areas that place people far from the streets and high in towers will create different incentives than dense areas that put people where they can easily see their streets. Cisneros (1996) points out how the latter example acts as defensible space. This was one of the central arguments in Jane Jacobs's book about how housing should be developed to put people in frequent and easy contact with the streets of their neighborhood: "A well-used street is apt to be a safe street" (1961, 44). Some policies that urban planners might consider to create this defensible density are building codes and lot development ordinances that encourage residences to be built closer to the street and discourage apartment towers more than a few stories high.

The density-crime relationship is one of the most interesting associations to look at from an economic perspective. The negative association between density and crime rates found across all regressions in this study rejects the null hypothesis and opens up the possibility for new discussion the role of density in either increasing or decreasing the probability of apprehension.

Conclusions

The ambiguous results for the Gini coefficient in comparison to other studies suggest that the level of measurement for inequality is an important consideration. The level of measurement is also something important to consider in the differences between individual criminal actors and victims compared to aggregated individuals. This is particularly of concern in considering the behaviors of individuals of different income levels. Aggregating individuals by a measure of per capita income or poverty rate certainly limits the understanding here. The negative and significant relationship between density and crime rates also suggests that policymakers need to consider not only how city or county level density relates to crime, but also how density within neighborhoods relates to it.

This study presents important findings about population density and residential stability upon which policymakers and researchers can build. The hypothesized negative relationship between population density and crime rates proves true. The hypothesized positive relationship between income inequality and crime rates proves true only in a few instances, and not in

Chicago, the city primarily analyzed here. Policymakers can find value in this information about crime rates on the Census tract level in order to combat crime using neighborhood-oriented policies related to urban design.

VIII. Limitations and Considerations for Future Study

There are a number of limitations in this study. First, the lack of time-series data on this topic prevents researchers from assembling a panel data set that would allow researchers to examine how changes in racial composition, vacancy rates, and other variables over time correspond with changes in crime at the neighborhood level. A time-series study would also help determine whether or not there are endogeneity problems with vacancy or the percent of recent movers. Additionally, expanding the study to more cities would allow closer examinations of patterns across different types of cities. Differences in urban development patterns over time and differences between older, industrial cities versus newer, car-oriented cities could be particularly telling. Racial composition also varies widely across cities and more specific results might emerge from an expanded study.

A qualitative look at neighborhoods would be important to understand the planning paradigms and housing trends present in the city of Chicago. Data do not tell us everything about how humans live and how neighborhoods are structured. Understanding a neighborhood's character and history is as important as understanding its demographic characteristics. This also would allow a researcher to understand how policies could actually be implemented in an area. Sometimes existing physical infrastructure or lack of civic engagement hinders the planning and policy process. Another important step for better understanding the quantitative results in terms of policy is a close examination of details like the differences between high percentages of recent movers due to revitalization versus a historically high rate of residential turnover.

Aspects of urban life are highly intertwined and it can be difficult to differentiate the impact of certain factors just by looking at a regression result. Policymakers must always keep in mind the limits of neoclassical economic theory and statistical models and consider broader perspectives based in the realities and peculiarities of individuals lives.

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Appendix

Gini Sensitivity Test

This sensitivity test is referred to in Section IV. The assumptions on the upper and lower groups of the income distribution for grouped household income data are varied to examine the variation of the coefficient with different assumptions. The lower bound is the assumed group mean for the *Less than $10,000* group and the upper bound is the assumed mean for the *Greater than $200,000* group.

Table A.1: Gini Coefficient Sensitivity Test

Lower Bound	*Upper Bound*	*Mean*	*Median*	*SD*	*Percent Change from Mean*
5000.00	750000.00	0.406	0.398	0.102	-
0.00	200000.00	0.454	0.430	0.107	11.89
0.00	1500000.00	0.414	0.404	0.202	2.16
9999.00	200000.00	0.351	0.365	0.178	-13.38
9999.00	1500000.00	0.351	0.365	0.178	-13.38

Post-estimation and Diagnostic Tests

The Breusch-Pagan test confirmed the presence of heteroskedasticity in the two OLS specifications. The problem of heteroskedasticity in an OLS is the violation of the assumption that the error terms are normally distributed. This issue is easily corrected by generating robust standard errors. The results reported in Table 6.1 were not generated using robust standard errors. The Breusch-Pagan test (Table 6.1b) indicates a χ^2 value of 38.53 for the violent crime regression and of 88.82 for the property crime regression.[12] This rejects the null hypothesis that there is constant variance in the error terms (homoscedasticity), indicating that there is heteroskedasticity. Choosing to regress with robust standard errors does not change the coefficients of the model, but does impact the standard errors and significance. This is evident by comparing the coefficients and standard errors of the non-robust negative binomial models in Table 6.1 to the robust results for property crime in Table 6.3 and violent crime in Table 6.4.

