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Essays On Applications Of Spatial Econometric Models

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CHAPTER 1 "SPATIAL INTERACTION OF CRIME IN THE CITY OF DETROIT: EVIDENCE FROM SPATIAL DATA MODELS"

Introduction

Crime study is of great interest to economists since the study of economic analysis of crime (Gary Becker, 1968). Crime affects economic growth and development directly and indirectly and also affects our daily life. Illegal activities have huge impacts on our economy and living environment since they generate inefficiency and deteriorate the living environment of the communities. Crime also has significant economic costs for society and leads to social instability, which lower social welfare and people's sense of security. Resources that can be used for legal and efficient activities will be converted to inefficient ones. The costs of crime and related social interactions are important for decision-makers concerned with crime and its impact on society and the economy as well. Therefore, better understanding the story of crime can help to improve social stability, economic efficiency and reallocate public safety resources efficiently and wisely.

Detroit, Michigan, is well-known in the U.S, not only for its most significant auto industries but also for its high crime rates. Since the infamous riot of 1967, high crime rates and negative media reports have labeled this city as one of the most dangerous cities in the U.S., and a huge number of residents have moved out of this city in the past few decades. This situation has also brought tremendous pressure on the government. Strong attention has been drawn to scholars and researchers to answer what and why this happened in Detroit and how to provide positive information for policymakers and public.

In literature, the causes and theories of crime have already been developed and investigated by many disciplines, such as geography, sociology, economics, etc. Among these disciplines, socio-economic variables are known to affect crime rates and types of crime as well as spatial factors (Ratcliffe and McCullagh, 1999; Kakamu, Polasek and Wago, 2008; Menezes, Silveira-Neto, Monteiro and Ratton, 2013). Particularly, spatial interaction has been taken into account and discussed in many articles. It may refer to a dynamic movement of human activity from one place to another or nearby locations; for example, criminal activities. Furthermore, the presence of spatial interactions shows the commonly used ordinary least squares (OLS) models are misspecified and biased without considering the inter-relationship among dependent variables (Anselin, 1988; Anselin and Luc, 2001; Menezes, Silveira-Neto, Monteiro and Ratton, 2013). Theoretical work in economics, sociology, and criminology has also underlined the concepts of inter-relationships, such as peer effects, social norms, neighborhood effects, etc., which indirectly support the importance of spatial interaction.

Spatial models; therefore, are being introduced and used for crime studies. Spatial analysis of crime was proposed around the 1970s. In the beginning, most of them were location or geographical based studies. Hotspot mapping and modeling, distance statistics and other geospatial techniques are widely used in analyzing the spatial characteristics of crimes (Pyle, Gerald, et al, 1974; Brantingham and Brantingham, 1984; Ratcliffe and McCullagh, 1999; Chainey, Tompson and Uhlig, 2008; Ratcliffe, 2010, Leitner and Michael, 2013). Followed by the development and improvement of econometric methodologies, more researchers of different fields find it more precise and convincing to use spatial econometric models for their own researches of crime (Brown, 1982; Kakamu, Polasek and Wago, 2008; Scorzafave and Soares, 2009; Menezes, Silveira-Neto and Monteiro, 2013; Shi and Lee, 2017).

As one of the most widely used spatial econometric approaches, the spatial autoregressive model (SAR) is continuously being developed and improved to support empirical analysis. It contains spatially lagged dependent variable and weighting matrix addition to regular OLS estimation terms. Especially, determination of the weighting matrix is crucial in the spatial autoregressive model, which is non-stochastic and the spatial dependence among cross-sectional units. Distance-based techniques are ways to construct spatial weighting matrices in geography and were used in some studies in economics as independent variables as well (Anselin, Cohen, Cook, et al, 2000; McMillen, 2010). In this study, we introduced a geographical methodology: inverse distance weighting (IDW), which is mainly used to estimate distance based weighting from a scattered set of points (Chang 2015). Furthermore, aggravated assault, assault, and weapons offenses in violent crime; burglary, robbery and stolen vehicle in property crime combined with six different scaled weighting matrices are estimated and discussed.

However, analysis of crime is still not well-developed, and few studies are investigating the consequences of criminal activities in the city of Detroit. The spatial pattern of crime is considered to be related to a variety of socioeconomic and crime opportunity factors. This paper evaluates the impact of socioeconomic variables on crime and space interactions of crime rates among block groups by using spatial autoregressive models, crime data, and socioeconomic data. It also applies spatial data models with individual and time unobservable effects. Furthermore, it introduces a rich set of controls into the model, including block group level characteristics, such as demographics, education level, employment rates, household income, etc. This paper is an important and policy-relevant topic that has seldom been studied in the past. The study will not only enhance our understanding of spatial interactions in regional criminal activities but also provide implications for policymaking or law enforcement agencies.

The rest of this article is organized as follows: section II synthesizes existing literature of crime analysis and applications of spatial autoregressive models. In section III, we introduce methodology and model specifics of the estimation. Two types of spatial models are used for comparison and discussion. Detailed data description and origin are presented in section IV. Section V concentrates on empirical evidence and main findings of socioeconomic impacts and space interactions of crime. The last section concludes and summarizes findings and proposed directions for future researches.

Literature Review

Theories of crime have been well developed by many disciplines, and interest in empirical studies of crime and approaches to better understand it is still growing. By the desire of supporting communities and providing significant insights for law enforcement agencies, a large number of crime studies have been completed in literature (Becker and Gary, 1968; Miethe, Stafford and Long, 1987; Bonta, Law and Hanson, 1998; Lochner and Moretti, 2004; Chainey and Ratcliffe, 2013; Vera and Fabian, 2016). All these significant and comprehensive analyses of crime play critical roles in crime control and crime reduction strategies. Meanwhile, with efforts and contributions of scholars in various social sciences, plenty of crime-relevant factors and variables are found, and different methodologies are being applied to crime studies.

Demographic factors of crime are regularly used, by crime-related scholars, law enforcement agencies and federal bureaus, to understand the nature and characteristics of the crime. Socio-economic and legal factors have also been proved important for crime analysis. Howsen and Jarrell (1987) analyze property crimes by applying simultaneous system equations and state that socio-economic and law enforcement variables are significant and important. Gender and race have also been advanced to strong factors of crime by criminologists. Arrest and victimization data reflect gender and race are key determinants in crime research (Steffensmeier and Allan, 1996; Messerschmidt, 1997).

Additionally, detailed individual-level datasets are examined for violent and property crime rates by Gould, Weinberg and Mustard (2002). They look into the causal relationship between the labor market and crime rates and conclude that the income of unskilled workers plays a significant role in the long run crime reduction. Change in unemployment rates is also significantly related to crime rate variations. Furthermore, evidence has clearly shown that higher education levels lower incidences of crime (Lochner and Moretti, 2004). Machin, Marie and Vujić (2011) find that increase the leaving age of school can generate social benefits and decrease crime rates significantly. To achieve the long term benefits of society, the education level of criminals and potential criminals has to be taken into account and need to be improved.

Likewise, alcohol and drugs were highly related to property and violent crimes and have been considered as critical factors of crime since the 1980s (Cordilia and Ann, 1985; Parker and Auerhahn, 1998). Alcohol and drugs are costly and could be addictive, and they yield incentives for offenders to commit crimes. Haggård-Grann, Ulrika, et al., (2006) confirm the strong relationship between the misuse of alcohol and violent crimes. Misuse of drugs is also shown to be related to the robbery, burglary and other drug-related crimes (Benson, Kim, Rasmussen and Zhehlke, 1992; Corman and Mocan, 2000; Bennett, Holloway and Farrington, 2008). In particular, dangerous drugs, such as heroin and cocaine, are often associated with both property and violent crimes.

Besides, the methodology of crime analysis is another concern of researchers. In addition to criminal justice statistics and experimental methods in criminology, data modeling and techniques are commonly used in literature, such as OLS regression, Poisson and negative binomial regressions, logistic regression, structural modeling of system equations, time series, etc. Osgood and Wayne, (2000) apply Poisson-based models to analyze arrest rates of robbery for juvenile and conclude that the Poisson-based negative binomial model fits the data better compare with OLS models. Moreover, time-series data and models were used and strongly supported the deterrence hypothesis of crime (Corman and Mocan, 2000). Osgood, Finken and McMorris, (2002) also propose to use Tobit regression for a better fit of the self-reported offenses, and it provides a small improvement over regular OLS models as well. However, as the special attention given on computerized mapping, spatial statistics and the consideration of individual interactions in theoretical work of social science, more spatial data and models have been using and developing due to theoretical concerns and the estimation strength of the models since 1990s.

Spatial analysis has a long history in geography literature. Spatial autoregressive modeling is inspired by the geography and then became the core of spatial econometrics. Gradually, it becomes a great interest for economists, criminologists, and other scholars to analyze spatially related data nowadays, especially when data observations are not truly independent. Many of the current spatial studies of crime are based on geography and sociology techniques and theories. Hotspot mapping is one of the primary and geographical ways to predict spatial crime patterns and possible police resource reallocations (Chainey, Tompson and Uhlig, 2008). They provided methodology comparisons and discussions of crime in predictions and applications. Ingram and Marchesini (2015) look into five types of homicide across Brazil by examining the effects of family disruption, marginalization, and the geographic diffusion of violence. etc. Their findings help law enforcement agencies to identify the content of violence reduction policies and how to target policies by type of homicide and geographic patterns for optimal effect.

Furthermore, crime control and crime rate reductions are top priorities and concerns for social stability and government intervention. However, if the distribution of crime incidents is random or not traceable, then studies of crime patterns are not likely to be the optimal and efficient strategy. Anselin, Cohen, Cook, et al (2000) discuss and summarize theoretical and empirical research methodologies in spatial analysis of crime, which are well used and standard approaches in crime analysis. He states that research should be extended to more disciplines, and more empirical studies are needed to support and improve the theoretical analysis of crime. Besides, a relatively comprehensive overview of spatial methodologies was again discussed by Anselin (2002). He combines the views of geology, biostatistics, and traditional econometrics and provides considerable and valuable perspectives and guidance for econometricians in future spatial researches. In short, an efficient model and relationship between crime and location are still needed to be explored and improved.

As unceasing growth and advancements of spatial analysis methodologies, spatial econometrics has matured and been developed in regional science. Motivated by the use of spatial data and the existence of spatial effects in regression, spatial models have been adopted by many researchers. Cracolici and Uberti (2009) investigate crime patterns in 103 Italian provinces and use different spatial weighting matrices in spatial models. They found that socioeconomic variables have impacts on crime activities but not for all types and all time. Torres, Polanco and Tinoco (2015) examine the effects of crime on regional economic growth in Mexico by using a spatial panel data model. They found crime has a total negative effect on economic growth across Mexican states, particularly homicides and robbery. In addition, significant spatial interactions seem to increase the negative impact on regional economic growth. Alternatively, Hoshino (2016) applies semiparametric spatial autoregressive models to estimate crime data. His model allows for endogenous regressors and the heterogeneous effects across spatial units. Moreover, the latest and hot topic of the impact of gun control on crime was examined by Shi and Lee (2017). They assume unobserved time effects are the same among states and find positive spatial effects in crime by using a dynamic spatial panel data with interactive fixed effects.

From a technical perspective, unknown heteroskedasticity generally leads to inconsistent estimators for SAR models. Lin and Lee (2010) propose a generalized method of moments (GMM) estimation of spatial autoregressive models for the possible existence of heteroskedastic disturbances. Based on their models and assumptions, experimental results are shown to be consistent and asymptotically normal. They also mention that efficient estimation can be achieved if optimal weights could be constructed. Issues in spatial data analysis in crime are discussed by McMillen (2010) as well. Biased estimators and spatially correlated errors exist in models. They proposed spatial lag models for large dataset analysis compared with standard distance-based models, and fixed effect models are also suggested under certain conditions. Lee and Yu (2010) propose two approaches with fixed effects for panel data analysis, and methods were evaluated by small Monte Carlo experimental simulations and were verified efficiently under certain conditions. Discussion focuses on the time scale and individual fixed effect in two models and provides inspirational ideas for future empirical studies. In addition to the above, the random effects of spatial models are also discussed by Kapoor, Kelejian and Prucha (2007) and Baltagi, Egger and Pfaffermayr (2013).

By combining spatial autoregressive models with controllable inverse distance weighting, this paper contributes to the current literature in several aspects. Firstly, it will increase our understanding of the spatial interactions of crime in the city of Detroit based on block group level data. Secondly, it seeks to establish rational and more precise econometric models and show more accurate spatial interactions among different entities when data observations are not truly independent and homogeneous. It would empirically support and verify Lee and Yu's (2010) theoretical work. It will also add to our knowledge about how much security conditions will be affected and influenced by our surrounding area. In addition, as the hotspot city of high crime rates, a closer look into the conditions and empirical evidence of the crime of Detroit city will attract more attention of police, public, and government officials.

Model Specification

A: Methodology Background

Interest in crime places has been growing for decades. Many theoretical and empirical studies have put special attention to the relationship between spatial characteristic and crime. For instance, routine activity theory (Cohen and Felson, 1979) states that criminal activities are closely related to our surroundings and neighborhood environment. Places that people are all living together or facilities that people are frequently using invisibly attract criminals, especially for property offenders in a rich environment. Other theories and empirical evidence (Brantingham and Brantingham, 1984; Cracolici and Uberti, 2009; Torres, Polanco and Tinoco, 2015) also support the importance of place to crime.

For approaches of analyzing crime places, hotspot mapping is one of those ways to show visualization and concentration of crime incidents in certain areas, specifically in the way of high occurrence areas versus low occurrence areas. Likewise, hotspot modeling is applied to provide descriptive statistics and basic linear regression models for a better understanding of crime patterns. However, these two methods are not sufficient to identify the relationship between crime and place. Therefore, more attention has been placed on the research of analyzing spatial data and spatial autocorrelation. Based on geographic theories and techniques, to the best of my belief, the analysis of spatial crime data can be divided into three categories: point pattern analysis, distance statistics, and regional analysis. All these methods are used to capture spatial characteristics of crime incidents and evaluate the likelihood of occurrence of crime.

More specifically, addition to methods that use average distance as an exogenous variable or dummy variable, the most popular way of analyzing spatial autocorrelation is spatial weighting matrix. Moran’s I and Geary’s C are widely used and considered as the standard measurements of spatial autocorrelation in geography, and they are also inversely related (Cliff and Ord, 1973). Moran's I is regularly used as a measurement of global spatial autocorrelation, and Geary's C is more often used to measure local spatial autocorrelation. These two methods consist of the variable of interest (x), mean of x and a matrix of spatial weights with zeros on the diagonal. Their weighting matrix is often assigned the value of 1 if two areas are neighbors and assigned 0 if two regions are not neighbors, or constructed by particular distance functions. However, spatial autocorrelation still cannot be captured efficiently in linear regression models with the above two measurements since they could be easily converted into distance based exogenous variables instead of variables of endogenous effects. In this paper, we introduce a more comprehensive and accurate method to estimate weighted values, which is discussed in details by the following part.

In the literature on criminal justice, the regression model plays a vital role in investigating the determinants of criminal activities. Based on many advantages and improvements compare with baseline models, SAR models are adopted in this paper. In particular, as pointed by Lee (2003, 2004 and 2007), one can identify endogenous effects by exploring the information of the error term even if there are not sufficient exogenous variables. In short, compared with methods and models we have discussed previously, SAR models with individual and time fixed effects, which also contain spatially lagged error terms, are applied and used in this paper.

B: SAR Models

Spatial autoregressive model is a great improvement over the standard OLS model. An original and straightforward spatial autoregressive model is shown as follows, which contains a spatially lagged term of dependent variable y,

$$y = \rho W y + \beta X + \varepsilon \qquad (1)$$

It is very similar to a standard linear regression where the first term consists of a n×n spatial weighting matrix, W; observed dependent variable, y; and a spatial autoregressive parameter, ρ, which needs to be estimated from the data. X is independent variables with parameter β. ε is disturbance. Briefly speaking, a spatial lag model is the idea that variables at a certain location are related and connected to the same variables at nearby locations. The spatial weighting matrix is generally row normalized such that its rows sum up to 1. In other words, the weighted averages of neighboring values are considered in the model.

This paper is following approaches proposed by Lee and Yu (2010) to find out spatial correlation and causal relationship among crime rates, socio-economic variables, and Detroit block groups, and it will also provide empirical support and evidence for theoretical spatial methodology. Models that are using can be shown as follows:

$$\mathrm{Y_{nt}} = \lambda_0 \mathrm{W_n Y_{nt}} + \beta_0 \mathrm{X_{nt}} + \mathrm{c_{n0}} + \alpha_{t0} \mathrm{l_n} + \mathrm{U_{nt}},$$

$$\mathrm{U_{nt}} = \rho_0 \mathrm{M_n U_{nt}} + \mathrm{V_{nt}}, \qquad t = 1,2,3,\dots\dots,T \qquad (2)$$

where logarithm of crime rates $\mathrm{Y_{nt}}$ and $\mathrm{V_{nt}}$ are n×1 column vectors, and $\mathrm{V_{nt}}$ is i.i.d. across n and t with zero mean and variance σ_0^2. Also, $\mathrm{W_n}$ and $\mathrm{M_n}$ are n×n spatial weights, which are non-stochastic and generate the spatial dependence among cross-sectional units Y_{nt}. W_n is usually row normalized from a symmetric matrix, which ensures that all the weights are between 0 and 1, and weighting operations can be interpreted as an average of the neighboring values; or in this analysis, be calculated by inverse distance weighting. Particularly, based on Lee and Yu (2010), we assume that W_n and M_n are the same. X_{nt} is an n×k_x matrix of non-stochastic independent variables. λ_0 represents spatial interactions (spatial effects), ρ_0 shows the spatial coefficient of error term since we assume that unobserved variables are also interdependent. c_{n0} is n×1 column vector of individual fixed effects, α_{t0} is a scalar of time effect, and l_n is n×1 column vector of ones. The parameter we are estimating is: $(\beta', \lambda, \sigma^2)'$.

The next step is to apply a dynamic spatial model (Yu, Jong and Lee, 2008) for estimation and comparison. The model is constructed as below:

$$Y_{nt} = \lambda_0 W_n Y_{nt} + \gamma_0 Y_{n,t-1} + \rho_0 W_n Y_{n,t-1} + \beta_0 X_{nt} + c_{n0} + \alpha_{t0} l_n + V_{nt},$$
$$t = 1,2,3,\dots,T \qquad (3)$$

In model (3), most term descriptions and constructions are the same as in model (2). But, we introduced Y_{n0} in the model, which is the logarithm of previous year's (the year 2009) crime rates. ρ_0 now represents endogenous effects based on previous year's crime rates. The error term is not as assumed interdependent as well. Additionally, the weighting matrix W_n is evaluated in six different scales, which are the same evaluations as in model (2). The parameter we are estimating is: $(\delta', \lambda, \sigma^2)'$, where: $\delta = (\gamma, \rho, \beta')'$.

C: Spatial Weight Matrix

Followed by standard convention, the spatial weight matrix is assumed strictly exogenous. The assumption holds especially when spatial weights are constructed by geographic distances. In particular, based on geography concept, the centroid point is a region's geographical center and a radial projection of a region, and it is also commonly used in the spatial analysis of geography. Centroid points; thus, are used to get a scattered set of location points of Detroit block groups to estimate physical distances (see Figure 1).

Based on centroid distances, k-nearest neighbor (KNN) (Altman, 1992) and radial distance/radius are mainly used to build spatial weights. In brief, for KNN, the matrix is often assigned the value of 1 for k regions that are closest to the region being estimated and assigned value of 0 otherwise. Likewise, in the estimation of radial distance, the matrix is regularly assigned the value of 1 for locations within a threshold distance and 0 for locations beyond the threshold. However, there are no standard ways or criteria to determine the optimal number of k closest regions (Beyer, Goldstein, Ramakrishnan and Shaft, 1999) and threshold distance if there is no particular information about spatial influence within a certain distance. Specifically, in geography, there is a tradeoff between biasness and variance. In other words, the bigger value of k will decrease variance and increase bias, and vice versa. One might use a weighted average of the distance to overcome the bias of KNN, but it still cannot precisely capture and describe the true relationship among locations.