Table A.2: Breusch-Pagan Test

	χ^2
Violent Crime	38.53**
Property Crime	88.82**

[12] Note that this χ^2 statistics differs from the goodness-of-fit measure in the Poisson regressions.

Table A.3: Ramsey Test	
	F-stat
Violent Crime	16.77**
Property Crime	4.63*

The Ramsey omitted variable test (Table 6.1c) indicates whether there may be a bias due to an omitted variable in the model. The F-statistic of 16.77 for the violent crime OLS regression and 4.63 for the property crime OLS for Chicago indicates that there is an omitted variable in each model.[13] Omitted variable bias causes the coefficients of one or more of the independent variables to inflate because it captures the impact of an omitted variable. After exhausting possible combinations of variables available in the dataset, no combination seemed to help bring these values down. The problems from omitting a variable may be overshadowed by the benefits from reducing the multicollinearity present in the model by removing it. This brings up another issue.

Table A.4: Variance Inflation Factors	
Variable	*VIF*
log.DENSITY*POVERTY	204.46
log.POVERTY	173.62
log.DENSITY	20.93
log.PERCAP	9.74
log.PCHISP	8.59
log.FHH	6.07
log.NEWIMM	6.07
log.PCBLK	5.97
log.RDI	5.08
log.HSGRAD	4.43
log.PCASN	3.73
log.UNEMP	3.70
log.PCRENT	3.15
log.MOVER	2.31
log.GINI	1.74
log.POP	1.56
log.VACANT	1.35
log.HSVALU	1.29
Mean VIF	25.80

Multicollinearity exists if two or more independent variables are highly correlated with one another. The original model used for this paper included per capita income for each tract. This variable was expected to be highly collinear with other variables. A number of other variables were also found to be collinear. A Variance Inflation Factor (VIF) test is commonly used to measure the increase in variance caused by collinearity. Any time the VIF for any one variable is greater than 10, the variable has collinearity with others in the model.

The VIF test remains the same across all regressions, so long as the independent variables included are the same. One could expect that the multiplicative interaction term of the log of density times the log of poverty is collinear with

[13] These F-statistics differ from those used to assess goodness-of-fit in an OLS model.

both poverty and density. Since this is anticipated anytime there is an interaction term, the VIF scores can be disregarded.

Per capita income has a VIF score of 9.74, suggesting it is closely related to many other variables. In contrast, housing value, a variable which may be thought to indicate income, has the lowest VIF at 1.29. The researcher can provide, on request, a more thorough set of VIF scores showing that poverty and density do not have high VIF scores when the interaction term is removed from the model. The percent of whites was excluded from the model to begin with because it would have nearly perfect collinearity with the other percent racial composition variables.

The other cities in this study had statistically significant Moran's I values just as Chicago did. However, none of the results from the spatial lag regressions indicated that spatial autocorrelation impacted the models significantly.

Table A.5: Spatial Autocorrelation Figures

	Dallas.		*Houston*		*Los Angeles*	
	Moran's I	*p-value*	*Moran's I*	*p-value*	*Moran's I*	*p-value*
VIOLRT	-0.018	0.000	-0.006	0.087	-0.007	0.000
PROPRT	-0.014	0.000	-0.003	0.389	-0.001	0.414

Table A.6: Negative Binomial Regressions with Population Exposure for Dallas

N= 800	Total Violent Crimes		Total Property Crimes	
VARIABLE	*β*	*SE*	*β*	*SE*
log.DENSITY	-0.164	0.299	0.074	0.235
log.DENSITY * log.POVERTY	0.023	0.088	-0.082	0.069
log.POVERTY	0.296	0.671	0.835	0.521
log.GINI	-0.252	0.354	-0.218	0.308
log.PCINC	0.267	0.246	0.473	0.208*
log.POP	-0.120	0.087	-0.143	0.074
log.UNEMP	0.281	0.108**	0.184	0.088*
log.HSVALU	0.024	0.014	0.008	0.021
log.HSGRAD	-0.808	0.245**	-0.513	0.218*
log.FHH	-0.168	0.134	-0.267	0.108*
log.NEWIMM	-0.261	0.098**	-0.262	0.074**
log.PCBLK	0.153	0.065*	0.086	0.055
log.PCHISP	0.003	0.091	0.073	0.070
log.PCASN	-0.071	0.060	-0.097	0.051
log.RDI	-0.376	0.199	-0.327	0.162*
log.VACANT	0.326	0.065**	0.076	0.056
log.MOVER	0.116	0.230	0.325	0.207
log.PCRENT	0.289	0.118*	0.283	0.102**
Constant	-1.012	4.854	-3.448	3.405
α	0.158	0.017**	0.123	0.011**
Test of χ^2	4075.02**		2.4E04**	