Besides, spatial weights can also be calculated and constructed based on shared boundaries of geographic units. The simplest way of constructing it is to assign the value of 1 to spatial units that are sharing at least a boundary or corner point, and assign 0 if they do not share any boundaries or corner points. Similarly, shared boundary weight is a more precise way of doing so, which can be described as the fraction of the length shared with a specific unit over the length of total shared boundaries of all connected units. However, the common issue of these two methods is that they all automatically exclude the influence and effect of nearby regions that are not sharing any boundaries or corner points on the region being estimated.

In this paper, inverse distance weighting is introduced. It is mainly used to estimate distance based weighting from a scattered set of location points in geography. Based on geographic theory (Bolstad and Paul, 2005), locations that are close to one another are more likely to be connected and influenced. In other words, farther a point is from the point being estimated, the less weight it has in estimation. The equation is as shown below:

$$\lambda_{ij} = \frac{\frac{1}{d_{ij}^{p}}}{\sum_{i=1,j=1}^{N} \frac{1}{d_{ij}^{p}}} \tag{4}$$

where λ_{ij} represents the unit of distance weights between location i and j, and d_{ij} is the physical distance of centroid points i and j. In the equation above, greater values of p allocate greater influence to locations closest to the point being estimated. In addition, the range of p values in 0.5-3.0 is mostly chosen by geographers and is considered optimal in practice (Lu and Wong, 2008). Especially, when p=0, block groups are all equally weighted; and if p goes to infinity, block groups tend to be geographically identical, which violates the reality.

Besides, inverse distance weighting enables us to have good control of the weighting matrix, which is better than predetermined and constant weights. More specifically, the value of p starts from 0.5 to 3.0 with an increment of 0.5, so that means it has six different scales of weighting. Although this strategy cannot perfectly satisfy the assumption of homogeneity of entities (block groups) or solved the issue of "ecological fallacy" mentioned in Anselin, Cohen, Cook, et al. (2000), it still provides new insights and alternative way of interpretation of spatial effects. In other words, influence to locations from nearest to farthest to the point being estimated can be controlled and adjusted; therefore, we can see how spatial interactions change by the allocation of influence (p), and if influence reallocation is significant in research.

Data

Crime data was collected from Detroit Open Data Portal, which provides extracted data from the Detroit Police Department's (DPD) records management system. Crime data reflects reported criminal offenses that have occurred in the city of Detroit since January 1, 2009, and it consists of 43 types of crimes with incidents' locations. Due to privacy, approximate locations given in the data are used at the block group level. This study analyzes data date from January 1, 2010 to December 31, 2010 and six types of crime in two categories: aggravated assault, assault, and weapons offenses in violent crime; burglary, robbery and stolen vehicle in property crime. Furthermore, block group level Detroit census data 2010 are cooperated and used as explanatory variables[1].

The city of Detroit has 879 block groups in total. One of 879 block groups is dropped since it contains many 0s and blank information only (see Figure 2 marked in red). City of Highland Park and Hamtramck city are excluded as well since they are not part of Detroit city (see Figure 2). Moreover, only people who are 18 years and older are included in this study. Michigan still treats 17 years old people as adults. However, some states declare 18 as the minimum age of criminal responsibility. People between age 10 and 17 can be arrested and taken to court if they committed a crime, but they will be charged differently from adults. So, based on the need of this research and the accuracy of crime rates calculation, we choose to include people who are 18 years and older only.

The Dependent Variables

The logarithm of crime rates of six selected types is used as dependent variables. Crime rates were calculated by the standard definition of criminology, which is the number of crime incidents per 100 people in each block group. All crime incidence rates are used as a comparison and base result.

The Independent Variables

Independent variables are extracted from 2010 U.S. census data and DPD records, which include race, median age, selected population characteristics in

[1] Integration and combination of census and crime data were completed with the help of China Data Center, University of Michigan, Ann Arbor. In particular, block group boundaries were slightly modified to better fit the data, which yields a very small difference between block groups used in this research and official census blocks (block groups).

each category, number of vacant housing units, median household income, median number of school years, total of vehicles of occupied units, employment ratio, number of law enforcement workers that are living in each block group, etc. In particular, the employment ratio was calculated as a number of employed/number of population18 years and older in the block group. Incidents of dangerous drugs and liquor are also included as prime factors.

Table 1 shows the detailed descriptions and definitions of dependent and independent variables used in this research. Variables are chosen based on a review of previous literature which has been mentioned in section II. Variable summary statistics of 878 block groups of the year 2009 and 2010 is shown in table 2. All incidents include 43 types of crimes, and a total number of all crime incidents is 179,955 in 2009 and 168,551 in 2010. More specifically, in 2009, aggravated assault is 11,012 in total; assault is 20,251 in total; weapons offenses are 1,929 in total; burglary is 20,886 in total; robbery is 6,845 in total; stolen vehicle is 15,029 in total; dangerous drug incidents are 5,050 in total; liquor incidents are 189 in total; in 2010, aggravated assault is 10,535 in total; assault is 19,902 in total; weapons offenses are 1,957 in total; burglary is 18,596 in total; robbery is 6,070 in total; stolen vehicle is 13,626 in total; dangerous drug incidents are 4,101 in total; liquor incidents are 151 in total. Densities of crime incidents of block groups are shown in Figure 3a and 3b as well.

In addition, population 18 years and older in 2009 is 516,870 and is 523,430 in 2010. The population of the year 2009 used in the model (3) was estimated based on 2010 census data. Specifically, in 2009, 11.43% are whites;

82.64% are blacks; 0.37% are Native Americans; 0.0181% are Hawaiian; 2.53% are other race; in 2010, 11.44% are whites; 82.71% are blacks; 0.38% are Native Americans; 0.0181% are Hawaiian; 2.53% are other race. Besides, in 2010, 22.83% housing units are vacant; the population of employed are 216,188; a number of total of vehicles of occupied housing units is 320,041; a total number of law enforcement workers that are living in Detroit is 2,166. A median number of household income, the median age of each block group and the median number of school years are also used based on the distribution and trend of our data. Other statistics of variables are as shown in table 2.

Empirical Analysis and Main Findings

A: All Crime Incidents

All incidents, other than crimes mentioned in this study, are included in the regression, such as arson, fraud, homicide, kidnapping, traffic offenses, etc. Table 3 (a) shows the results of OLS and model (2) of all crime incidents. Results of the model (2) are estimated by six different scales of weights compare with OLS estimators. From the table, increases in the population of white, black and other race reduce crime rates significantly through all models. Similar empirical results can also be found in the literature (e.g., Liska, Logan and Bellair, 1998; Hipp, 2007; Hipp, 2011). In particular, the population of black contributes more to crime reduction even after we considered spatial interactions. The population of white decreases crime rates more after we included spatial effects. Likewise, the parameters of the population of other race have a small decrease compare with OLS and are still significant. Intuitively, one possible reason for crime reduction could be due to low crime report rates among black people, black neighborhood and ethnic minorities (Davis and Henderson, 2003; Desmond, Papachristos and Kirk, 2016), and whites contribute the least in crime reduction.

In general, a growing number of vacant housing units increase crime rates, but our finds are inconsistent with the findings of other researchers in the literature (Spelman, 1993; Cui and Walsh, 2015). In both model (2) and (3), no significant parameters of vacant housing are found. Furthermore, median household income shows weak evidence of decreasing crime rates, and it is significant only for the model (1) - (3) in table 3 (a). In particular, when more weights are put on nearby area, the effects of household income became insignificant. This could be due to the density of communities, in other words; people with similar income are more like to live in the same area because of housing prices, neighborhood conditions and environment, criminals are more intended to commit crimes far away from their neighborhood. The increase of age, household size and years of schooling help to reduce crime rates significantly; especially, increase the number of household size reduce crime rates by around 0.19%[2]. Moreover, for the model (3) - (7), we find strong and significant spatial correlations among crime rates and block groups. Especially, spatial correlation (λ) decreases from 0.9412 to 0.6436 as we put more weight on nearby block groups. In other words, compared with nearby block groups, crime rates are more related to farther block groups' crime rates and conditions. However, larger spatial coefficients in the error term are significant only when p=1 with 0.9175 and 1.5 with 0.7949.

[2] Approximations are used. Coefficients of variables vary due to different weights.

In table 3 (b), the population of white and black have significant but less impact on crime rates. Household size and years of schooling are still significant but become less important in the model (3). Crime rates of the previous year are highly and significantly related to current crime rates, which can be seen from significant values of γ in table 3 (b). Number of law enforcement workers shows no impact on crime reduction in both model (2) and (3). Also, no spatial interactions are found in the model (3), which implies that spatial interactions decrease and become insignificant as time goes by.

B: Violent Crimes

Three violent crimes are analyzed: aggravated assault, assault, and weapons offenses. Especially, assault involves minor injuries and verbal attacks. In contrast, aggravated assaults involve severe injuries or intend to kill, and some cases have weapon involved. Weapons offenses include law violations and misuse of weapons.

Firstly, the results of aggravated assaults are shown in table 4 (a) and (b)[3]. In table 4 (a), white, black and other race are positively and significantly related to the reduction of aggravated assault. Impact of white and black populations on crime rates increases as spatial interactions are included, but the influence of other race on crime rates decreased a bit compared with the OLS model. Moreover, the increase in household income, Employment ratio, use of liquor, age and years of schooling contributes to decrease rates of aggravated assaults. In particular, Employment ratio of each block group reduce aggravated

[3] Approximated coefficients of results are used in all interpretations for estimation of different weights.

assaults by around 0.13%, household income and use of liquor reduce aggravated assaults by around 0.075%. More educated and mature people are less likely to involve in aggravated assault, they also help to reduce crime by around 0.075%. Average household size matters only when p=1.5, and it is not very significant. A number of law enforcement workers has very small coefficients and is insignificant.

On the other hand, strong spatial interactions are also found in the model (2), and the interactions roughly decrease as p-value increases, which imply aggravated assaults are more connected and happened in block groups other than its own neighborhood. However, none of the spatial coefficients in the error term are significant for aggravated assault in the model (2), as well as the spatial coefficients of previous years' aggravated assault rates in the model (3). Insignificant value of λ can be found in table 4 (b), which implies that spatial interactions do not have time continuity for aggravated assault. But, significant γ indicates strong correlation with previous years' crime rates. Besides, the effects of population of white, black and other race become weaker, but they are still significant indicators of crime reduction compare with the model (2). Whites are only valid when p=0.5, 1, 1.5, which suggest numbers of whites has no help for crime reduction of nearby area. In addition, incidents of dangerous drugs have almost constant effects on the increase of aggravated assaults. Years of schooling also have no effects on neighborhood aggravated assault reduction.

Secondly, in table 5 (a) and (b), household income and employment ratio have no impact on assault rates as well as a number of law enforcement workers.

Apart from the above, effects of whites, black, other race and number of vacant housing units on assaults are similar to aggravated assault, except insignificant factor of other race in the model (3). Drug misuse and violations are significantly related to incident rates of assaults, by 0.165% in the model (2) and 0.08% in the model (3) with consideration of spatial effects. The increase of liquor incidents, median age, average household size and median number of school years significantly decrease assaults in both models, but effects are weaker in the model (3) after the consideration of previous years' rates of assaults. Furthermore, when more weight put on nearby locations or block groups, spatial interactions tend to decrease in two models, it ranges from 0.8849 to 0.3397 in the model (2) and 0.5930 to 0.1580 in the model (3). This indicates that assault is not very much neighborhood connected and persisting over time. Spatial coefficients in the error term and previous years' assault rates are insignificant as in aggravated assault case.

Thirdly, spatial interactions cannot be found for weapons offense in table 6 (a) and (b). Moreover, no significant spatial coefficients of the error term and previous years' weapons offenses rates are found as well. In contrast, populations of black, native American and other race help to reduce weapons offenses with the model (2), but their effects turn to insignificant in the model (3) except effects of other race when p=2.5 and 3. In addition, increase the number of vacant housing units tends to decrease weapons offenses by around 0.0725% only when p takes values from 1 to 2.5. Employment ratio now has a weak impact on weapons offense decrease if spatial effects are considered in both models. Moreover, increasing the rate of drug incidents is the only factor which is highly and positively related to the increased rate of weapon offenses in two models, by around 0.185% in the model (2) and 0.15% in the model (3). Median age increased positively reduces rates of weapons offenses, but other variables are found to be ineffective. Small but significant correlations (γ) are found with previous years' rates in the model (3) as well.

C: Property Crimes

Three property crimes are analyzed in this section: burglary, robbery and stolen vehicle. First of all, the growth of the white population tends to decrease the rates of burglary as spatial interactions are included in two models. But, the population of black contributes about six to eight times more than whites in the model (2) and nearly three times more than whites in the model (3). More significant effects from population of black groups to reduce burglary could be due to reasons that black populations are relatively poor than whites on average, and they may not report a small loss of their properties. Other race plays a less important role in the reduction of burglary only when p=0.5 and 1 in the model (2), which implies it has no impact on burglary rates of the nearby area.

Additionally, an increase of median household income and incidents of dangerous drugs consistently increase the rate of burglary by around 0.95% for both in the model (2), and by 0.08% and 0.048% respectively in the model (3). A number of liquor violations is a more stable and strong factor for a decrease in burglary rates than the median age, and median age are effective when appropriate weights are used in both models. A median number of school years takes effects without considering burglary rates of the previous year, and it helps to decrease the burglary rate by around 0.065%. Besides, from table 7 (a), strong spatial interactions can be found when p takes values from 1.5 to 3.0. It also implies that burglary is more neighborhoods related and connected crime compare with crimes mentioned above, and spatial coefficients of the error term are significant only when p=1.5, 2.5 and 3.0. Spatial interactions found in table 7 (b) provide strong evidence as well, but they show to diminish as including of previous years' burglary rates and impact of time.

In the story of robbery, increased growth rates of the black population consistently and strongly decrease rates of robbery through all models. Whites and other race have weaker but still significant effects on robbery reduction; notably, they are valid when specific weights are selected in the model (3). Also, a number of vacant housing units account for about 0.1% decrease in robbery rates only in the model (2). Impact of dangerous drugs on robbery rates increase is positive and almost constant, and stronger in the model (2) than in model (3). Moreover, the increase of liquor-related incidents and average household size reduce rates of robbery in both models (2) and (3). Other variables have no relationship for a change of robbery rates, such as growth rates of the population of Native American and Hawaiian, median household income, employment ratio, median age, the median number of the school year and the number of law enforcement workers. Furthermore, in the model (2), spatial interaction exists only when p=1.5, 2.0 and 2.5, and no significant spatial coefficients are found. In model (3), spatial interactions take effects for all p values except p=0.5. Based on this fact, robbery is not likely to happen or happen again in nearby locations of the location being estimated or is fewer neighborhoods connected crime. Additionally, previous years' crime rates still significantly account for more than 0.4% of current years' rates.

The third, total number of vehicles of occupied units in each block group is included and added in the analysis of the stolen vehicle. However, there is no clear evidence shows that a total number of vehicles of occupied units is related to the crime of stolen vehicle in all models other than OLS regressions. Besides, growth rates of the population of black and other race significantly decrease rates of stolen vehicle, and black population contributes far more than other race in the model (2), by about three to six times greater. Impact of the growth rate of whites and other race on stolen vehicle reduction vary in the model (3) based on different weighting matrices. Whereas a number of vacant housing units have a weak but significant impact on vehicle stolen, and it also shows that vacant housing units are more like to gather in one place. Median household income increases rates of a stolen vehicle as well as the employment ratio in the model (2), but the employment ratio shows no influence in the model (3).

Dangerous drugs are costly and more related to property crime, and it positively contributes to the increase of stolen vehicle, by about 0.11% and 0.06% in two models respectively. In contrast, liquor and average household size are negatively and significantly related to rates of stolen vehicle. Likewise, median age and median number of the school year are also contributed to the reduction of stolen vehicle, but only in the model (2). Besides, strong and high connections with neighborhood area are found in the model (2), which vary from 0.9240 to 0.7977. Spatial interactions still can be found significant but weaker in the model (3) than in model (2). The same as burglary, significant spatial coefficients of the error term of stolen vehicle exist only when p=1.5, 2.5 and 3.0. In particular, high values of ρ also show the close relationship and large spatial effects with previous years' rates of stolen vehicle.

Conclusion and Discussion

In this paper, we discuss causal relationships among socioeconomic variables on crime and spatial interactions of crime rates of each block group by using spatial autoregressive models, crime data, and socioeconomic data. Particularly, we summarize spatial interactions of all types of crime in table 10 (a) and (b)[4]. Strong spatial interactions are found in this paper, except for weapons offenses. In model (2), results reveal that property crimes are more neighborhoods connected and influenced than violent crimes, especially for burglary and stolen vehicle. Significant spatial interactions are also shown in the model (3) for assault, burglary, robbery, and stolen vehicle. They show high interaction and connection with neighborhood and nearby block groups. They also imply time persisting and stability of crime occurrence.

More specifically, with controllable spatial influences between block groups, the results of this paper provide strong empirical evidence and guidance for re-allocation of police resource in certain patrol areas. Generally, spatial crime

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[4] Based on the likelihood values of each table: p=2 is optimal in table 3(a), 3(b), 4(a), 4(b), 5(b), 6(a), 7(a), 7(b), 8(a), 8(b), 9(a) and 9(b); p=1.5 is optimal in table 5(a); p=3 is optimal in table 6(b). Thence, p=2 is relatively significant and optimal in this study.

patterns are shown and predicted by hotspot mapping, but it fails to reveal the spatial relationship of crime rates between spatially connected regions. However, based on spatial interactions of different types of crime, we can conclude how strong spillover effects of crime rates are under certain spatial influences, and how much they affect crime rates of nearby and distant regions.

Furthermore, this paper enables us to observe changes in the spillover effects when models are estimated under different p values. For example, for all types of crime (except for weapons offenses) in table 10 (a) and (b), if block groups are more geographically or may be more socially connected or influenced, spatial interactions of crime actually tend to decrease, which implies that criminals are more likely to choose a relatively close area, not the closest area to his/her previously committed crime location, to commit the next crime. Compare with violent crimes, property crimes are more spatially concentrated and neighborhood connected. In particular, when we take crime rates of 2009 into account, in table 10 (b), spatial interactions only show in the assault as well as in all crime incidents, which may indicate severe or weapon involved assault and all incidents, in general, do not have spillover effects over time. In contrast, weapons offenses do not have any spatial interactions in both models (2) and (3), which is impossible to conclude from hotspot mapping or crime distribution statistics. In other words, crimes, such as weapons offenses, that do not have spatial interactions should not occupy too much police resource for deterrence or crime prevention. Thence, police resource should be more efficiently distributed by spatial influences and interactions, especially for setting up targeted patrol areas for crime deterrence and reduction.

We also evaluate the impact of socioeconomic variables on crime and find a considerable number of significant parameters with the help of inverse distance weighting. Growth rates of white, black and other race contribute to reduce crime rates as well as liquor, median age, average household size and median number of the school year. Drug issues are severe and positively related to all types of crime, but the coefficients of law enforcement workers are insignificant through all crimes and models. Impact of vacant housing units, median household income and employment ratio on crimes vary by types of crime and different weights. Furthermore, with different scale of weights, we can catch sight of how spatial interactions vary by the power of weight put on nearby block groups. This provides the insights of a new way to find out optimal weights and comparisons among models of different weights. Also, this approach offers more information and reference for further researchers.

This paper is an essential and policy-relevant topic that has seldom been studied in the past. The city of Detroit has experienced poverty rates and the crime rates much higher than the national average, and there has been a high rate of population loss in the past few years. As the hotspot city of crime, this paper will attract more attention from police departments, public agencies, and government officials to know how security conditions will be affected and influenced by our surroundings and how strong they are connected. With consideration of spatial interaction, this study enhances our understanding of spatial interactions of crime based on socioeconomic data of Detroit city. More specifically, spatial interactions between geographical regions have to be taken into account in empirical models for analyzing crime data and other spatial related topics. Secondly, strong and significant spatial interactions indicate that crime rates are not independent of nearby regions, which imply that the spillover effects of crime exist and crime incidents are not autonomous or self-reliant. This paper provides useful insights and valuable implications of spatial crime analysis for policymaking and future research.

Because of the limited sample size, some proportions of predictors are not significant. Increasing the sample size could be helpful to improve the predictive capability of the model. Further analysis can be extended to use different measures of weighting since geographic contiguity may not be the only source of the spatial effects. On the other hand, although alternative interpretation has been provided, the question about the homogeneity of entities (block groups) still cannot be answered. Other spatial interpolation methods and cartographic modeling could be solutions to construct a weighting matrix and improve estimation efficiency.

CHAPTER 2 "PEER EFFECTS IN STUDENT ACADEMIC PERFORMANCE: EVIDENCE FROM RANDOM ROOMMATE ASSIGNMENT"

Introduction

Study of peer effects is of great interest to social scientists since the report given by Coleman (1966). In peer effects, individuals' outcomes can be influenced directly or indirectly by peers around them. For instance, students can learn from one another, intelligent and hardworking students can affect their peers through knowledge sharing and their positive impacts on the classroom. In contrast, the less intelligent and not diligent students may disrupt the classroom, and force their teachers to spend more time and energy on the maintenance of class order. Thence, students' academic performance may be influenced and affected by the characteristics and behavior of their peers and instructors (Ding and Lehrer, 2007). Therefore, to optimize socioeconomic outcomes and to provide policy implications in education, peer effects have to be taken into account.

Besides, the study of peer effects is an essential and policy-relevant topic. Researchers are; therefore, motivated to find evidence of peer effects and ways of optimizing students' academic performance and skills. Implications of peer effects studies are also provided for policymakers to find out optimal teaching strategies and school organizations. Hoxby (2000) applies different approaches to identify the existence of peer effects and states that evidence of peer effects could yield opportunities and insights for social welfare interventions and optimization. More efficient policy intervention could help to allocate human capital and resources effectively, especially for educational outcomes. As pointed by Lin (2010), a better understanding of peer effects leads to the more efficient investment of human capital and may generate social gains from an economics perspective. In particular, students can gain and benefit from the efficient allocation of school resources and policy intervention of teaching.

Peer effects studies are also driven by theoretical developments and methodology improvements in economics researches. Epple and Romano (1998) construct a theoretical model to identify the effects of vouchers and peer group externalities. Under the evidence of positive and significant peer effects, appropriate tuition voucher program and relevant policy change may increase competition of public school and efficient allocation of human capital. Some other articles also present supportive evidence of the importance of peer effects and its positive impact on educational outcomes (Nechyba, 2000; Caucutt, 2001). In addition, based on the presence of peer effects and analytical concerns, commonly used ordinary least squares (OLS) models are considered misspecified and biased without taking the inter-relationship among dependent variables into account (Anselin, 1988; Anselin and Luc, 2001; Menezes, Silveira-Neto, Monteiro and Ratton, 2013). Theoretical work in sociology and criminology has also underlined the concepts of inter-relationships and the importance of analyzing approaches.

As one of the most widely used spatial econometric approaches, the spatial autoregressive model (SAR), which contains spatially lagged dependent variable and weighting matrix addition to regular OLS estimation terms, is continuously being developed and improved for empirical analysis. In recent decades, various studies have used this methodology in different fields of research, such as educational research, regional science, crime analysis, geographic information science (GIS), etc. With the improvement and extension of the SAR model (Lee, 2007; Lee and Yu, 2010), this approach becomes more applicable to the analysis of peer effects and other social interaction studies. It is also capable of resolving the “reflection problem” and identify the existence of both endogenous and contextual effects (Lin, 2010). Moreover, SAR models with individual and time fixed effects are used as an alternative way to solve omitted variable issues (Lee and Yu, 2010), which are also applied by this paper as analytical approaches.

Although adequate theoretical work of peer effects has been developed and matured, there is still a lack of empirical evidence to verify the impact of peer effects on educational outcomes. However, identifying peer effects is a difficult work (Manski, 2000; Moffitt, 2001) due to several well-known identification challenges, which include the “reflection problem” (Manski, 1993), the omitted variable bias (Hanushek, Kain, Markman, et al, 2003; Lin, 2010), the endogeneity of peer group formation (Carrell, Sacerdote and West, 2013) as well as the selection bias. In particular, varieties of approaches are used by researchers to avoid selection bias, such as instrumental variables (IV), randomization methods and weighting (Horvitz and Thompson, 1952; Evans, Oates and Schwab, 1992; Hoxby, 2000; Sacerdote, 2001). In this paper, selection bias is addressed by using random classmate and roommate assignments. Additionally, there are no other changes of the above two assignments within three years once students were assigned to specific classroom and dormitory, which differs from other studies with only one-year observation.

Besides, little research on peer effects has been done for students of China, and existing literature of the studies appears to have insufficient empirical evidence and support for peer effects. By applying proposed SAR models with individual and time fixed effects (Lee and Yu, 2010) to the unique dataset we have collected, this study is to examine whether peer groups affect students' academic achievements in Chinese junior high school and also provide policy implications for educational outcomes. Furthermore, we investigate peer effects in both classroom and dormitory on student achievements; especially, we provide evidence of peer effects from random roommate assignment and seek to add to our knowledge of peer effects on student academic achievement under Chinese educational system.

The rest of this article is organized as follows: section II synthesizes existing literature on peer effects and applications of spatial autoregressive models. In section III, we introduce methodology and model specifics of the estimation. Two types of spatial models are used for comparison and discussion. Detailed data description and origin are presented in section IV. Section V concentrates on empirical evidence and main findings of peer effects based on our unique data. The last section concludes and summarizes findings and proposed directions for future researches.

Literature Review

Researchers have been exploring the key factors that determine students' academic achievement for decades. In particular, peer effects have already been taken into account and discussed theoretically and empirically by many scholars (e.g., Coleman, 1966; Becker, 1974). Based on existing literature, strong and significant empirical evidence not only verifies the existence of peer effects but also shows both positive and negative peer effects (Hoxby, 2000; Zimmer and Toma, 2000; Angrist and Lang, 2004; Ding and Lehrer, 2007; Lin, 2010; Sacerdote, 2011; Lin, 2015). For example, as stated by Sacerdote (2011), both positive and negative peer effects exist for students, and the positive peer effects can also be offset by the negative peer effects from a social welfare point of view. Likewise, Zimmer and Toma (2000) state that the effects of peers appear to be greater for low-ability students than for high-ability students. Lin (2015) finds peer effects influence adolescent’s outcomes positively in a variety of ways and explores the robustness of the results. Besides, researchers also emphasized the importance and the significance of peer effects studies on educational policymaking, school optimization and even on optimal human capital investment (Kremer, 1993; Epple and Romano, 1998; Hoxby, 2000).

Most studies of peer effects on students' outcomes are mainly focused on the data from elementary and high schools. Some other studies are based on students’ grades and characteristics in colleges and universities. Hoxby (2000) analyzes public school data in grades 3-6 by implementing different empirical estimation strategies and finds positive and strong peer effects, especially for intraracial groups. Likewise, the existence and evidence of peer effects are also confirmed and revealed by employing the data of secondary schools of China (Ding and Lehrer, 2007). In addition, a comprehensive and detailed longitudinal data of students in grades 7 to 12 are examined and investigated by Lin (2010, 2015) to identify both endogenous and contextual effects in peer effects. For a more comprehensive analysis, discussion of peer effects in Grade Point Average (GPA) and exploration of social behavior of college or university students play a significant role in peer effects studies as well (Sacerdote, 2001; Kremer and Levy, 2008; Sacerdote, 2011; Eisenberg, Golberstein and Whitlock, 2014). Besides, supportive evidence of peer effects among private and public schools are also compared and discussed in the literature (Epple and Romano, 1998; Zimmer and Toma, 2000).

Alternatively, much of the research attempts to reveal the mechanisms of the peer effects in classroom and dormitory by implementing different strategies and methodologies. To capture the robust and significant results of peer effects in the classroom, variation and characteristic of data are commonly utilized to avoid potential analyzing issues. Hoxby (2000) uses two practical strategies, which rely on the data variations of peers in gender and racial groups, to overcome selection bias problem. As a result, strong intra-race and nonlinear peer effects in the classroom are confirmed in his research. Similarly, the reflection problem can also be eliminated by employing unique and rich data to achievement functions (e.g., Ding and Lehrer, 2007). Besides, to solve omitted variables and reflection issues, instrumental variables and group equations are adopted to identify the existence of peer effects in the classroom as well (Angrist and Lang, 2002; Kang, 2007). Differently, Burke and Sass (2013) use individual fixed effects with linear-in-means specifications and find that peer effects in the classroom have a significant impact on individual achievements.

Correspondingly, other authors examine dormitory peer effects not only in student achievement but also in student social behavior. Sacerdote (2001) measures peer effects among college roommates by applying data of randomly assigned accommodation to overcome the selection bias. The result of his work shows peers have an impact on average grade and decisions to join social groups, which directly provides strong evidence that peer effects exist. Similar work that employs data of random roommate assignments to avoid selection issues can also be found in Zimmerman (2003). In his paper, quasi-experimental strategies are used, and estimation shows that students may have worse grades if they share a room with a student who is in the bottom 15% of the verbal SAT score. Additionally, peers' behavior and characteristics may also influence their peers' academic performance (Kremer and Levy, 2008). For example, Eisenberg, Golberstein and Whitlock (2014) conduct more in-depth research of peer effects for risky behaviors of college roommates and find significant peer effects for misuse of alcohol.

Additionally, significant and supportive evidence of peer effects in student achievement is also confirmed and verified by many studies with different models and analytical strategies (e.g., Ding and Lehrer, 2007; Lin, 2010; Burke and Sass, 2013; Lin, 2015). From a technical perspective, a methodology that uses to capture the peer effects effectively is crucial, and it gradually becomes the primary concern of researchers. Spatial autoregressive modeling; therefore, is being introduced and used for studies of peer effects. Spatial analysis has a long history in geography literature. Spatial autoregressive modeling, which relies on spatially lagged dependent variable and weighting matrix, is inspired by geography and then became the core of spatial econometrics. In particular, the weighting matrix is critical in the spatial autoregressive model. It is non-stochastic and represents the spatial dependence among cross-sectional units or weighted averages of neighboring values.

Motivated by the use of rich datasets and the existence of "interaction," spatial autoregressive models have been developed and adopted by many researchers in economics studies, especially in the study of peer effects. Since the discussion of spatial autoregressive modeling by Anselin (1980), more theoretical and empirical principles on methodologies have been formulated and derived (e.g., Kelejian and Prucha, 1998; Lee, 2003; Lee, 2004; Lee, 2007). More specifically, according to Manski (1993), "reflection problem"[5] is impossible to identify. However, SAR models are capable of analyzing peer effects and are also able to identify both endogenous and contextual effects. With the continuous and progressive improvements of SAR models (Lee, 2003, 2004, 2007), Lin (2010) uses spatial autoregressive models with group fixed effects and finds strong evidence for both endogenous and contextual effects on student academic achievement. Besides, Lee and Yu (2010) have also made a significant contribution to spatial autoregressive panel data models. Their

[5] Two types of social effects: behavioral effects (endogenous) and contextual effects (exogenous).

discussion focuses on time scale and individual fixed effect in two models and provides inspirational ideas for future empirical studies of social interactions. Apart from the above, the random effects of spatial models are also discussed by Kapoor, Kelejian and Prucha (2007) and Baltagi, Egger and Pfaffermayr (2013).

Furthermore, unknown heteroskedasticity generally leads to inconsistent estimators for SAR models. Lin and Lee (2010) propose a generalized method of moments (GMM) estimation of spatial autoregressive models for the possible existence of heteroskedastic disturbances. Based on their models and assumptions, experimental results are shown to be consistent and asymptotically normal. Likewise, quasi-maximum likelihood and dynamic SAR models that yield consistent estimators are also proposed and evaluated in the literature (e.g., Yu, Jong and Lee, 2008; Lee and Yu, 2010). Possible solutions for other issues in spatial data analysis are discussed by McMillen (2010) as well. He states that biased estimators and spatially correlated errors exist in models. He suggests using spatial lag models for large dataset analysis compared with standard distance-based models, and fixed effect models are also indicated under certain conditions and assumptions.

By focusing on the study of peer effects, this paper contributes to the current literature in several aspects. Firstly, it aims to further our understanding of the impact of dormitory and classroom peer effects on student achievement, which could provide implications for educational policy-making and optimal organization of schools. By using the unique dataset of Chinese junior high school, it seeks to provide rational and considerable empirical results and show more accurate interactions between different entities when data observations are not truly independent. Secondly, it would empirically support and verify Lee and Yu's (2010) theoretical work. A closer look into the conditions and empirical evidence of peer effects will attract more attention of public and policymakers. Lastly, potential issues and suggestions are discussed and provided for future researchers.

Model Specification

A: Identification Problems of Peer Effects

In literature, the baseline model of identifying peer effects is as follows:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 P + \epsilon_i \qquad (1)$$

where Y_i is student i's academic achievement, X_i is a vector of exogenous variables of student i, such as gender, race, age, years of schooling, etc. P could be peer groups' characteristics and weighted or average academic grades of a certain peer group for student i. This model was adopted by many researchers in the early and following stages of peer effects studies (Hoxby 2000; Ding and Lehrer, 2007; Kang, 2007; Carrell, Sacerdote and West, 2013). However, by running OLS on this model, the coefficient β_2 could be biased due to unobservable characteristics or omitted variables. Although estimation accuracy can be improved by several ways, such as using instrumental variables (Angrist and Lang, 2002; Angrist and Lang, 2004), fixed effects (Ding and Lehrer, 2007; Burke and Sass, 2013) and datasets that are free of selection bias (Sacerdote, 2001; Kremer and Levy, 2003; Carrell, Sacerdote and West, 2013), it still cannot accurately identify and capture the effects of peer interactions on individual's learning outcomes.

Also, the linear-in-means model is considered as a standard model of social interaction analysis. This model is also widely used and discussed in the literature. Based on Manski (1993), the model can be written as below:

$$y = \alpha + \lambda E(y|p) + \beta_1 E(x|p) + \beta_2 x + u \qquad (2)$$

where y is an individual's academic achievement, and x is individual's characteristics. $E(y|p)$ is the mean of y in a particular peer group p, and $E(x|p)$ is the mean of the exogenous variables x within the same peer group as y. Furthermore, λ captures the endogenous effects of how an individual's academic outcome is affected by peers' academic performance, and β_1 represents the exogenous effects (contextual effects) of how an individual's academic outcome is affected by peers' characteristics, such as race, gender, social behavior, family background, etc. β_2 shows the direct effects of an individual's own characteristics.

The issue of this model is the so-called "reflection problem," which can be easily seen from the reduced form model below:

$$y = \frac{\alpha}{1-\lambda} + \frac{\beta_1 + \lambda\beta_2}{1-\lambda} E(x|p) + \beta_2 x + u \qquad (3)$$

With λ≠1, parameter $\frac{\beta_1+\lambda\beta_2}{1-\lambda}$ can be identified, but it is impossible to distinguish two social interaction effects between λ and β_1. This is due to $E(y|p)$ and $E(x|p)$ are linearly dependent, and one cannot separate endogenous effects λ from $\frac{\beta_1+\lambda\beta_2}{1-\lambda}$ if no sufficient information on some parameters or exogenous variables x is obtained and provided, for example, if we assume that β_1=0. Apart from these two models, other linear and nonlinear endogenous effects models, such as dynamic linear models and binary response models, are discussed and applied by many researchers as well.

Based on many advantages and improvements, SAR models are adopted by us. SAR model is free of “reflection problem.” Besides, as pointed by Lee (2003, 2004 and 2007), one can identify endogenous effects by exploring the information of the error term even if there are not sufficient exogenous variables. Thence, compare with models that have discussed previously, SAR models with individual and time fixed effects, which also contain spatially lagged error terms, are considered and used in this paper.

B: SAR Models

Spatial autoregressive model is a great improvement over the standard OLS model. An original and straightforward spatial autoregressive model is shown as follows, which contains a spatially lagged term of dependent variable y,

$$y = \rho W y + \beta X + \varepsilon \tag{4}$$

It is very similar to a standard linear regression where the first term consists of an n×n spatial weighting matrix, W; observed dependent variable, y; and a spatial autoregressive parameter, ρ, which needs to be estimated from the data. X represents independent variables with parameter β. ε is disturbance. Briefly speaking, a spatial lag model is the idea that variables at a certain location are related and connected to the same variables at nearby locations. The spatial weighting matrix is generally row normalized such that its rows sum up to 1. In other words, the weighted averages of neighboring values are considered in the model.

This paper is following approaches proposed by Lee and Yu (2010) to find out spatial correlation and causal relationship among student achievements and a limited number of socio-economic variables, and it will also provide empirical support and evidence for theoretical spatial methodology. Models that are using can be shown below:

$$Y_{nt} = \lambda_0 W_n Y_{nt} + \beta_0 X_{nt} + c_{n0} + \alpha_{t0} l_n + U_{nt}, \qquad (5)$$

$$U_{nt} = \rho_0 M_n U_{nt} + V_{nt}, \qquad t = 1,2,3, \ldots \ldots, T$$

where standardized students' grades Y_{nt} and V_{nt} are n×1 column vectors, and V_{nt} is i.i.d. across n and t with zero mean and variance σ_0^2. Also, W_n and M_n are n×n spatial weights, which are non-stochastic and generate the spatial dependence among cross-sectional units Y_{nt}. W_n is usually row normalized from a symmetric matrix, which ensures that all the weights are between 0 and 1, and weighting operations can be interpreted as an average of the neighboring values; Particularly, based on Lee and Yu (2010), we assume that W_n and M_n are the same. X_{nt} is an n× k_x matrix of non-stochastic independent variables. λ_0 represents spatial interactions (endogenous effects), ρ_0 shows the spatial coefficient of error term since we assume that unobserved variables are also interdependent. c_{n0} is n×1 column vector of individual fixed effects, α_{t0} is a scalar of time effect, and l_n is n×1 column vector of ones. The parameter we are estimating is: $(\beta', \lambda, \sigma^2)'$.

The next step is to apply a dynamic spatial model (Yu, Jong and Lee, 2008) for estimation and comparison. The model is constructed as below:

$$Y_{nt} = \lambda_0 W_n Y_{nt} + \gamma_0 Y_{n,t-1} + \rho_0 W_n Y_{n,t-1} + \beta_0 X_{nt} + c_{n0} + \alpha_{t0} l_n + V_{nt}, \qquad (6)$$

$$t = 1,2,3, \dots, T$$

In model (6), most term descriptions and constructions are the same as in model (5). However, we introduce Y_{n0} in the model, which is standardized students' grades of the previous year. ρ_0 now represents endogenous effects of students based on grades of the previous year. The error term is not as assumed interdependent as well. The parameter we are estimating is: $(\delta', \lambda, \sigma^2)'$, where: $\delta = (\gamma, \rho, \beta')'$.

Data

This research focuses on a junior high school of a county in Xinjiang province, China. Based on request and terms of use, school officials allowed us to collect unique data of students' academic grades. This dataset consists of 2,576[6] students in grades 1-3 of junior high school (equivalent to grades in 7-9), and most of them are students between the ages of 13 and 15. In particularly, 2,219 (86.14%) of these students are living on campus, which enables us to analyze the peer effects in dormitories on their academic achievements. In this data, students were randomly selected to each classroom and dormitory, which eliminates the concern of selection bias. Students also stay in the same classroom and dormitory for three years without any changes until they are graduated, except those students who transferred to other schools or dropped

[6] This number includes 657 students who have already graduated.

out[7]. Notably, students who live off-campus, transferred to other schools and dropped-out have already been excluded from the whole sample size based on different analysis needs.