**Significant at the 5% level, **Significant at the 1% level*

Table A.6a: Total Marginal Effects

	Violent Crime	*Property Crime*	*Sample Mean*
Density	-0.102	-0.149*	2475.41
Poverty	0.468**	0.217*	19.03

Table A.7: Negative Binomial Regressions with Population Exposure for Houston

N= 800	Total Violent Crimes		Total Property Crimes	
VARIABLE	*β*	*SE*	*β*	*SE*
log.DENSITY	-0.116	0.244	-0.537	0.274*
log.DENSITY * log.POVERTY	0.059	0.077	0.095	0.088
log.POVERTY	-0.180	0.577	-0.748	0.677
log.GINI	0.518	0.208*	0.277	0.231
log.PCINC	-0.043	0.119	0.029	0.135
log.POP	-0.189	0.058**	-0.240	0.065**
log.UNEMP	0.090	0.109	0.148	0.119
log.HSVALU	-0.045	0.095	-0.053	0.102
log.HSGRAD	-0.436	0.209*	0.045	0.237
log.FHH	-0.280	0.113*	-0.213	0.126
log.NEWIMM	-0.102	0.071	-0.069	0.078
log.PCBLK	0.165	0.042**	-0.017	0.045
log.PCHISP	0.012	0.079	-0.005	0.078
log.PCASN	-0.042	0.051	-0.002	0.054
log.RDI	-0.258	0.175	-0.290	0.175
log.VACANT	0.160	0.073*	0.059	0.081
log.MOVER	-0.231	0.188	-0.042	0.231
log.PCRENT	0.329	0.135*	0.567	0.165**
Constant	3.348	3.323	5.601	3.852
α	0.139	0.016**	0.167	0.020**
Test of χ^2	5041.26**		4.2 E 04**	

**Significant at the 5% level, **Significant at the 1% level*

Table A.7a: Total Marginal Effects

	Violent Crime	*Property Crime*	*Sample Mean*
Density	0.055	-0.246**	2082.26
Poverty	0.264*	0.037	20.76

Table A.8: Negative Binomial Regressions with Population Exposure for Los Angeles

N= 789 VARIABLE	Total Violent Crimes β	SE	Total Property Crimes β	SE
log.DENSITY	0.064	0.125	0.155	0.141
log.DENSITY * log.POVERTY	-0.072	0.039	-0.191	0.043**
log.POVERTY	0.694	0.326*	1.520	0.388**
log.GINI	0.553	0.169**	0.603	0.187**
log.PCINC	-0.545	0.123**	-0.535	0.115**
log.POP	-0.252	0.059**	-0.313	0.068**
log.UNEMP	0.165	0.072*	0.051	0.074
log.HSVALU	0.001	0.019	0.002	0.017
log.HSGRAD	0.006	0.147	-0.017	0.141
log.FHH	-0.206	0.097*	-0.247	0.079**
log.NEWIMM	0.060	0.070	0.195	0.064**
log.PCBLK	0.214	0.029**	0.121	0.030**
log.PCHISP	-0.061	0.057	-0.373	0.056**
log.PCASN	0.037	0.027	0.040	0.029
log.RDI	0.075	0.112	-0.107	0.101
log.VACANT	0.221	0.047**	0.098	0.046*
log.MOVER	-0.236	0.138	0.080	0.140
log.PCRENT	0.204	0.075**	0.240	0.078**
Constant	2.506	2.432	5.568	2.355*
α	0.181	0.014**	0.181	0.014**
Test of χ^2	1.8 E04**		5.6 E 04**	

**Significant at the 5% level, **Significant at the 1% level*

Table A.8a: Total Marginal Effects

	Violent Crime	Property Crime	Sample Mean
Density	-0.147**	-0.408**	6416.23
Poverty	0.088	0.095	22.55

Table A.9: Dallas Descriptive Statistics					
N = 224					
Variable	*Mean*	*S.D.*	*Median*	*Min*	*Max*
Crimes					
VIOLRT	15.49	17.97	10.65	0.47	143.33
PROPRT	77.00	59.63	63.78	18.84	519.05
VIOL	176.06	139.53	147.00	2.00	629.00
PROP	896.93	535.66	818.50	108.00	3579.00
Tract Characteristics					
POP	4293.72	1922.22	4032.50	993.00	11091.00
DENSITY	2475.41	2206.13	1983.14	189.50	22281.71
AREA	2.63	2.99	2.06	0.35	36.57
Economic & Social Characteristics					
POVERTY	19.03	13.30	18.28	0.59	78.61
UNEMP	7.90	6.42	6.37	0.00	41.27
PCINC	25294.67	22036.53	16012.00	3532.00	150000.00
GINI	0.42	0.07	0.41	0.21	0.64
HSVALU (000s)	120.00	110.00	81.20	0.00	1000.00
HSGRAD	67.65	22.90	69.95	19.70	99.41
NEWIMM	13.04	12.19	9.88	0.00	57.30
YMALE	7.76	3.41	7.82	0.73	20.24
FHH	16.06	11.27	14.32	0.00	66.76
VACANT	6.75	4.69	5.73	0.00	29.33
MOVER	53.34	15.67	50.76	25.44	91.16
PCRENT	51.13	27.11	48.08	0.54	100.00
Racial Composition					
PCWHT	36.45	32.57	24.52	0.00	97.96
PCBLK	26.28	30.37	11.18	0.00	98.67
PCASN	2.10	3.23	0.89	0.00	27.10
PCHISP	33.76	28.63	24.40	0.00	94.43
RDI	5967.95	1892.92	5696.17	2454.00*	9736.39