In addition, a relatively large number of minorities (around 47%) are included, such as hui, Kazakh and other minorities. Limited family background information is also collected, which includes family financial difficulties, parents' occupations[8] and head of household information. Students are also categorized into three regions based on their home address: local city, local rural area, and other cities. Besides, school subjects consist of mathematics, Chinese, English, politics, history, biology, chemistry, geography, PE, etc. For each subject, students' grades are standardized to 100 points in total. Moreover, grades of entrance examination are included for use in the model (6). Entrance examination contains mathematics and Chinese only, which are key measurements of the learning abilities of students from elementary school. These two exams are also determinant factors for admission of junior high school.

The Dependent Variables

Standardized Chinese and mathematics grades, the average grade of Chinese and mathematics (AVGCM), average grade (AVG) of all subjects as well as entrance examination grades of both Chinese and mathematics are evaluated as dependent variables.

The Independent Variables

[7] Students who have transferred to other schools or dropped-out do not affect the current accommodation arrangements.
[8] Students of grade 1 have no information about parents' occupations.

In addition to students' age and gender, minority groups, such as han, hui, Kazakh and other minorities, family financial difficulties, parents occupations, home locations, such as local city, local rural area and other cities and head of household are used as dummy variables.

Table 1[9] shows the detailed descriptions and summary statistics of dependent and independent variables used in our models. The whole sample consists of 2,219 observations in addition to 357 students who live off-campus. The mean age of the sample is about 14. Particularly, due to special education policy for minority students, younger and overage students are allowed to attend school; thence, sample age is range from 7 to 29. Among our observations, 53.18% are male, 46.82% are female, 53.27% are han, 6.13% are hui, 38.67% are Kazakh and 1.94% are other minorities. Besides, the farmer is a low-income occupation in China, and 96.04% of the students are from farmer families. But, 94.28% of them have no financial issues to support their study and living expenses. Students who are from high-income families are 3.96% of the sample size. The region is another concern of this study, and 48.99% are from the local city, 36.19% are from a rural area nearby the city, 14.83% are from cities that are far away from the local city. Head of the household is also considered in our article since he/she could be the person who supervises and disciplines student's study and behavior. Most families (95.85%) are father and grandparents headed, and only 4.15% are mother-headed families.

Besides, Chinese and mathematics are core courses and are also evaluated as the critical indicators of students' learning ability in elementary

[9] More detailed summary statistics of each grade are shown in table 1a and 1b. See Appendix.

school. In table 1, the average grade of Chinese of entrance examination is 59.4308, and an average grade of the mathematics of entrance examination is 55.206. Particularly, entrance examination grades are applied and estimated in the model (6) only. Besides, the average grade of Chinese and mathematics in junior high school are 63.4964 and 48.3052 respectively. The average grade of all subjects in junior high school is 57.3020. Especially, minorities like Kazakh, they have their language system which is different from the Chinese language, but they are taught by han teachers who speak Chinese in all subjects. Because of the language barrier, it may explain the relatively low average grades of all categories in table 1.

Empirical Analysis and Main Findings

A: Classroom Peer Effects

1. Model (5)

Table 2a summarizes estimated results of classroom endogenous effects in the model (5) for different grades: students of grade 1, grade 2, grade 3 and grade 3 (graduates). Analysis models exclude transfer students and students who have blank information of background or grades. No strong and significant peer effects are found in all models except the weak and negative coefficient of λ in regression (8) of whole sample analysis in table 2a. The same results are shown in table 3a as well, but significant spatial coefficients of the error term, which imply some unobservable characteristics of classmates are interdependent and have strong and positive effects on students' academic achievements.

Moreover, in table 3a, age is found to be negatively related to students' grades on average. Besides, boys have poorer grades than girls. Han students perform better than other minority groups in the second year of study, and Kazakh students perform poorer in grade 1 and better in grade 2. Family financial conditions seem not very important in classroom estimation as well as the factor of the parents’ occupation. Additionally, students from local city perform poorer on average grades by 2.8154 to 5.9779 points through all three years of study. Students from the local rural area have significant and negative coefficients on Chinese, mathematics and average grades through grade 2 to 3. The role of head of household seems not essential, but it still shows a positive and significant effect on the third-year average grade of Chinese and mathematics.

2. Model (6)

Combined with average grades of Chinese and mathematics of entrance examinations, table 4a shows summarized results of classroom endogenous effects in the model (6). For students of grade 1, only ρ is found to be negative and significant at 2.3376, but it violates the assumption of the model (6) for the parameter space of ρ and λ. For students of grade 2, first and second-year grades of Chinese and first-year mathematics are significantly related to entrance examination scores by around 0.10. Coefficients of ρ are significant and negatively related to entrance examination scores only in the first year study of Chinese and mathematics. Values of λ are all significant throughout two years of study of grade 2 students. In particular, mathematics grades are more sensitive and easy to be influenced by peers' academic performance in the classroom. In grade 3[10], first-year average grade and second-year grade are highly correlated with each other by around 0.8, and no evidence is found significant for other corresponding years. ρ value of first and second year's Chinese scores is negative and significant at 0.3388. Moreover, the coefficients of λ are positive and significant through regression 1-5 and 7 for most likely only one year of studying in the same classroom.

In the estimation of graduates, the average grade of each year is closely related to the rest of two years' grades in the range from 0.6135 to 0.8436. ρ values are significant through regression 4 to 6 and positively related to Chinese and negatively related to mathematics grades. For λ, the only value of regression 1 is found significant at 0.2590. Lastly, in the whole sample analysis, significant correlation values of γ decrease from 0.6126 to 0.2962 gradually. Likewise, significant values of ρ also decrease from 0.4181 to 0.2559, which imply negative and diminishing endogenous effects on peers' academic grades. In contrast, the coefficients of λ are all significant and increase from 0.4720 to 0.6670 for overall average grades when students stay in the same class for more years. For Chinese and mathematics, coefficients of λ decrease respectively based on estimation with entrance examinations.

In table 5a, overaged students tend to have lower average grades by around 1 point and especially by approximately 1.9 points for mathematics in regression 6. The same as in table 3a, male students in table 5a still have poorer grades than female students, except results in regression 8 and 9. Compare with

[10] Other detailed estimation and summary results of Chinese and mathematics for grade 3 students and graduates are shown in table 4c.

the first-year study, han students perform better in mathematics and average grades of the second year. Besides, hui and Kazakh students perform poorer in first-year mathematics study but have higher overall average grades in the second year of study. Chinese as a second language, Kazakh students also have higher Chinese grade in the second year of study. Family financial situation, parent's occupation and head of household have insufficient evidence to support their importance. However, students from the local city are more likely to have lower performance through all regressions, and students from the local rural area also have poorer grades especially in the last two years of study.

B: Dormitory Peer Effects

1. Model (5)

Correspondingly, table 2b summarizes estimated results of dormitory endogenous effects in the model (5) by different grades as well. Neither ρ nor λ is found to be significant for students of grade 1. In grade 2, the coefficients of ρ are positive and significant in all four regressions, and coefficients of λ are found to be negative but significant from 0.6913 to 0.9866. For grade 3 students, coefficients of ρ are positive and significant for only the first two years' average grades. Values of λ are -1.0 for first-year average grades and -0.8995 for second-year average grades. For results of graduated students, values of λ are positive and significant only for their second year's grades: 0.398 for average Chinese and mathematics and 0.5573 for average overall grades. Similarly, ρ values are significant except the first and second years' average Chinese and mathematics grades. Comparatively, all coefficients of both λ and ρ are significant for whole sample analysis. In particular, λ values vary from -0.4149 to -1.0.

Based on the analysis of dormitory, in table 3b, coefficients of age are negatively and significantly related to average grades but the first-year average grade of Chinese and mathematics. Male students have poorer grades than girls as well, but gender differences are gradually reduced to -0.5671 from -2.4821. Besides, han, hui and Kazakh students have higher average grades in the second year. In particular, han students have better average grades of Chinese and mathematics in the third year than other students. Kazakh students still perform poorer in the first two years. Besides, family financial condition and parents' occupation only show the impact on first-year average grades of Chinese and mathematics. Students from poorer families have higher grades by 3.3174 points, and students from farmer families with less-educated parents have lower grades by 3.6523 points. In addition, students from the local city have poorer grades for all three years, and students from the rural area only have low grades for last year of study. For mother-headed families, students seem likely to perform better in the previous year of study by around 2 points.

2. Model (6)

As is shown in table 4b, we listed the results of dormitory endogenous effects of the model (6). Unlike the analysis of classroom in the model (6), we find unique and consistent coefficients of endogenous effects (λ) in dormitory analyses. Coefficients of λ are all positive and significant at 0.3820. For grade 2, ρ is found to be negative and significant at 0.1395 in regression 2. Values of γ are positive and significant in regression 1 to 3, which have similar results as in table 4a. In grade 3[11], both γ and ρ are significant in regression 3, 4 and 7; particularly, coefficients of ρ show negative endogenous effects with previous year's grades. In other words, average grades of second-year are significantly related to first-year grades, and first-year endogenous effects have a negative impact on the second year's average grades.

For graduated students, negative and significant endogenous effects based previous years grades exist throughout all three years of study including Chinese and mathematics grades, and these effects are also diminishing when students live longer in the same dormitory. In addition, γ values are positive and significant as well through regressions 3 to 9 range from 0.5957 to 0.8320. From the results of the whole sample, only mathematics grade of the first year is related to entrance examination grade. However, the average grade of each year is significantly correlated with the rest of two years. ρ values are also significant and show negative endogenous effects with grades of the previous year. In contrast to λ values, coefficients of ρ are diminishing when students live longer together.

As we have discussed above, in table 5b, overaged students still have lower grades on Chinese, mathematics and overall average grades but grades of the first year. Male students tend to have lower grades in both Chinese and mathematics except mathematics grade of the third year, and also have lower grades in second-year study. Additionally, han and hui students have higher

[11] Other detailed estimation and summary results of Chinese and mathematics for grade 3 students and graduates are shown in table 4d.

grades in the second-year study, especially in mathematics. Kazakh students perform better in the second year than in the first year. The family financial difficulty tends to increase mathematics grade of the first year and lower Chinese grade of the third year. Students from the local city still tend to have poorer grades in all three years, and students from rural area tend to have poorer grades only in the previous year of study and second-year Chinese grade. Besides, students from mother-headed families are more likely to have higher grades in the last year of study, especially in previous year mathematics grade.

Conclusion and Discussion

In this paper, we discuss peer effects in student academic performance of a junior high school in Xinjiang Province, China where students were randomly selected to each classroom and dormitory that avoids selection bias issue. Our analyses are also based on limited variables of students' background information. Classroom and dormitory endogenous effects are investigated in both two SAR models. Stands on assumptions and model specifications proposed in the literature (Lee and Yu, 2010; Yu, Jong and Lee, 2008), we found significant and robust evidence of peer effects.

By applying the unique data from junior high school of China, insufficient evidence supports the existence of peer effects in the classroom in the model (5). However, in dormitory analyses, both positive and negative peer effect coefficients are found to be significant in grades 1 to 3. Besides, overaged and male students are more likely to have lower grades in two analytical models. Han and hui students perform better than Kazakh students in general, especially in the first year of study. Family financial conditions and parents occupations are not key determinants of students’ academic grades. Besides, students who are from the local city and have better physical living environment perform poorer than students from the rural area, particularly in dormitory models. Lastly, students from mother-headed families have higher grades in the last year of study. This may because of mother cares more about student academic achievements, and third-year performance will be the key determinant whether students can be admitted by high school smoothly.

Compare with the results in model (5), positive and significant peer effects are found in the model (6) for both classroom and dormitory analyses. In particular, peer effects in the dormitory are not only significant but also consistent and unique. In addition, both positive and negative peer effects based on previous years' grades are found significant. Besides, grades of the previous year have a positive and significant impact on the following years' grades, and the influence of entrance examination grades also contribute to Chinese and mathematics grades of grade 2 students. Moreover, in both classroom and dormitory analyses, overaged students still perform poorer on average grades, especially in the last year of study. Male students tend to have lower grades in the first and second year of study, and the gender difference seems unimportant in the previous year of school. Han students perform better on mathematics and average grades of the second year as well as hui students in dormitory case. Kazakh students tend to have lower grades in Chinese and mathematics for the first year of school, and they have higher grades on average for the second year.

Likewise, students from local city tend to have lower grades in both classroom and dormitory cases throughout all three years of school. Students from rural area tend to have lower grades on second-year Chinese and last year average grades. In dormitory analysis, mother-headed families play a stronger role in grades of last year than in classroom case.

In conclusion, this study focuses on peer effects in both the classroom and dormitory. Significant coefficients of peer effects are found in both cases, which provide new insight and implications for educational policymaking from data of the remote area of China. Based on two comparable SAR models, this paper provides relatively rational and considerable empirical results and shows more accurate interdependence results. In particular, consistent and unique dormitory peer effect coefficients are presented in our model. It also empirically confirms and supports the theoretical work of previous studies in SAR modeling. Lastly, one limitation of this study is that students' characteristics, such as hobby and behavior, and more detailed family background and teachers' information are not included.

APPENDIX 1

Table 1: Description of Variables

Variable	Description
All Incidents	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Aggravated Assault	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Assault	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Weapons Offenses	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Burglary	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Robbery	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Stolen Vehicle	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
White 18+	Logarithm: Population in block group: White 18+
Black 18+	Logarithm: Population in block group: Black 18+
Native American 18+	Logarithm: Population in block group: Native American 18+
Hawaiian 18+	Logarithm: Population in block group: Hawaiian 18+
Other Race 18+	Logarithm: Population in block group: Other Race 18+
Vacant Housing Units	Logarithm: Number of Vacant Housing Units
Median Household Income	Logarithm: Median Household Income
Employment Ratio 18+	Logarithm: Employment Ratio 18+ (Employed/ Block group population 18+)
Total of Vehicles of Occupied Units	Logarithm: Total Number of Vehicles of Occupied Units in the block group
Dangerous Drugs	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Liquor	Logarithm: Total number of crime incidents in block group (per 100 people 18+)
Median Age	Median Age of Population in the block group
Average Household Size	Average Household Size (Number of Household Members) in the block group
Median Number of School Year	Median Number of School Years in block group (people 25+)
Law Enforcement Workers	Number of Law Enforcement Workers in the block group

Table 2: Variable Summary Statistics, 2009 and 2010

Variable	Mean	Std. Dev.	Min	Max
2009				
All Incidents	204.9601	143.4320	30	1794
Aggravated Assault	12.5421	7.2447	0	57
Assault	23.0649	12.9687	3	154
Weapons Offenses	2.1970	2.1561	0	15
Burglary	23.7882	12.8213	1	124
Robbery	7.7961	6.3849	0	52
Stolen Vehicle	17.1173	12.8932	0	172
Dangerous Drugs	5.7517	5.9427	0	62
Liquor	0.2153	0.5300	0	5
2010				
All Incidents	191.9180	127.2037	50	1874
Aggravated Assault	11.9989	6.7298	0	65
Assault	22.6651	12.2019	0	149
Weapons Offenses	2.2267	2.2199	0	14
Burglary	21.1765	11.3034	1	82
Robbery	6.9134	5.5500	0	49
Stolen Vehicle	15.5159	14.9913	0	262
White: Adult 18+	68.1925	122.2490	0	901
Black: Adult 18+	493.0854	237.0892	1	2023
Native American: Adult 18+	2.2506	3.4165	0	48
Hawaiian: Adult 18+	0.1082	0.5084	0	6
Other Race: Adult 18+	15.1071	52.4353	0	471
Vacant Housing Units	90.8030	60.6680	0	653
Median Household Income	29193.0330	12715.6833	0	99999
Population of Employed	246.2278	138.3855	0	1148
Total of Vehicles of Occupied Housing Units	364.5114	188.2541	0	1890
Dangerous Drugs	4.6708	4.4856	0	42
Liquor	0.1720	0.4835	0	5
Median Age	44.0154	4.7815	19	61
Average Household Size	2.7335	0.5865	0	5
Median Number of School Years	12.1595	0.7411	2	17
Law Enforcement Workers: including supervisors	2.4670	7.1934	0	67

Table 3 (a): All Crime Incidents in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.8569	**0.9412****	**0.9537*****	**0.9200*****	**0.7801*****	**0.6436*****
		(1.4837)	**(0.3863)**	**(0.0564)**	**(0.0560)**	**(0.0812)**	**(0.0859)**
ρ		0.8671	**0.9175***	**0.7949*****	0.1886	-0.0343	-0.0554
		(1.3766)	**(0.5338)**	**(0.1782)**	(0.1403)	(0.1342)	(0.1189)
White 18+	**-0.0298****	**-0.0395*****	**-0.0497*****	**-0.0548*****	**-0.0518*****	**-0.0472*****	**-0.0440*****
	(0.0133)	**(0.0133)**	**(0.0136)**	**(0.0141)**	**(0.0149)**	**(0.0153)**	**(0.0152)**
Black 18+	**-0.3671*****	**-0.3682*****	**-0.3851*****	**-0.4232*****	**-0.4648*****	**-0.4696*****	**-0.4558*****
	(0.0271)	**(0.0277)**	**(0.0283)**	**(0.0282)**	**(0.0289)**	**(0.0288)**	**(0.0282)**
Native American 18+	-0.0130	-0.0098	-0.0016	0.0116	0.0207	0.0202	0.0168
	(0.0232)	(0.0228)	(0.0223)	(0.0216)	(0.0211)	(0.0207)	(0.0207)
Hawaiian 18+	-0.1292	-0.1212	-0.1147	-0.1127	-0.0950	-0.0755	-0.0691
	(0.0982)	(0.0958)	(0.0926)	(0.0884)	(0.0853)	(0.0834)	(0.0832)
Other Race 18+	**-0.1217*****	**-0.1109*****	**-0.0965*****	**-0.0784*****	**-0.0628*****	**-0.0663*****	**-0.0806*****
	(0.0167)	**(0.0169)**	**(0.0175)**	**(0.0186)**	**(0.0198)**	**(0.0200)**	**(0.0194)**
Vacant Housing Units	0.0037	-0.0012	-0.0014	0.0052	0.0213	0.0254	0.0234
	(0.0268)	(0.0276)	(0.0276)	(0.0271)	(0.0274)	(0.0275)	(0.0276)
Median Household Income	**-0.0680****	**-0.0610***	**-0.0531***	-0.0457	-0.0471	-0.0462	-0.0442
	(0.0324)	**(0.0320)**	**(0.0311)**	(0.0299)	(0.0292)	(0.0289)	(0.0289)
Employment Ratio 18+	0.0049	0.0168	0.0222	0.0199	0.0146	0.0140	0.0145
	(0.0457)	(0.0451)	(0.0437)	(0.0420)	(0.0408)	(0.0401)	(0.0401)
Median Age 18+	**-0.0261*****	**-0.0241*****	**-0.0201*****	**-0.0158*****	**-0.0142*****	**-0.0144*****	**-0.0157*****
	(0.0040)	**(0.0039)**	**(0.0039)**	**(0.0039)**	**(0.0039)**	**(0.0038)**	**(0.0038)**
Average Household Size	**-0.2181*****	**-0.2175*****	**-0.2119*****	**-0.2022*****	**-0.1921*****	**-0.1889*****	**-0.1936*****
	(0.0305)	**(0.0301)**	**(0.0300)**	**(0.0301)**	**(0.0308)**	**(0.0310)**	**(0.0310)**
Median Number of School Year	**-0.0441****	**-0.0423***	**-0.0421****	**-0.0435****	**-0.0444****	**-0.0450****	**-0.0454****
	(0.0222)	**(0.0217)**	**(0.0212)**	**(0.0205)**	**(0.0201)**	**(0.0198)**	**(0.0199)**
Law Enforcement Workers	-0.0016	-0.0014	-0.0011	-0.0009	-0.0008	-0.0008	-0.0009
	(0.0022)	(0.0021)	(0.0021)	(0.0020)	(0.0019)	(0.0019)	(0.0019)
σ^2		**0.1856*****	**0.1743*****	**0.1611*****	**0.1540*****	**0.1515*****	**0.1528*****
		(0.0168)	**(0.0158)**	**(0.0144)**	**(0.0136)**	**(0.0136)**	**(0.0140)**
Likelihood Value		736.9890	761.8131	790.3932	801.2712	798.6305	791.8438
R-squared		0.3690	0.4073	0.4523	0.4763	0.4850	0.4806
Rbar-squared		0.3610	0.3998	0.4453	0.4697	0.4784	0.4740

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3 (b): All Crime Incidents in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.0001	0.3850	0.3070	0.1549	0.0850	0.0500
		(0.6487)	(0.3261)	(0.1950)	(0.1154)	(0.0775)	(0.0595)
γ		**0.8262*** **	**0.8211*** **	**0.8142*** **	**0.8103*** **	**0.8099*** **	**0.8110*** **
		(0.0166)	**(0.0169)**	**(0.0173)**	**(0.0176)**	**(0.0178)**	**(0.0178)**
ρ		0.4695	-0.0705	-0.0629	0.0231	0.0475	0.0548
		(0.6737)	(0.3410)	(0.2023)	(0.1194)	(0.0812)	(0.0634)
White 18+	**-0.0298** **	**-0.0131* **	**-0.0140** **	**-0.0145** **	**-0.0139** **	**-0.0129* **	**-0.0121* **
	(0.0133)	**(0.0068)**	**(0.0068)**	**(0.0068)**	**(0.0067)**	**(0.0066)**	**(0.0066)**
Black 18+	**-0.3671*** **	**-0.0578*** **	**-0.0600*** **	**-0.0629*** **	**-0.0638*** **	**-0.0636*** **	**-0.0629*** **
	(0.0271)	**(0.0147)**	**(0.0147)**	**(0.0148)**	**(0.0148)**	**(0.0148)**	**(0.0148)**
Native American 18+	-0.0130	-0.0014	-0.0011	-0.0006	-0.0003	-0.0003	-0.0003
	(0.0232)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Hawaiian 18+	-0.1292	-0.0446	-0.0448	-0.0458	-0.0460	-0.0458	-0.0453
	(0.0982)	(0.0487)	(0.0487)	(0.0485)	(0.0485)	(0.0485)	(0.0486)
Other Race 18+	**-0.1217*** **	-0.0082	-0.0083	-0.0081	-0.0081	-0.0086	-0.0091
	(0.0167)	(0.0087)	(0.0087)	(0.0087)	(0.0086)	(0.0086)	(0.0086)
Vacant Housing Units	0.0037	-0.0145	-0.0151	-0.0166	-0.0183	-0.0186	-0.0184
	(0.0268)	(0.0135)	(0.0135)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
Median Household Income	**-0.0680** **	0.0004	0.0013	0.0024	0.0029	0.0028	0.0026
	(0.0324)	(0.0162)	(0.0161)	(0.0161)	(0.0161)	(0.0161)	(0.0162)
Employment Ratio 18+	0.0049	0.0144	0.0156	0.0161	0.0157	0.0152	0.0149
	(0.0457)	(0.0228)	(0.0227)	(0.0227)	(0.0226)	(0.0226)	(0.0226)
Median Age 18+	**-0.0261*** **	-0.0028	-0.0026	-0.0022	-0.0021	-0.0021	-0.0023
	(0.0040)	(0.0020)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Average Household Size	**-0.2181*** **	**-0.0463*** **	**-0.0466*** **	**-0.0472*** **	**-0.0477*** **	**-0.0480*** **	**-0.0481*** **
	(0.0305)	**(0.0155)**	**(0.0155)**	**(0.0154)**	**(0.0154)**	**(0.0155)**	**(0.0155)**
Median Number of School Year	**-0.0441* **	**-0.0204* **	**-0.0203* **	**-0.0204* **	**-0.0208* **	**-0.0210* **	**-0.0211* **
	(0.0222)	**(0.0110)**	**(0.0110)**	**(0.0110)**	**(0.0110)**	**(0.0110)**	**(0.0110)**
Law Enforcement Workers	-0.0016	0.0014	0.0015	0.0015	0.0015	0.0015	0.0014
	(0.0022)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
σ^2		**0.0479*** **	**0.0477*** **	**0.0474*** **	**0.0474*** **	**0.0475*** **	**0.0476*** **
		(0.0045)	**(0.0045)**	**(0.0045)**	**(0.0045)**	**(0.0044)**	**(0.0044)**
Likelihood Value		392.8788	394.2550	396.1455	396.6086	396.0405	395.3656

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4 (a): Aggravated Assault in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.7051	0.8481***	0.8678***	0.7632***	0.5260***	0.3231***
		(1.2808)	(0.2977)	(0.1079)	(0.1182)	(0.1191)	(0.1115)
ρ		0.7467	0.7409	0.2318	-0.1503	-0.1073	-0.0109
		(1.0890)	(0.4573)	(0.2388)	(0.1821)	(0.1397)	(0.1113)
White 18+	-0.0576***	-0.0647***	-0.0712***	-0.0754***	-0.0768***	-0.0701***	-0.0626***
	(0.0171)	(0.0173)	(0.0180)	(0.0192)	(0.0201)	(0.0198)	(0.0190)
Black 18+	-0.2974***	-0.3003***	-0.3201***	-0.3578***	-0.3829***	-0.3673***	-0.3435***
	(0.0363)	(0.0369)	(0.0379)	(0.0391)	(0.0401)	(0.0394)	(0.0384)
Native American 18+	-0.0120	-0.0065	0.0070	0.0226	0.0299	0.0247	0.0164
	(0.0298)	(0.0294)	(0.0292)	(0.0291)	(0.0289)	(0.0289)	(0.0291)
Hawaiian 18+	-0.0246	-0.0187	-0.0124	-0.0050	0.0137	0.0259	0.0244
	(0.1258)	(0.1237)	(0.1219)	(0.1199)	(0.1178)	(0.1179)	(0.1196)
Other Race 18+	-0.0942***	-0.0836***	-0.0706***	-0.0625**	-0.0641**	-0.0822***	-0.0942***
	(0.0218)	(0.0220)	(0.0229)	(0.0246)	(0.0258)	(0.0249)	(0.0236)
Vacant Housing Units	0.1480***	0.1429***	0.1411***	0.1554***	0.1706***	0.1662***	0.1560***
	(0.0344)	(0.0359)	(0.0367)	(0.0371)	(0.0376)	(0.0377)	(0.0376)
Median Household Income	-0.0806*	-0.0757*	-0.0716*	-0.0751*	-0.0801**	-0.0786*	-0.0769*
	(0.0416)	(0.0415)	(0.0412)	(0.0407)	(0.0404)	(0.0404)	(0.0408)
Employment Ratio 18+	-0.1287**	-0.1218**	-0.1222**	-0.1321**	-0.1392**	-0.1345**	-0.1272**
	(0.0585)	(0.0581)	(0.0576)	(0.0569)	(0.0563)	(0.0564)	(0.0571)
Dangerous Drugs	0.2733***	0.2714***	0.2638***	0.2559***	0.2524***	0.2553***	0.2607***
	(0.0242)	(0.0238)	(0.0237)	(0.0238)	(0.0239)	(0.0240)	(0.0241)
Liquor	-0.0812**	-0.0805**	-0.0777**	-0.0747**	-0.0728**	-0.0726**	-0.0737**
	(0.0336)	(0.0331)	(0.0327)	(0.0324)	(0.0321)	(0.0321)	(0.0325)
Median Age 18+	-0.0201***	-0.0180***	-0.0140***	-0.0109**	-0.0102*	-0.0122**	-0.0145***
	(0.0051)	(0.0051)	(0.0052)	(0.0052)	(0.0053)	(0.0053)	(0.0052)
Average Household Size	-0.0350	-0.0436	-0.0586	-0.0668*	-0.0649	-0.0595	-0.0525
	(0.0391)	(0.0389)	(0.0394)	(0.0406)	(0.0416)	(0.0415)	(0.0408)
Median Number of School Year	-0.0861***	-0.0828***	-0.0779***	-0.0746***	-0.0737***	-0.0746***	-0.0765***
	(0.0285)	(0.0281)	(0.0279)	(0.0278)	(0.0276)	(0.0277)	(0.0280)
Law Enforcement Workers	0.0009	0.0010	0.0010	0.0005	0.0003	0.0002	0.0001
	(0.0028)	(0.0027)	(0.0027)	(0.0027)	(0.0026)	(0.0026)	(0.0027)
σ^2		0.3088***	0.3013***	0.2949***	0.2902***	0.2924***	0.2979***
		(0.0214)	(0.0208)	(0.0201)	(0.0198)	(0.0203)	(0.0207)
Likelihood Value		514.6142	523.9249	530.7208	530.9244	527.3192	524.3123
R-squared		0.3930	0.4078	0.4204	0.4297	0.4252	0.4144
Rbar-squared		0.3839	0.3989	0.4117	0.4211	0.4165	0.4056

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4 (b): Aggravated Assault in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.0001	0.0090	0.1540	0.1140	0.0760	0.0590
		(0.6325)	(0.4160)	(0.2046)	(0.1145)	(0.0759)	(0.0580)
γ		0.4768***	0.4709***	0.4645***	0.4619***	0.4623***	0.4635***
		(0.0300)	(0.0303)	(0.0306)	(0.0307)	(0.0307)	(0.0307)
ρ		1.3510	0.6405	0.2684	0.1739	0.1357	0.1122
		(0.8311)	(0.4504)	(0.2189)	(0.1259)	(0.0874)	(0.0693)
White 18+	-0.0576***	-0.0269*	-0.0265*	-0.0251*	-0.0224	-0.0201	-0.0187
	(0.0171)	(0.0152)	(0.0152)	(0.0151)	(0.0150)	(0.0150)	(0.0150)
Black 18+	-0.2973***	-0.1489***	-0.1492***	-0.1526***	-0.1538***	-0.1539***	-0.1540***
	(0.0363)	(0.0327)	(0.0327)	(0.0327)	(0.0326)	(0.0326)	(0.0326)
Native American 18+	-0.0120	0.0193	0.0209	0.0230	0.0236	0.0233	0.0228
	(0.0298)	(0.0259)	(0.0259)	(0.0259)	(0.0259)	(0.0259)	(0.0259)
Hawaiian 18+	-0.0246	0.0441	0.0440	0.0424	0.0417	0.0419	0.0427
	(0.1258)	(0.1090)	(0.1089)	(0.1088)	(0.1087)	(0.1088)	(0.1088)
Other Race 18+	-0.0942***	-0.0571***	-0.0563***	-0.0556***	-0.0571***	-0.0590***	-0.0603***
	(0.0218)	(0.0191)	(0.0191)	(0.0191)	(0.0191)	(0.0190)	(0.0190)
Vacant Housing Units	0.1480***	0.0304	0.0251	0.0229	0.0215	0.0217	0.0227
	(0.0344)	(0.0311)	(0.0314)	(0.0317)	(0.0319)	(0.0319)	(0.0318)
Median Household Income	-0.0806*	0.0051	0.0075	0.0089	0.0098	0.0100	0.0096
	(0.0416)	(0.0365)	(0.0366)	(0.0366)	(0.0367)	(0.0367)	(0.0367)
Employment Ratio 18+	-0.1287**	-0.0771	-0.0777	-0.0787	-0.0796	-0.0798	-0.0797
	(0.0585)	(0.0509)	(0.0508)	(0.0507)	(0.0507)	(0.0507)	(0.0507)
Dangerous Drugs	0.2733***	0.1669***	0.1658***	0.1646***	0.1632***	0.1623***	0.1618***
	(0.0242)	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0220)	(0.0220)
Liquor	-0.0812**	-0.0435	-0.0431	-0.0424	-0.0417	-0.0414	-0.0413
	(0.0336)	(0.0292)	(0.0291)	(0.0291)	(0.0291)	(0.0291)	(0.0291)
Median Age 18+	-0.0201***	-0.0056	-0.0051	-0.0046	-0.0046	-0.0048	-0.0050
	(0.0051)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Average Household Size	-0.0350	-0.0124	-0.0156	-0.0200	-0.0220	-0.0223	-0.0218
	(0.0391)	(0.0340)	(0.0340)	(0.0341)	(0.0341)	(0.0342)	(0.0342)
Median Number of School Year	-0.0861***	-0.0426*	-0.0417*	-0.0410*	-0.0401	-0.0395	-0.0393
	(0.0285)	(0.0248)	(0.0248)	(0.0248)	(0.0248)	(0.0249)	(0.0249)
Law Enforcement Workers	0.0009	0.0026	0.0027	0.0026	0.0025	0.0024	0.0023
	(0.0028)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
σ^2		0.2384***	0.2380***	0.2376***	0.2375***	0.2376***	0.2377***
		(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)
Likelihood Value		-312.1120	-311.4165	-310.7577	-310.6325	-310.8542	-311.0986

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5 (a): Assault in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.7867	**0.8849***	**0.8563***	**0.8058***	**0.6032***	**0.3397***
		(1.5740)	**(0.4735)**	**(0.1316)**	**(0.1072)**	**(0.1129)**	**(0.1194)**
ρ		0.8168	0.8576	0.4197	-0.1514	-0.1623	0.0107
		(1.3493)	(0.5719)	(0.2562)	(0.1846)	(0.1474)	(0.1222)
White 18+	**-0.0529***	**-0.0610***	**-0.0708***	**-0.0770***	**-0.0814***	**-0.0754***	**-0.0636***
	(0.0132)	**(0.0133)**	**(0.0138)**	**(0.0146)**	**(0.0154)**	**(0.0154)**	**(0.0146)**
Black 18+	**-0.2084***	**-0.2099***	**-0.2227***	**-0.2442***	**-0.2630***	**-0.2591***	**-0.2401***
	(0.0279)	**(0.0282)**	**(0.0288)**	**(0.0296)**	**(0.0307)**	**(0.0303)**	**(0.0293)**
Native American 18+	-0.0070	-0.0032	0.0052	0.0132	0.0157	0.0119	0.0056
	(0.0229)	(0.0225)	(0.0223)	(0.0222)	(0.0220)	(0.0219)	(0.0222)
Hawaiian 18+	-0.0361	-0.0281	-0.0196	-0.0189	-0.0134	-0.0090	-0.0164
	(0.0968)	(0.0949)	(0.0930)	(0.0914)	(0.0896)	(0.0892)	(0.0914)
Other Race 18+	**-0.0670***	**-0.0603***	**-0.0514***	**-0.0454****	**-0.0446****	**-0.0532***	**-0.0630***
	(0.0168)	**(0.0169)**	**(0.0175)**	**(0.0187)**	**(0.0199)**	**(0.0195)**	**(0.0182)**
Vacant Housing Units	**0.0590****	**0.0543****	**0.0504***	**0.0549***	**0.0678****	**0.0675****	**0.0588****
	(0.0265)	**(0.0276)**	**(0.0281)**	**(0.0282)**	**(0.0286)**	**(0.0287)**	**(0.0287)**
Median Household Income	-0.0281	-0.0244	-0.0200	-0.0183	-0.0217	-0.0211	-0.0192
	(0.0321)	(0.0318)	(0.0314)	(0.0310)	(0.0307)	(0.0307)	(0.0312)
Employment Ratio 18+	0.0227	0.0299	0.0325	0.0257	0.0145	0.0123	0.0181
	(0.0450)	(0.0446)	(0.0439)	(0.0434)	(0.0429)	(0.0428)	(0.0437)
Dangerous Drugs	**0.1775***	**0.1755***	**0.1692***	**0.1635***	**0.1604***	**0.1603***	**0.1654***
	(0.0186)	**(0.0183)**	**(0.0181)**	**(0.0181)**	**(0.0182)**	**(0.0183)**	**(0.0184)**
Liquor	**-0.0891***	**-0.0878***	**-0.0839***	**-0.0800***	**-0.0773***	**-0.0766***	**-0.0800***
	(0.0259)	**(0.0254)**	**(0.0249)**	**(0.0247)**	**(0.0244)**	**(0.0244)**	**(0.0248)**
Median Age 18+	**-0.0243***	**-0.0226***	**-0.0194***	**-0.0171***	**-0.0167***	**-0.0179***	**-0.0201***
	(0.0040)	**(0.0039)**	**(0.0039)**	**(0.0040)**	**(0.0040)**	**(0.0040)**	**(0.0040)**
Average Household Size	**-0.1598***	**-0.1605***	**-0.1594***	**-0.1566***	**-0.1510***	**-0.1488***	**-0.1536***
	(0.0301)	**(0.0299)**	**(0.0301)**	**(0.0309)**	**(0.0318)**	**(0.0319)**	**(0.0313)**
Median Number of School Year	**-0.1103***	**-0.1076***	**-0.1042***	**-0.1026***	**-0.1030***	**-0.1041***	**-0.1054***
	(0.0220)	**(0.0216)**	**(0.0213)**	**(0.0212)**	**(0.0210)**	**(0.0211)**	**(0.0214)**
Law Enforcement Workers	0.0005	0.0005	0.0004	-0.0001	-0.0003	-0.0004	-0.0004
	(0.0021)	(0.0021)	(0.0021)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
σ^2		**0.1819***	**0.1752***	**0.1712***	**0.1683***	**0.1689***	**0.1742***
		(0.0139)	**(0.0130)**	**(0.0124)**	**(0.0121)**	**(0.0126)**	**(0.0131)**
Likelihood Value		746.5177	760.8100	769.0142	768.3587	763.5543	759.0730
R-squared		0.3861	0.4085	0.4222	0.4319	0.4299	0.4120
Rbar-squared		0.3769	0.3996	0.4135	0.4234	0.4214	0.4031