**This value is lower than the expected minimum of 2500 because the racial category "Other" was not included.*

Table A.10: Houston Descriptive Statistics

N = 297

Variable	*Mean*	*S.D.*	*Median*	*Min*	*Max*
Crimes					
VIOLRT	12.38	8.38	10.63	0.71	44.47
PROPRT	61.42	45.15	52.38	8.50	474.84
VIOL	187.85	150.38	154.00	6.00	954.00
PROP	940.44	707.66	736.00	99.00	4661.00
Tract Characteristics					
POP	5602.33	3683.63	4646.00	888.00	23960.00
DENSITY	2082.26	1164.03	1897.15	240.00	10717.75
AREA	3.36	3.38	2.38	0.82	35.66
Economic & Social Characteristics					
POVERTY	20.76	12.23	20.41	0.53	70.36
UNEMP	8.90	5.93	7.82	0.41	56.98
PCINC	25146.15	21539.67	16241.00	5400.00	120000.00
GINI	0.43	0.07	0.43	0.17	0.68
HSVALU (000s)	110.00	110.00	71.70	24.80	1000.00
HSGRAD	*66.93*	*20.91*	66.52	*22.76*	100.00
NEWIMM	12.11	8.99	10.69	0.00	44.12
YMALE	7.52	2.70	7.50	2.01	27.76
FHH	16.05	9.59	14.16	0.55	50.71
VACANT	8.01	4.35	6.95	0.00	27.36
MOVER	50.07	15.08	47.83	19.87	87.44
PCRENT	50.12	22.99	48.70	3.20	97.72
Racial Composition					
PCWHT	31.46	29.35	19.66	0.00	95.35
PCBLK	26.21	31.25	10.23	0.00	98.16
PCASN	3.95	5.51	1.59	0.00	37.83
PCHISP	36.92	27.81	30.39	0.00	96.49
RDI	5691.82	1834.51	5376.69	2318.00*	9637.47

**This value is lower than the expected minimum of 2500 because the racial category "Other" was not included.*

Table A.11: Los Angeles Descriptive Statistics

N = 789

Variable	*Mean*	*S.D.*	*Median*	*Min*	*Max*
Crimes					
VIOLRT	12.88	11.94	10.12	0.18	173.15
PROPRT	33.63	39.37	26.59	0.18	800.72
VIOL	165.59	138.97	136.00	1.00	1976.00
PROP	418.74	311.54	350.00	1.00	3690.00
Tract Characteristics					
POP	4417.59	1333.44	4274.00	533.00	10941.00
DENSITY	6416.23	5247.73	4918.96	160.20	35583.20
AREA	1.33	1.89	0.89	0.11	21.99
Economic & Social Characteristics					
POVERTY	22.55	13.63	20.69	0.83	74.00
UNEMP	9.83	5.22	9.08	0.75	48.12
PCINC	20911.34	17889.69	14233.00	3988.00	140000.00
GINI	0.44	0.07	0.43	0.12	0.71
HSVALU (000s)	230.00	150.00	180.00	0.00	1000.00
HSGRAD	62.47	23.55	62.11	15.50	100.00
NEWIMM	15.65	9.74	14.02	0.71	57.13
YMALE	7.47	3.57	7.38	0.89	42.59
FHH	15.72	8.03	14.88	0.47	65.22
VACANT	4.72	3.04	3.84	0.00	23.52
MOVER	49.87	10.90	49.27	22.55	94.43
PCRENT	60.79	26.14	64.68	0.99	100.00
Racial Composition					
PCWHT	29.08	29.22	17.23	0.00	91.35
PCBLK	10.50	16.61	3.87	0.00	91.65
PCASN	9.80	10.31	6.56	0.00	81.40
PCHISP	47.68	29.25	49.83	0.58	99.20
RDI	5427.33	1686.40	5159.21	2335.30*	9841.57

**This value is lower than the expected minimum of 2500 because the racial category "Other" was not included.*