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5 (b): Assault in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.1400	**0.5930****	**0.4990*****	**0.3140*****	**0.2110*****	**0.1580*****
		(0.5630)	**(0.2413)**	**(0.1708)**	**(0.1069)**	**(0.0731)**	**(0.0568)**
γ		**0.5377*****	**0.5294*****	**0.5234*****	**0.5236*****	**0.5265*****	**0.5289*****
		(0.0259)	**(0.0261)**	**(0.0262)**	**(0.0263)**	**(0.0263)**	**(0.0263)**
ρ		1.1685	0.1695	-0.0007	0.0026	0.0046	0.0069
		(0.7240)	(0.3133)	(0.1912)	(0.1165)	(0.0815)	(0.0647)
White 18+	**-0.0529*****	**-0.0277****	**-0.0296*****	**-0.0292*****	**-0.0265****	**-0.0240****	**-0.0225****
	(0.0132)	**(0.0109)**	**(0.0108)**	**(0.0107)**	**(0.0107)**	**(0.0106)**	**(0.0106)**
Black 18+	**-0.2084*****	**-0.0655*****	**-0.0697*****	**-0.0736*****	**-0.0744*****	**-0.0740*****	**-0.0734*****
	(0.0279)	**(0.0234)**	**(0.0233)**	**(0.0232)**	**(0.0232)**	**(0.0232)**	**(0.0232)**
Native American 18+	-0.0070	-0.0135	-0.0112	-0.0093	-0.0095	-0.0105	-0.0113
	(0.0229)	(0.0184)	(0.0184)	(0.0183)	(0.0183)	(0.0183)	(0.0183)
Hawaiian 18+	-0.0361	0.0295	0.0304	0.0288	0.0263	0.0245	0.0235
	(0.0968)	(0.0778)	(0.0775)	(0.0772)	(0.0772)	(0.0772)	(0.0773)
Other Race 18+	**-0.0670*****	-0.0101	-0.0088	-0.0088	-0.0102	-0.0119	-0.0131
	(0.0168)	(0.0138)	(0.0138)	(0.0137)	(0.0137)	(0.0137)	(0.0136)
Vacant Housing Units	**0.0590****	0.0007	-0.0008	-0.0020	-0.0021	-0.0009	0.0002
	(0.0265)	(0.0220)	(0.0221)	(0.0223)	(0.0224)	(0.0223)	(0.0223)
Median Household Income	-0.0281	0.0231	0.0238	0.0247	0.0247	0.0240	0.0234
	(0.0321)	(0.0259)	(0.0259)	(0.0258)	(0.0258)	(0.0258)	(0.0258)
Employment Ratio 18+	0.0227	0.0443	0.0450	0.0442	0.0427	0.0416	0.0409
	(0.0450)	(0.0363)	(0.0362)	(0.0360)	(0.0360)	(0.0360)	(0.0360)
Dangerous Drugs	**0.1775*****	**0.0826*****	**0.0821*****	**0.0813*****	**0.0804*****	**0.0800*****	**0.0798*****
	(0.0186)	**(0.0156)**	**(0.0155)**	**(0.0155)**	**(0.0155)**	**(0.0156)**	**(0.0156)**
Liquor	**-0.0891*****	**-0.0565*****	**-0.0559*****	**-0.0549*****	**-0.0544*****	**-0.0545*****	**-0.0549*****
	(0.0259)	**(0.0208)**	**(0.0207)**	**(0.0207)**	**(0.0207)**	**(0.0207)**	**(0.0207)**
Median Age 18+	**-0.0243*****	**-0.0081****	**-0.0073****	**-0.0068****	**-0.0069****	**-0.0072****	**-0.0074****
	(0.0040)	**(0.0033)**	**(0.0033)**	**(0.0033)**	**(0.0033)**	**(0.0033)**	**(0.0033)**
Average Household Size	**-0.1598*****	**-0.0887*****	**-0.0905*****	**-0.0913*****	**-0.0910*****	**-0.0907*****	**-0.0905*****
	(0.0301)	**(0.0244)**	**(0.0243)**	**(0.0242)**	**(0.0242)**	**(0.0242)**	**(0.0243)**
Median Number of School Year	**-0.1103*****	**-0.0744*****	**-0.0736*****	**-0.0731*****	**-0.0730*****	**-0.0731*****	**-0.0732*****
	(0.0220)	**(0.0177)**	**(0.0176)**	**(0.0176)**	**(0.0176)**	**(0.0176)**	**(0.0176)**
Law Enforcement Workers	0.0005	0.0019	0.0018	0.0017	0.0016	0.0015	0.0015
	(0.0021)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
σ^2		**0.1214*****	**0.1205*****	**0.1197*****	**0.1196*****	**0.1198*****	**0.1201*****
		(0.0071)	**(0.0071)**	**(0.0070)**	**(0.0070)**	**(0.0071)**	**(0.0071)**
Likelihood Value		-15.8002	-13.2953	-11.0196	-10.9752	-11.8495	-12.6471

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 6 (a): Weapons Offenses in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		-1.0000	-0.3170	-0.2671	-0.1743	-0.0594	0.0226
		(3.2688)	(1.1157)	(0.5948)	(0.3871)	(0.2927)	(0.2434)
ρ		0.0714	0.4863	0.4557	0.2992	0.1550	0.0581
		(1.7072)	(0.6149)	(0.4148)	(0.3164)	(0.2651)	(0.2336)
White 18+	-0.0178	-0.0155	-0.0183	-0.0180	-0.0166	-0.0164	-0.0174
	(0.0220)	(0.0212)	(0.0212)	(0.0208)	(0.0208)	0.0214 ()	(0.0221)
Black 18+	**-0.1427***	**-0.1384***	**-0.1438***	**-0.1453***	**-0.1442***	**-0.1448***	**-0.1474***
	(0.0466)	**(0.0457)**	**(0.0456)**	**(0.0450)**	**(0.0449)**	**(0.0455)**	**(0.0464)**
Native American 18+	**-0.0857**	**-0.0892**	**-0.0843**	**-0.0818**	**-0.0820**	**-0.0823**	**-0.0819**
	(0.0382)	**(0.0379)**	**(0.0379)**	**(0.0378)**	**(0.0378)**	**(0.0379)**	**(0.0381)**
Hawaiian 18+	0.1443	0.1431	0.1441	0.1423	0.1406	0.1433	0.1483
	(0.1614)	(0.1602)	(0.1601)	(0.1599)	(0.1598)	(0.1600)	(0.1598)
Other Race 18+	**-0.0779***	**-0.0806***	**-0.0720**	**-0.0674**	**-0.0686**	**-0.0729***	**-0.0767***
	(0.0280)	**(0.0285)**	**(0.0283)**	**(0.0286)**	**(0.0286)**	**(0.0290)**	**(0.0293)**
Vacant Housing Units	-0.0703	-0.0703	**-0.0727***	**-0.0753***	**-0.0759***	**-0.0748***	-0.0726
	(0.0441)	(0.0431)	**(0.0431)**	**(0.0427)**	**(0.0427)**	**(0.0436)**	(0.0446)
Median Household Income	0.0220	0.0225	0.0231	0.0239	0.0240	0.0247	0.0258
	(0.0534)	(0.0528)	(0.0528)	(0.0527)	(0.0526)	(0.0528)	(0.0530)
Employment Ratio 18+	-0.1273	**-0.1241***	**-0.1248***	**-0.1232***	**-0.1228***	**-0.1250***	**-0.1279***
	(0.0751)	**(0.0742)**	**(0.0742)**	**(0.0741)**	**(0.0742)**	**(0.0745)**	**(0.0747)**
Dangerous Drugs	**0.1887***	**0.1902***	**0.1880***	**0.1855***	**0.1842***	**0.1852***	**0.1868***
	(0.0311)	**(0.0307)**	**(0.0307)**	**(0.0307)**	**(0.0309)**	**(0.0313)**	**(0.0314)**
Liquor	-0.0080	-0.0077	-0.0081	-0.0079	-0.0077	-0.0088	-0.0109
	(0.0431)	(0.0427)	(0.0427)	(0.0425)	(0.0425)	(0.0426)	(0.0427)
Median Age 18+	**-0.0143**	**-0.0154**	**-0.0138**	**-0.0131**	**-0.0132**	**-0.0134**	**-0.0134**
	(0.0066)	**(0.0065)**	**(0.0065)**	**(0.0065)**	**(0.0065)**	**(0.0066)**	**(0.0066)**
Average Household Size	-0.0372	-0.0322	-0.0409	-0.0450	-0.0446	-0.0439	-0.0442
	(0.0502)	(0.0496)	(0.0495)	(0.0492)	(0.0492)	(0.0498)	(0.0505)
Median Number of School Year	-0.0019	-0.0034	-0.0012	-0.0003	-0.0004	-0.0006	-0.0008
	(0.0366)	(0.0363)	(0.0362)	(0.0361)	(0.0360)	(0.0361)	(0.0363)
Law Enforcement Workers	0.0024	0.0024	0.0024	0.0025	0.0024	0.0023	0.0021
	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
σ^2		**0.5144***	**0.5141***	**0.5122***	**0.5115***	**0.5129***	**0.5139***
		(0.0179)	**(0.0178)**	**(0.0181)**	**(0.0187)**	**(0.0184)**	**(0.0177)**
Likelihood Value		291.4679	291.6121	292.2481	292.2614	292.0560	291.9818
R-squared		0.1375	0.1380	0.1411	0.1422	0.1400	0.1382
Rbar-squared		0.1245	0.1250	0.1281	0.1293	0.1270	0.1253

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 6 (b): Weapons Offenses in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.0001	0.1570	0.2330	0.1530	0.1100	0.0830
		(0.6404)	(0.3927)	(0.2042)	(0.1159)	(0.0769)	(0.0589)
γ		**0.1928*** **	**0.1905*** **	**0.1894*** **	**0.1897*** **	**0.1900*** **	**0.1903*** **
		(0.0343)	**(0.0343)**	**(0.0343)**	**(0.0343)**	**(0.0343)**	**(0.0343)**
ρ		2.0712	0.6549	0.1084	-0.0194	-0.0514	-0.0595
		(1.9095)	(0.7037)	(0.3032)	(0.1583)	(0.1028)	(0.0783)
White 18+	-0.0178	-0.0109	-0.0102	-0.0108	-0.0108	-0.0109	-0.0110
	(0.0220)	(0.0215)	(0.0215)	(0.0215)	(0.0215)	(0.0215)	(0.0215)
Black 18+	**-0.1427*** **	-0.0742	-0.0742	-0.0759	-0.0763	-0.0771	-0.0775
	(0.0466)	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)
Native American 18+	**-0.0857** **	-0.0575	-0.0569	-0.0556	-0.0561	-0.0567	-0.0574
	(0.0382)	(0.0376)	(0.0376)	(0.0375)	(0.0375)	(0.0375)	(0.0375)
Hawaiian 18+	0.1443	0.1255	0.1256	0.1255	0.1259	0.1273	0.1285
	(0.1614)	(0.1572)	(0.1572)	(0.1571)	(0.1571)	(0.1571)	(0.1571)
Other Race 18+	**-0.0779*** **	-0.0371	-0.0374	-0.0415	-0.0467	**-0.0501***	**-0.0521***
	(0.0280)	(0.0299)	(0.0296)	(0.0291)	(0.0286)	**(0.0283)**	**(0.0281)**
Vacant Housing Units	-0.0703	-0.0620	-0.0629	-0.0620	-0.0599	-0.0582	-0.0568
	(0.0441)	(0.0433)	0.0433 ()	(0.0433)	(0.0433)	(0.0433)	(0.0432)
Median Household Income	0.0220	0.0192	0.0191	0.0196	0.0199	0.0200	0.0198
	(0.0534)	(0.0521)	(0.0521)	(0.0520)	(0.0520)	(0.0520)	(0.0520)
Employment Ratio 18+	-0.1273	**-0.1387***	**-0.1390***	**-0.1424***	**-0.1446** **	**-0.1459** **	**-0.1468** **
	(0.0751)	**(0.0733)**	**(0.0733)**	**(0.0733)**	**(0.0733)**	**(0.0733)**	**(0.0732)**
Dangerous Drugs	**0.1887*** **	**0.1509*** **	**0.1495*** **	**0.1483*** **	**0.1490*** **	**0.1499*** **	**0.1509*** **
	(0.0311)	**(0.0310)**	**(0.0310)**	**(0.0310)**	**(0.0310)**	**(0.0311)**	**(0.0311)**
Liquor	-0.0080	-0.0025	-0.0025	-0.0024	-0.0026	-0.0030	-0.0032
	(0.0431)	(0.0420)	(0.0420)	(0.0420)	(0.0420)	(0.0420)	(0.0420)
Median Age 18+	**-0.0143** **	**-0.0114***	**-0.0110***	**-0.0110***	**-0.0117***	**-0.0122***	**-0.0126***
	(0.0066)	**(0.0066)**	**(0.0066)**	**(0.0066)**	**(0.0065)**	**(0.0065)**	**(0.0065)**
Average Household Size	-0.0372	-0.0301	-0.0311	-0.0290	-0.0251	-0.0225	-0.0204
	(0.0502)	(0.0502)	(0.0501)	(0.0498)	(0.0496)	(0.0495)	(0.0494)
Median Number of School Year	-0.0019	0.0144	0.0142	0.0148	0.0152	0.0156	0.0158
	(0.0366)	(0.0358)	(0.0358)	(0.0358)	(0.0358)	(0.0358)	(0.0358)
Law Enforcement Workers	0.0024	0.0029	0.0029	0.0028	0.0028	0.0028	0.0028
	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
σ^2		**0.4969*** **	**0.4968*** **	**0.4964*** **	**0.4963*** **	**0.4962*** **	**0.4960*** **
		(0.0176)	**(0.0176)**	**(0.0176)**	**(0.0176)**	**(0.0176)**	**(0.0176)**
Likelihood Value		-634.5400	-634.4764	-634.3556	-634.3528	-634.3213	-634.1836

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 7 (a): Burglary in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.8307	0.9349	0.9280***	0.9209***	0.8128***	0.7037***
		(2.6947)	(0.7350)	(0.0858)	(0.0549)	(0.0719)	(0.0744)
ρ		0.8446	0.9203	0.7112***	-0.0590	-0.2818**	-0.2859**
		(2.4745)	(0.8926)	(0.2285)	(0.1574)	(0.1394)	(0.1201)
White 18+	-0.0234	-0.0290*	-0.0395**	-0.0491***	-0.0532***	-0.0524***	-0.0489***
	(0.0153)	(0.0156)	(0.0157)	(0.0164)	(0.0175)	(0.0179)	(0.0178)
Black 18+	-0.2154***	-0.2287***	-0.2561***	-0.2923***	-0.3277***	-0.3325***	-0.3232***
	(0.0324)	(0.0324)	(0.0337)	(0.0337)	(0.0349)	(0.0350)	(0.0344)
Native American 18+	-0.0419	-0.0351	-0.0201	-0.0038	0.0044	0.0043	0.0009
	(0.0266)	(0.0261)	(0.0255)	(0.0249)	(0.0245)	(0.0239)	(0.0235)
Hawaiian 18+	-0.0545	-0.0558	-0.0640	-0.0750	-0.0626	-0.0461	-0.0354
	(0.1122)	(0.1098)	(0.1063)	(0.1024)	(0.0990)	(0.0959)	(0.0945)
Other Race 18+	-0.0587***	-0.0521***	-0.0400*	-0.0278	-0.0151	-0.0181	-0.0269
	(0.0194)	(0.0196)	(0.0207)	(0.0216)	(0.0231)	(0.0232)	(0.0227)
Vacant Housing Units	-0.0457	-0.0409	-0.0334	-0.0211	-0.0023	0.0046	0.0034
	(0.0307)	(0.0306)	(0.0310)	(0.0311)	(0.0318)	(0.0319)	(0.0318)
Median Household Income	0.1111***	0.1057***	0.1003***	0.0997***	0.0934***	0.0927***	0.0951***
	(0.0371)	(0.0365)	(0.0357)	(0.0347)	(0.0341)	(0.0335)	(0.0332)
Employment Ratio 18+	0.0363	0.0241	-0.0006	-0.0248	-0.0380	-0.0388	-0.0326
	(0.0522)	(0.0513)	(0.0500)	(0.0485)	(0.0474)	(0.0462)	(0.0458)
Dangerous Drugs	0.1048***	0.1026***	0.0981***	0.0939***	0.0910***	0.0905***	0.0908***
	(0.0216)	(0.0212)	(0.0207)	(0.0203)	(0.0203)	(0.0200)	(0.0200)
Liquor	-0.0686**	-0.0709**	-0.0742***	-0.0767***	-0.0759***	-0.0736***	-0.0710***
	(0.0300)	(0.0294)	(0.0285)	(0.0277)	(0.0270)	(0.0264)	(0.0262)
Median Age 18+	-0.0206***	-0.0181***	-0.0130***	-0.0083*	-0.0064	-0.0064	-0.0075*
	(0.0046)	(0.0046)	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0044)
Average Household Size	0.0265	0.0125	-0.0125	-0.0327	-0.0307	-0.0318	-0.0311
	(0.0349)	(0.0359)	(0.0354)	(0.0350)	(0.0359)	(0.0359)	(0.0358)
Median Number of School Year	-0.0738***	-0.0703***	-0.0648***	-0.0617***	-0.0623***	-0.0629***	-0.0651***
	(0.0255)	(0.0251)	(0.0244)	(0.0237)	(0.0234)	(0.0229)	(0.0227)
Law Enforcement Workers	0.0017	0.0015	0.0010	0.0006	0.0006	0.0007	0.0008
	(0.0025)	(0.0024)	(0.0024)	(0.0023)	(0.0022)	(0.0021)	(0.0021)
σ^2		0.2434***	0.2290***	0.2152***	0.2075***	0.2011***	0.1996***
		(0.0206)	(0.0192)	(0.0178)	(0.0168)	(0.0168)	(0.0173)
Likelihood Value		618.2312	642.1104	665.0191	670.9771	668.1686	661.7835
R-squared		0.2458	0.2904	0.3333	0.3571	0.3769	0.3816
Rbar-squared		0.2345	0.2798	0.3232	0.3474	0.3676	0.3723

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 7 (b): Burglary in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		**0.6470***	**0.8620***	**0.8310***	**0.5650***	**0.3820***	**0.2820***
		(0.2392)	**(0.0950)**	**(0.0954)**	**(0.0910)**	**(0.0672)**	**(0.0540)**
γ		**0.5802***	**0.5688***	**0.5588***	**0.5541***	**0.5536***	**0.5551***
		(0.0267)	**(0.0270)**	**(0.0270)**	**(0.0271)**	**(0.0272)**	**(0.0272)**
ρ		1.1479	0.1608	-0.1577	-0.1098	-0.0439	-0.0115
		(0.7421)	(0.2760)	(0.1545)	(0.1102)	(0.0807)	(0.0655)
White 18+	-0.0234	**-0.0317***	**-0.0343***	**-0.0333***	**-0.0309***	**-0.0292**	**-0.0280**
	(0.0153)	**(0.0122)**	**(0.0121)**	**(0.0120)**	**(0.0119)**	**(0.0119)**	**(0.0118)**
Black 18+	**-0.2154***	**-0.1028***	**-0.1065***	**-0.1094***	**-0.1101***	**-0.1092***	**-0.1075***
	(0.0324)	**(0.0265)**	**(0.0261)**	**(0.0256)**	**(0.0254)**	**(0.0254)**	**(0.0255)**
Native American 18+	-0.0419	-0.0080	-0.0045	-0.0022	-0.0023	-0.0030	-0.0040
	(0.0266)	(0.0208)	(0.0206)	(0.0204)	(0.0203)	(0.0203)	(0.0204)
Hawaiian 18+	-0.0545	-0.0926	-0.0941	-0.0965	-0.0982	-0.0987	-0.0978
	(0.1122)	(0.0873)	(0.0865)	(0.0854)	(0.0850)	(0.0852)	(0.0855)
Other Race 18+	**-0.0587***	-0.0151	-0.0134	-0.0137	-0.0158	-0.0178	-0.0191
	(0.0194)	(0.0153)	(0.0152)	(0.0149)	(0.0148)	(0.0149)	(0.0149)
Vacant Housing Units	-0.0457	0.0032	-0.0011	-0.0062	-0.0066	-0.0057	-0.0050
	(0.0307)	(0.0241)	(0.0238)	(0.0234)	(0.0233)	(0.0234)	(0.0235)
Median Household Income	**0.1111***	**0.0779***	**0.0799***	**0.0840***	**0.0869***	**0.0886***	**0.0895***
	(0.0371)	**(0.0291)**	**(0.0287)**	**(0.0283)**	**(0.0282)**	**(0.0282)**	**(0.0283)**
Employment Ratio 18+	0.0363	-0.0148	-0.0183	-0.0202	-0.0195	-0.0169	-0.0142
	(0.0522)	(0.0410)	(0.0406)	(0.0400)	(0.0398)	(0.0399)	(0.0400)
Dangerous Drugs	**0.1048***	**0.0456***	**0.0459***	**0.0473***	**0.0481***	**0.0481***	**0.0480***
	(0.0216)	**(0.0170)**	**(0.0168)**	**(0.0166)**	**(0.0165)**	**(0.0166)**	**(0.0166)**
Liquor	**-0.0686**	**-0.0444***	**-0.0464**	**-0.0475**	**-0.0475**	**-0.0473**	**-0.0469**
	(0.0300)	**(0.0234)**	**(0.0232)**	**(0.0229)**	**(0.0228)**	**(0.0228)**	**(0.0229)**
Median Age 18+	**-0.0206***	**-0.0083**	**-0.0067***	-0.0054	-0.0054	**-0.0062***	**-0.0069***
	(0.0046)	**(0.0037)**	**(0.0036)**	(0.0036)	(0.0035)	**(0.0035)**	**(0.0035)**
Average Household Size	0.0265	-0.0380	-0.0458	**-0.0492***	**-0.0511***	**-0.0521***	**-0.0512***
	(0.0349)	(0.0283)	(0.0283)	**(0.0280)**	**(0.0280)**	**(0.0280)**	**(0.0281)**
Median Number of School Year	**-0.0738***	-0.0312	-0.0300	-0.0301	-0.0307	-0.0311	**-0.0316***
	(0.0255)	(0.0199)	(0.0197)	(0.0195)	(0.0194)	(0.0194)	**(0.0195)**
Law Enforcement Workers	0.0017	0.0009	0.0008	0.0007	0.0006	0.0007	0.0008
	(0.0025)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
σ^2		**0.1534***	**0.1504***	**0.1464***	**0.1452***	**0.1458***	**0.1468***
		(0.0108)	**(0.0108)**	**(0.0109)**	**(0.0110)**	**(0.0111)**	**(0.0111)**
Likelihood Value		-119.0311	-111.7053	-102.6810	-100.4107	-102.1019	-104.5832

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 8 (a): Robbery in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.5760	0.7700	**0.6593****	**0.5184****	**0.3491****	0.2345
		(2.1578)	(0.6856)	**(0.3219)**	**(0.2223)**	**(0.1726)**	(0.1442)
ρ		0.5969	0.7216	0.3352	0.0334	0.0136	0.0384
		(2.0362)	(0.7914)	(0.3962)	(0.2589)	(0.1823)	(0.1427)
White 18+	**-0.0501****	**-0.0481****	**-0.0424***	**-0.0401***	**-0.0407***	**-0.0415***	**-0.0422***
	(0.0214)	**(0.0216)**	**(0.0225)**	**(0.0234)**	**(0.0240)**	**(0.0237)**	**(0.0231)**
Black 18+	**-0.3856*****	**-0.3844*****	**-0.3906*****	**-0.4045*****	**-0.4138*****	**-0.4088*****	**-0.4013*****
	(0.0454)	**(0.0473)**	**(0.0483)**	**(0.0489)**	**(0.0491)**	**(0.0484)**	**(0.0476)**
Native American 18+	-0.0233	-0.0229	-0.0183	-0.0109	-0.0069	-0.0079	-0.0099
	(0.0372)	(0.0369)	(0.0368)	(0.0367)	(0.0367)	(0.0366)	(0.0366)
Hawaiian 18+	0.0729	0.0756	0.0761	0.0700	0.0696	0.0728	0.0747
	(0.1572)	(0.1554)	(0.1535)	(0.1520)	(0.1509)	(0.1509)	(0.1516)
Other Race 18+	**-0.0664****	**-0.0685****	**-0.0735****	**-0.0747****	**-0.0755****	**-0.0763*****	**-0.0757*****
	(0.0272)	**(0.0277)**	**(0.0288)**	**(0.0298)**	**(0.0303)**	**(0.0296)**	**(0.0288)**
Vacant Housing Units	**0.1053****	**0.1001****	**0.0942****	**0.0971****	**0.1040****	**0.1034****	**0.1008****
	(0.0430)	**(0.0458)**	**(0.0464)**	**(0.0466)**	**(0.0468)**	**(0.0465)**	**(0.0460)**
Median Household Income	0.0421	0.0466	0.0548	0.0595	0.0599	0.0600	0.0592
	(0.0521)	(0.0524)	(0.0519)	(0.0515)	(0.0513)	(0.0512)	(0.0512)
Employment Ratio 18+	0.0597	0.0640	0.0664	0.0596	0.0497	0.0473	0.0491
	(0.0731)	(0.0733)	(0.0727)	(0.0722)	(0.0720)	(0.0720)	(0.0722)
Dangerous Drugs	**0.3180*****	**0.3178*****	**0.3145*****	**0.3121*****	**0.3129*****	**0.3148*****	**0.3162*****
	(0.0302)	**(0.0299)**	**(0.0298)**	**(0.0299)**	**(0.0301)**	**(0.0302)**	**(0.0302)**
Liquor	**-0.1177*****	**-0.1169*****	**-0.1138*****	**-0.1106*****	**-0.1094*****	**-0.1099*****	**-0.1108*****
	(0.0420)	**(0.0415)**	**(0.0412)**	**(0.0409)**	**(0.0408)**	**(0.0409)**	**(0.0410)**
Median Age 18+	0.0005	0.0011	0.0031	0.0047	0.0050	0.0043	0.0035
	(0.0064)	(0.0064)	(0.0065)	(0.0065)	(0.0066)	(0.0065)	(0.0065)
Average Household Size	**-0.1881*****	**-0.1847*****	**-0.1805*****	**-0.1833*****	**-0.1870*****	**-0.1895*****	**-0.1906*****
	(0.0489)	**(0.0490)**	**(0.0496)**	**(0.0504)**	**(0.0512)**	**(0.0509)**	**(0.0503)**
Median Number of School Year	-0.0372	-0.0386	-0.0420	-0.0434	-0.0431	-0.0420	-0.0407
	(0.0357)	(0.0353)	(0.0351)	(0.0350)	(0.0350)	(0.0351)	(0.0351)
Law Enforcement Workers	-0.0024	-0.0021	-0.0014	-0.0011	-0.0010	-0.0011	-0.0013
	(0.0035)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
σ^2		**0.4865*****	**0.4770*****	**0.4710*****	**0.4688*****	**0.4701*****	**0.4727*****
		(0.0244)	**(0.0241)**	**(0.0240)**	**(0.0241)**	**(0.0243)**	**(0.0241)**
Likelihood Value		315.6739	322.7531	327.3551	327.6202	326.3557	325.0626
R-squared		0.2967	0.3104	0.3190	0.3223	0.3203	0.3166
Rbar-squared		0.2861	0.3000	0.3088	0.3121	0.3101	0.3063

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 8 (b): Robbery in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.0001	**0.4980***	**0.3660****	**0.2050***	**0.1360***	**0.1030***
		(0.6324)	**(0.2766)**	**(0.1847)**	**(0.1107)**	**(0.0744)**	**(0.0572)**
γ		**0.4228*****	**0.4157*****	**0.4087*****	**0.4054*****	**0.4052*****	**0.4060*****
		(0.0280)	**(0.0282)**	**(0.0283)**	**(0.0285)**	**(0.0285)**	**(0.0285)**
ρ		1.1141	0.3843	0.2439	0.1898	0.1418	0.1119
		(0.9212)	(0.3965)	(0.2196)	(0.1284)	(0.0882)	(0.0690)
White 18+	**-0.0501****	**-0.0368***	**-0.0332***	-0.0306	-0.0296	-0.0292	-0.0292
	(0.0214)	**(0.0189)**	**(0.0188)**	(0.0188)	(0.0188)	(0.0188)	(0.0189)
Black 18+	**-0.3856*****	**-0.2431*****	**-0.2406*****	**-0.2413*****	**-0.2432*****	**-0.2443*****	**-0.2449*****
	(0.0454)	**(0.0411)**	**(0.0410)**	**(0.0409)**	**(0.0408)**	**(0.0408)**	**(0.0408)**
Native American 18+	-0.0233	-0.0113	-0.0110	-0.0094	-0.0082	-0.0077	-0.0076
	(0.0372)	(0.0328)	(0.0327)	(0.0326)	(0.0326)	(0.0326)	(0.0326)
Hawaiian 18+	0.0729	0.1384	0.1386	0.1351	0.1316	0.1301	0.1299
	(0.1572)	(0.1384)	(0.1380)	(0.1376)	(0.1375)	(0.1375)	(0.1376)
Other Race 18+	**-0.0664****	-0.0354	-0.0392	**-0.0402***	**-0.0399***	**-0.0403***	**-0.0406***
	(0.0272)	(0.0241)	(0.0240)	**(0.0239)**	**(0.0239)**	**(0.0239)**	**(0.0239)**
Vacant Housing Units	**0.1053****	0.0488	0.0396	0.0333	0.0326	0.0350	0.0378
	(0.0430)	(0.0390)	(0.0390)	(0.0391)	(0.0389)	(0.0387)	(0.0386)
Median Household Income	0.0421	**0.0979****	**0.1030****	**0.1056****	**0.1045****	**0.1029****	**0.1016****
	(0.0521)	**(0.0461)**	**(0.0459)**	**(0.0458)**	**(0.0457)**	**(0.0457)**	**(0.0457)**
Employment Ratio 18+	0.0597	-0.0120	-0.0061	-0.0034	-0.0039	-0.0044	-0.0049
	(0.0731)	(0.0649)	(0.0647)	(0.0645)	(0.0644)	(0.0644)	(0.0645)
Dangerous Drugs	**0.3180*****	**0.1978*****	**0.1975*****	**0.1958*****	**0.1940*****	**0.1934*****	**0.1935*****
	(0.0302)	**(0.0278)**	**(0.0277)**	**(0.0276)**	**(0.0276)**	**(0.0276)**	**(0.0277)**
Liquor	**-0.1177*****	**-0.0750****	**-0.0743****	**-0.0732****	**-0.0724****	**-0.0719***	**-0.0717***
	(0.0420)	**(0.0371)**	**(0.0369)**	**(0.0368)**	**(0.0368)**	**(0.0368)**	**(0.0368)**
Median Age 18+	0.0005	0.0022	0.0029	0.0037	0.0039	0.0037	0.0034
	(0.0064)	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Average Household Size	**-0.1881*****	**-0.1262*****	**-0.1234*****	**-0.1238*****	**-0.1254*****	**-0.1269*****	**-0.1280*****
	(0.0489)	**(0.0433)**	**(0.0431)**	**(0.0430)**	**(0.0430)**	**(0.0430)**	**(0.0430)**
Median Number of School Year	-0.0372	-0.0114	-0.0136	-0.0151	-0.0152	-0.0147	-0.0141
	(0.0357)	(0.0315)	(0.0314)	(0.0313)	(0.0313)	(0.0313)	(0.0313)
Law Enforcement Workers	-0.0024	0.0007	0.0010	0.0010	0.0008	0.0006	0.0005
	(0.0035)	(0.0031)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
σ^2		**0.3849*****	**0.3826*****	**0.3804*****	**0.3799*****	**0.3802*****	**0.3806*****
		(0.0202)	**(0.0203)**	**(0.0202)**	**(0.0200)**	**(0.0200)**	**(0.0200)**
Likelihood Value		-522.3370	-520.1800	-517.8972	-517.3229	-517.6589	-518.1539

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 9 (a): Stolen Vehicle in Model (2)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.9335	0.9575	**0.9240*****	**0.9166*****	**0.8779*****	**0.7977*****
		(2.7772)	(1.1829)	**(0.2615)**	**(0.0608)**	**(0.0517)**	**(0.0521)**
ρ		0.9404	0.9577	**0.8852****	0.1523	**-0.2851****	**-0.3496*****
		(2.4959)	(1.1772)	**(0.3672)**	(0.1599)	**(0.1235)**	**(0.1022)**
White 18+	**0.0406****	0.0186	0.0001	-0.0110	-0.0113	-0.0098	-0.0049
	(0.0170)	(0.0176)	(0.0171)	(0.0173)	(0.0184)	(0.0189)	(0.0188)
Black 18+	**-0.1885*****	**-0.2076*****	**-0.2355*****	**-0.2685*****	**-0.3004*****	**-0.3150*****	**-0.3145*****
	(0.0430)	**(0.0414)**	**(0.0416)**	**(0.0421)**	**(0.0439)**	**(0.0447)**	**(0.0441)**
Native American 18+	0.0216	0.0200	0.0173	0.0137	0.0134	0.0109	0.0087
	(0.0287)	(0.0273)	(0.0263)	(0.0253)	(0.0249)	(0.0240)	(0.0233)
Hawaiian 18+	-0.0528	-0.0335	-0.0112	0.0052	0.0200	0.0424	0.0565
	(0.1198)	(0.1139)	(0.1081)	(0.1031)	(0.1004)	(0.0958)	(0.0928)
Other Race 18+	**-0.0845*****	**-0.0719*****	**-0.0620*****	**-0.0575*****	**-0.0553****	**-0.0554****	**-0.0592****
	(0.0216)	**(0.0211)**	**(0.0212)**	**(0.0220)**	**(0.0236)**	**(0.0242)**	**(0.0237)**
Vacant Housing Units	**-0.0700****	**-0.0780****	**-0.0751****	**-0.0611***	-0.0416	-0.0249	-0.0169
	(0.0334)	**(0.0327)**	**(0.0323)**	**(0.0323)**	(0.0333)	(0.0334)	(0.0331)
Median Household Income	**0.1774*****	**0.1647*****	**0.1516*****	**0.1455*****	**0.1398*****	**0.1341*****	**0.1335*****
	(0.0448)	**(0.0426)**	**(0.0408)**	**(0.0393)**	**(0.0388)**	**(0.0377)**	**(0.0368)**
Employment Ratio 18+	**0.1077***	**0.1182****	**0.1148****	**0.1013****	**0.0878***	**0.0772***	0.0703
	(0.0563)	**(0.0538)**	**(0.0515)**	**(0.0494)**	**(0.0484)**	**(0.0467)**	(0.0456)
Total of Vehicles of Occupied Units	**-0.1155****	-0.0781	-0.0532	-0.0433	-0.0412	-0.0460	-0.0537
	(0.0517)	(0.0499)	(0.0482)	(0.0476)	(0.0485)	(0.0482)	(0.0475)
Dangerous Drugs	**0.1066*****	**0.1098*****	**0.1100*****	**0.1100*****	**0.1102*****	**0.1077*****	**0.1053*****
	(0.0238)	**(0.0227)**	**(0.0217)**	**(0.0210)**	**(0.0208)**	**(0.0204)**	**(0.0200)**
Liquor	**-0.0855*****	**-0.0851*****	**-0.0819*****	**-0.0753*****	**-0.0707*****	**-0.0649****	**-0.0612****
	(0.0320)	**(0.0304)**	**(0.0290)**	**(0.0278)**	**(0.0274)**	**(0.0264)**	**(0.0258)**
Median Age 18+	**-0.0168*****	**-0.0138*****	**-0.0092****	-0.0053	-0.0042	-0.0036	-0.0040
	(0.0050)	**(0.0048)**	**(0.0046)**	(0.0046)	(0.0046)	(0.0046)	(0.0045)
Average Household Size	**-0.2330*****	**-0.2377*****	**-0.2315*****	**-0.2137*****	**-0.2013*****	**-0.1853*****	**-0.1779*****
	(0.0378)	**(0.0364)**	**(0.0357)**	**(0.0354)**	**(0.0366)**	**(0.0367)**	**(0.0363)**
Median Number of School Year	**-0.0835*****	**-0.0756*****	**-0.0714*****	**-0.0723*****	**-0.0724*****	**-0.0723*****	**-0.0733*****
	(0.0272)	**(0.0260)**	**(0.0248)**	**(0.0239)**	**(0.0237)**	**(0.0230)**	**(0.0225)**
Law Enforcement Workers	0.0027	0.0026	0.0023	0.0019	0.0019	0.0021	0.0022
	(0.0026)	(0.0025)	(0.0024)	(0.0023)	(0.0022)	(0.0021)	(0.0021)
σ^2		**0.2611*****	**0.2365*****	**0.2178*****	**0.2127*****	**0.2028*****	**0.1973*****
		(0.0204)	**(0.0186)**	**(0.0169)**	**(0.0162)**	**(0.0160)**	**(0.0164)**
Likelihood Value		585.6656	626.9515	657.3867	660.0723	656.9928	649.3004
R-squared		0.2960	0.3625	0.4127	0.4266	0.4534	0.4681
Rbar-squared		0.2846	0.3521	0.4032	0.4173	0.4445	0.4595

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 9 (b): Stolen Vehicle in Model (3)

Explanatory Variable	(1) OLS	(2) p=0.5	(3) p=1	(4) p=1.5	(5) p=2	(6) p=2.5	(7) p=3
λ		0.0270	**0.5350****	**0.4820*****	**0.3550*****	**0.2730*****	**0.2200*****
		(0.4975)	**(0.2345)**	**(0.1580)**	**(0.0998)**	**(0.0689)**	**(0.0541)**
γ		**0.5485*****	**0.5255*****	**0.5030*****	**0.4928*****	**0.4934*****	**0.4990*****
		(0.0262)	**(0.0263)**	**(0.0263)**	**(0.0263)**	**(0.0263)**	**(0.0263)**
ρ		**2.9939*****	**0.9834*****	**0.5537*****	**0.4207*****	**0.3487*****	**0.3040*****
		(0.7580)	**(0.3513)**	**(0.2145)**	**(0.1256)**	**(0.0843)**	**(0.0656)**
White 18+	**0.0406****	**-0.0226***	**-0.0263****	**-0.0277****	**-0.0249***	-0.0203	-0.0158
	(0.0170)	**(0.0134)**	**(0.0133)**	**(0.0130)**	**(0.0128)**	(0.0127)	(0.0127)
Black 18+	**-0.1885*****	**-0.1189*****	**-0.1263*****	**-0.1311*****	**-0.1320*****	**-0.1311*****	**-0.1285*****
	(0.0430)	**(0.0328)**	**(0.0325)**	**(0.0320)**	**(0.0318)**	**(0.0317)**	**(0.0318)**
Native American 18+	0.0216	0.0144	0.0128	0.0104	0.0089	0.0090	0.0097
	(0.0287)	(0.0216)	(0.0214)	(0.0211)	(0.0209)	(0.0209)	(0.0210)
Hawaiian 18+	-0.0528	0.0011	0.0093	0.0156	0.0179	0.0178	0.0168
	(0.1198)	(0.0904)	(0.0893)	(0.0882)	(0.0876)	(0.0875)	(0.0878)
Other Race 18+	**-0.0845*****	**-0.0274***	-0.0263	-0.0262	**-0.0293***	**-0.0337****	**-0.0370****
	(0.0216)	**(0.0165)**	(0.0163)	(0.0161)	**(0.0159)**	**(0.0159)**	**(0.0159)**
Vacant Housing Units	**-0.0700****	**-0.0454***	**-0.0460***	**-0.0452***	**-0.0411***	-0.0358	-0.0322
	(0.0334)	**(0.0254)**	**(0.0251)**	**(0.0247)**	**(0.0245)**	(0.0245)	(0.0245)
Median Household Income	**0.1774*****	**0.0728****	**0.0730****	**0.0768****	**0.0817****	**0.0854*****	**0.0878*****
	(0.0448)	**(0.0340)**	**(0.0336)**	**(0.0332)**	**(0.0329)**	**(0.0329)**	**(0.0330)**
Employment Ratio 18+	**0.1077***	0.0406	0.0397	0.0356	0.0309	0.0287	0.0274
	(0.0563)	(0.0427)	(0.0422)	(0.0416)	(0.0413)	(0.0412)	(0.0413)
Total of Vehicles of Occupied Units	**-0.1155****	0.0062	0.0053	-0.0011	-0.0109	-0.0192	-0.0252
	(0.0517)	(0.0394)	(0.0389)	(0.0383)	(0.0379)	(0.0378)	(0.0379)
Dangerous Drugs	**0.1066*****	**0.0595*****	**0.0607*****	**0.0622*****	**0.0622*****	**0.0610*****	**0.0600*****
	(0.0238)	**(0.0181)**	**(0.0179)**	**(0.0177)**	**(0.0176)**	**(0.0175)**	**(0.0176)**
Liquor	**-0.0855*****	**-0.0488****	**-0.0498****	**-0.0495****	**-0.0485****	**-0.0477****	**-0.0476****
	(0.0320)	**(0.0242)**	**(0.0239)**	**(0.0236)**	**(0.0234)**	**(0.0234)**	**(0.0234)**
Median Age 18+	**-0.0168*****	-0.0052	-0.0037	-0.0022	-0.0017	-0.0020	-0.0025
	(0.0050)	(0.0038)	(0.0038)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Average Household Size	**-0.2330*****	**-0.1467*****	**-0.1471*****	**-0.1447*****	**-0.1403*****	**-0.1372*****	**-0.1363*****
	(0.0378)	**(0.0290)**	**(0.0287)**	**(0.0282)**	**(0.0280)**	**(0.0280)**	**(0.0281)**
Median Number of School Year	**-0.0835*****	-0.0126	-0.0145	-0.0180	-0.0210	-0.0222	-0.0225
	(0.0272)	(0.0207)	(0.0205)	(0.0202)	(0.0201)	(0.0200)	(0.0201)
Law Enforcement Workers	0.0027	0.0024	0.0022	0.0020	0.0017	0.0016	0.0016
	(0.0026)	(0.0020)	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
σ^2		**0.1637*****	**0.1599*****	**0.1557*****	**0.1535*****	**0.1533*****	**0.1542*****
		(0.0096)	**(0.0096)**	**(0.0095)**	**(0.0094)**	**(0.0093)**	**(0.0093)**
Likelihood Value		-147.0338	-137.2230	-126.4364	-121.1523	-121.2734	-124.0757

The sample size is 878 for all. Standard errors are in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 10 (a) Summary of Spatial Interactions Model (2)

Crime Category	P Values	(1) p=0.5	(2) p=1	(3) p=1.5	(4) p=2	(5) p=2.5	(6) p=3
	All Incidents	0.8569 (1.4837)	**0.9412**** **(0.3863)**	**0.9537***** **(0.0564)**	**0.9200***** **(0.0560)**	**0.7801***** **(0.0812)**	**0.6436***** **(0.0859)**
Violent Crimes	1. Aggravated Assault	0.7051 (1.2808)	**0.8481***** **(0.2977)**	**0.8678***** **(0.1079)**	**0.7632***** **(0.1182)**	**0.5260***** **(0.1191)**	**0.3231***** **(0.1115)**
	2. Assault	0.7867 (1.5740)	**0.8849*** **(0.4735)**	**0.8563***** **(0.1316)**	**0.8058***** **(0.1072)**	**0.6032***** **(0.1129)**	**0.3397***** **(0.1194)**
	3. Weapons Offenses	-1.0000 (3.2688)	-0.3170 (1.1157)	-0.2671 (0.5948)	-0.1743 (0.3871)	-0.0594 (0.2927)	0.0226 (0.2434)
Property Crimes	1. Burglary	0.8307 (2.6947)	0.9349 (0.7350)	**0.9280***** **(0.0858)**	**0.9209***** **(0.0549)**	**0.8128***** **(0.0719)**	**0.7037***** **(0.0744)**
	2. Robbery	0.5760 (2.1578)	0.7700 (0.6856)	**0.6593**** **(0.3219)**	**0.5184**** **(0.2223)**	**0.3491**** **(0.1726)**	0.2345 (0.1442)
	3. Stolen Vehicle	0.9335 (2.7772)	0.9575 (1.1829)	**0.9240***** **(0.2615)**	**0.9166***** **(0.0608)**	**0.8779***** **(0.0517)**	**0.7977***** **(0.0521)**

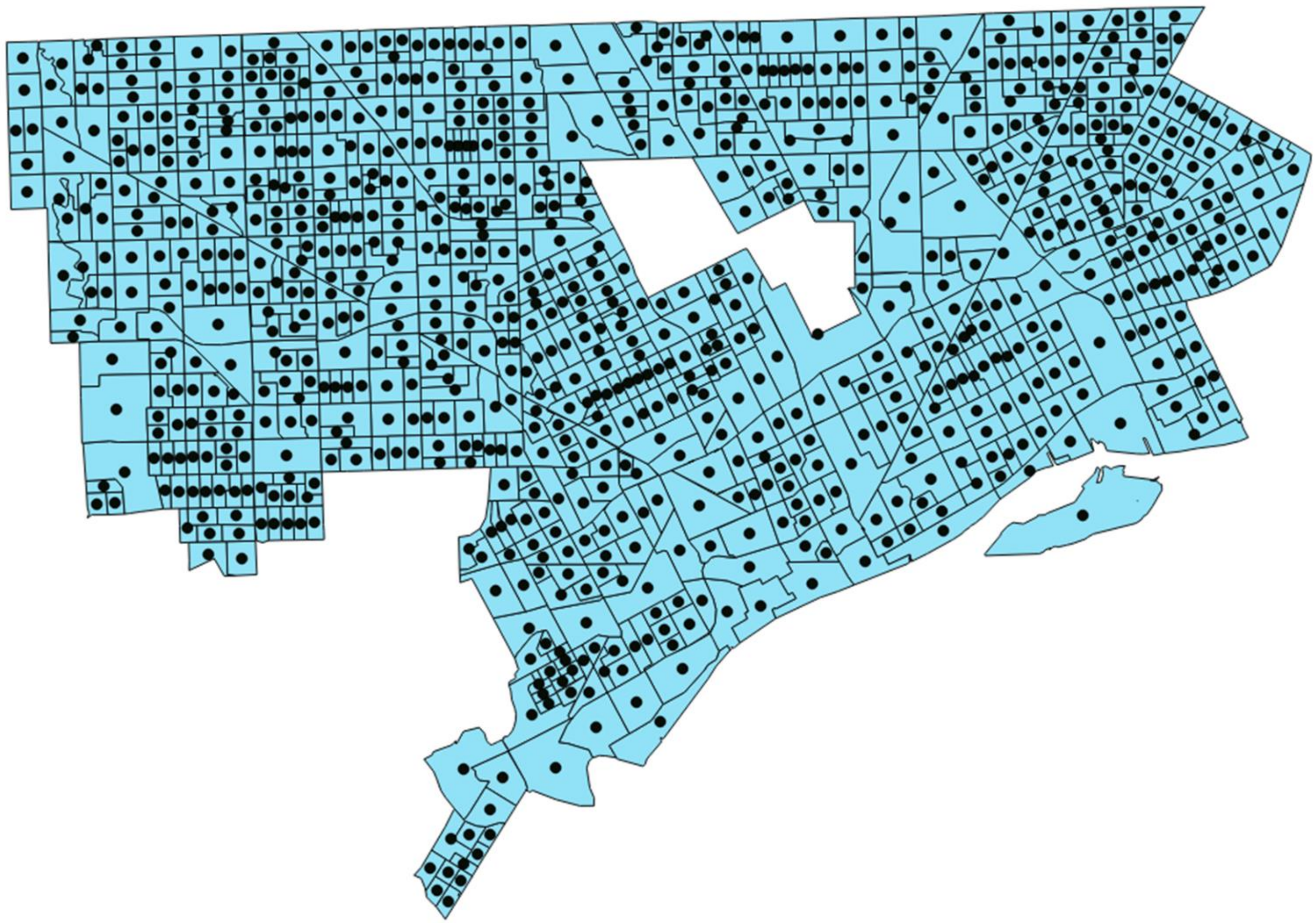
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 10 (b) Summary of Spatial Interactions Model (3)

Crime Category	P Values	(1) p=0.5	(2) p=1	(3) p=1.5	(4) p=2	(5) p=2.5	(6) p=3
	All Incidents	0.0001 (0.6487)	0.3850 (0.3261)	0.3070 (0.1950)	0.1549 (0.1154)	0.0850 (0.0775)	0.0500 (0.0595)
Violent Crimes	4. Aggravated Assault	0.0001 (0.6325)	0.0090 (0.4160)	0.1540 (0.2046)	0.1140 (0.1145)	0.0760 (0.0759)	0.0590 (0.0580)
	5. Assault	0.1400 (0.5630)	**0.5930**** **(0.2413)**	**0.4990***** **(0.1708)**	**0.3140***** **(0.1069)**	**0.2110***** **(0.0731)**	**0.1580***** **(0.0568)**
	6. Weapons Offenses	0.0001 (0.6404)	0.1570 (0.3927)	0.2330 (0.2042)	0.1530 (0.1159)	0.1100 (0.0769)	0.0830 (0.0589)
Property Crimes	4. Burglary	**0.6470***** **(0.2392)**	**0.8620***** **(0.0950)**	**0.8310***** **(0.0954)**	**0.5650***** **(0.0910)**	**0.3820***** **(0.0672)**	**0.2820***** **(0.0540)**
	5. Robbery	0.0001 (0.6324)	**0.4980*** **(0.2766)**	**0.3660**** **(0.1847)**	**0.2050*** **(0.1107)**	**0.1360*** **(0.0744)**	**0.1030*** **(0.0572)**
	6. Stolen Vehicle	0.0270 (0.4975)	**0.5350**** **(0.2345)**	**0.4820***** **(0.1580)**	**0.3550***** **(0.0998)**	**0.2730***** **(0.0689)**	**0.2200***** **(0.0541)**

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Figure 1: Centroid Points of Detroit City Block Groups



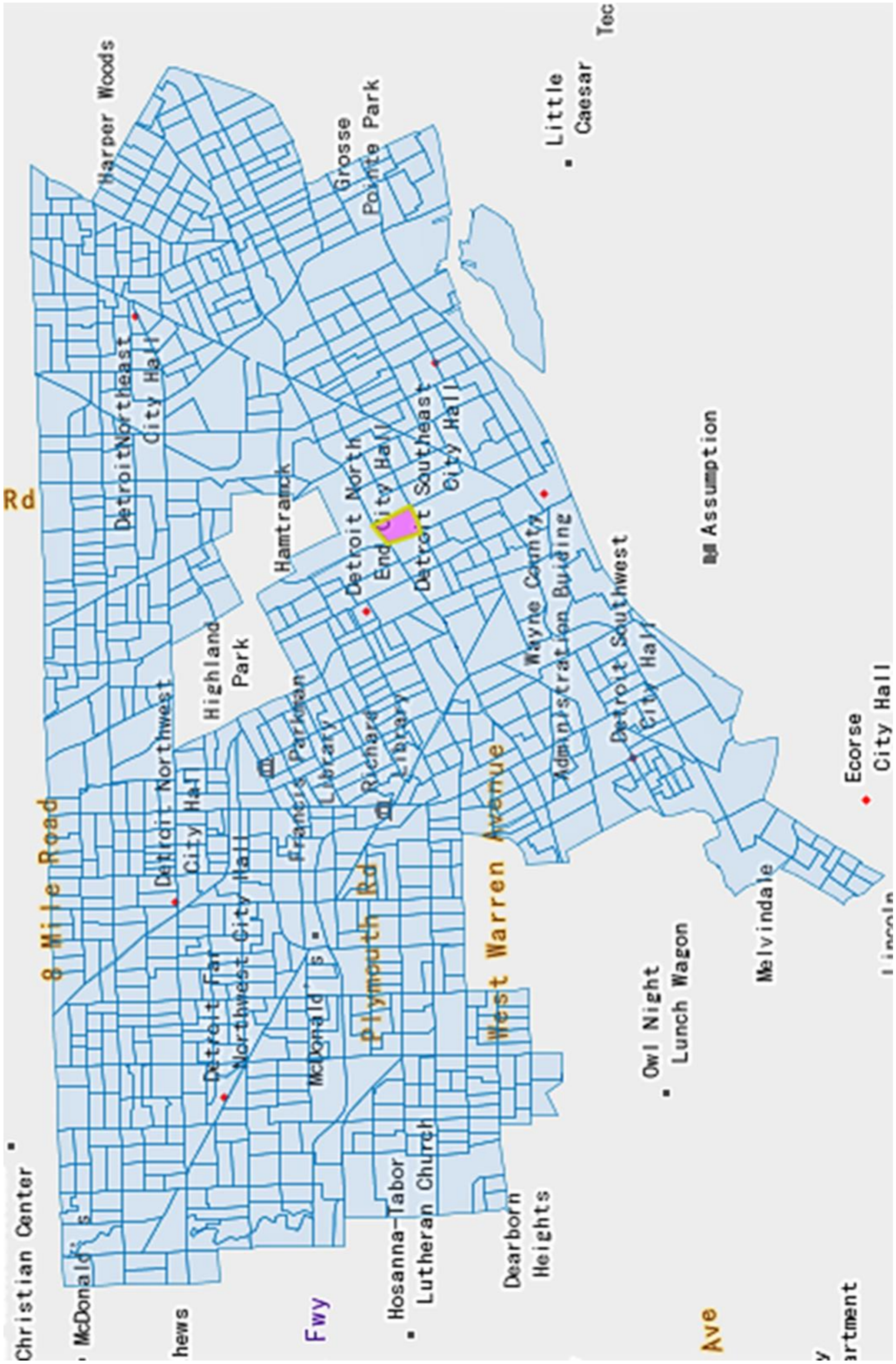


Figure 2: Map of Detroit City Block Groups

Figure 3a: Showing Ten Degrees of Density, The Distribution of Number of Crime Incidents

Figure 3b: Showing Ten Degrees of Density, The Distribution of Number of Crime Incidents

APPENDIX 2

Table 1: Variable Description and Summary Statistics

Variable	Definition	Mean	Std. Dev.	Min	Max
Chinese	Entrance examination: average grade of Chinese	59.4308	19.7064	2	98
Mathematics	Entrance examination: average grade of Mathematics	55.2060	21.1220	0	100
AvgCM0	Entrance examination: average grade of Mathematics and Chinese	57.3184	16.5277	2.5	96
AvgC	Average grade of Chinese	63.4964	13.8349	6.2222	90.2824
AvgM	Average grade of Mathematics	48.3052	20.9612	4.0741	99.5833
AvgCM	Average grade of Mathematics and Chinese	55.9008	15.9519	5.3703	92.5
AVG	Average grade of all subjects: Mathematics, Chinese, English, Politics, History, Biology, etc.	57.3020	14.6881	6.4259	92.2112
Age	Student age	14.3910	1.3073	7	28.8849
Male	If male; 0 otherwise	0.5318	0.4991	0	1
(Female)	If female; 0 otherwise	0.4682	0.4991	0	1
Han	If Han; 0 otherwise	0.5327	0.4990	0	1
Hui	If Hui; 0 otherwise	0.0613	0.2399	0	1
Kazakh	If Kazakh; 0 otherwise	0.3867	0.4871	0	1
(Other Minorities)	If other minorities; 0 otherwise	0.0194	0.1379	0	1
Financial Difficulties	If yes; 0 otherwise	0.0572	0.2323	0	1
(No Financial Difficulties)	If no; 0 otherwise	0.9428	0.2323	0	1
Parents Occupation: Farmer	If farmer; 0 otherwise	0.9604	0.1952	0	1
(Other Occupations: Officials, Teacher, Doctor)	If other occupation; 0 otherwise	0.0396	0.1952	0	1
In City	If from local city; 0 otherwise	0.4899	0.5000	0	1
Rural	If from local rural; 0 otherwise	0.3619	0.4807	0	1
(Other Cities)	If from other cities; 0 otherwise	0.1483	0.3554	0	1
Head of Household: Mother	If mother; 0 otherwise	0.0415	0.1994	0	1
(Head of Household: Father or Grandparents)	If father or grandparents; 0 otherwise	0.9585	0.1994	0	1

Note: g1 is grade of grade 1; g2 is grade of grade 2; g3 is grade of grade 3. g1_g2 represents g1 versus g2; g1_g3 represents g1 versus g3; g2_g3 represents g2 versus g3.

Table 2a: Summary Results of Classroom Peer Effects in Model (5)

Explanatory Variable	Grade 1		Grade 2			
	(1) AVGCM_g1	(2) AVG_g1	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g2	(4) AVG_g2
ρ	0.0926	0.0950	**0.7909*** **	**0.7513*** **	0.6916	**0.6755***
	(0.7566)	(0.6626)	**(0.0851)**	**(0.1018)**	(0.4337)	**(0.3455)**
λ	-1.0000	-1.0000	-1.0000	-1.0000	-1.0000	-1.0000
	(1.6649)	(1.4759)	(0.8410)	(0.8460)	(2.7145)	(2.0755)
Likelihood value	-904.7098	-868.2210	-1780.0330	-1688.4230	-999.0721	-938.5482
R-squared	0.0589	0.0697	0.5086	0.4528	0.1059	0.1162
Rbar-squared	0.0352	0.0463	0.5016	0.4451	0.0838	0.0944
Sample Size	327	327	646	646	374	374

Grade 3

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g2	(4) AVG_g2	(5) AVGCM_g3	(6) AVG_g3
ρ	**0.3928*** **	0.3242	**0.4085***	**0.4056***	0.4065	0.3982
	(0.1976)	(0.2401)	**(0.2273)**	**(0.2237)**	(0.5781)	(0.6602)
λ	0.2024	0.3017	0.2821	0.2219	-1.0000	-1.0000
	(0.2936)	(0.2767)	(0.3025)	(0.3217)	(1.9010)	(2.1345)
Likelihood value	-1615.0046	-1547.0009	-1642.2278	-1542.0758	-1426.7512	-1307.6201
R-squared	0.3146	0.2768	0.2863	0.2559	0.0399	0.0366
Rbar-squared	0.3037	0.2653	0.2752	0.2443	0.0249	0.0215
Sample Size	579	579	587	587	585	585

Grade 3 (Graduates)

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g2	(4) AVG_g2	(5) AVGCM_g3	(6) AVG_g3
ρ	**0.4854*** **	**0.3977***	**0.4647***	0.2536	0.1021	**0.4984*** **
	(0.2031)	**(0.2374)**	**(0.2658)**	(0.3920)	(0.3316)	**(0.2235)**
λ	-1.0000	-1.0000	-1.0000	-1.0000	0.0954	-1.0000
	(0.8173)	(0.8183)	(0.9992)	(1.0582)	(0.3658)	(0.9097)
Likelihood value	-1673.5391	-1554.5101	-1788.8962	-1707.4477	-1873.0017	-1726.2632
R-squared	0.2013	0.1560	0.1229	0.0959	0.1347	0.1331
Rbar-squared	0.1895	0.1435	0.1100	0.0826	0.1226	0.1210
Sample Size	618	618	621	621	651	651

Whole Sample

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g1	(4) AVG_g1	(5) AVGCM_g2	(6) AVG_g2	(7) AVGCM_g3	(8) AVG_g3
ρ	**0.5417*** **	**0.5173*** **	**0.5315*** **	**0.4660*** **	**0.7128*** **	**0.6898*** **	**0.6927*** **	**0.7842*** **
	(0.1207)	**(0.1189)**	**(0.1128)**	**(0.1201)**	**(0.0955)**	**(0.1035)**	**(0.1031)**	**(0.0595)**
λ	0.2395	0.1845	0.2179	0.1977	-1.0000	-1.0000	-1.0000	**-1.0000***
	(0.2100)	(0.2120)	(0.2018)	(0.1956)	(0.6639)	(0.6665)	(0.6794)	**(0.5729)**
Likelihood value	-6053.9771	-5738.0102	-5119.4940	-4837.7694	-4476.9907	-4240.5597	-3386.0705	-3126.4227
R-squared	0.3030	0.2666	0.3433	0.2895	0.2004	0.1888	0.1501	0.2681
Rbar-squared	0.3005	0.2639	0.3401	0.2860	0.1958	0.1842	0.1438	0.2627
Sample Size	2170	2170	1843	1843	1582	1582	1236	1236

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3a: Results of Classroom Peer Effects in Model (5)

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g1	(4) AVG_g1	(5) AVGCM_g2	(6) AVG_g2	(7) AVGCM_g3	(8) AVG_g3
Age	-0.8514**	-1.0654***	-0.8030**	-0.9493***	-0.3860	-0.6405**	-1.3929***	-1.5956***
	(0.3486)	(0.3133)	(0.3891)	(0.3401)	(0.3215)	(0.3187)	(0.4503)	(0.3905)
Gender (Male)	-4.6691***	-4.0521***	-5.5148***	-4.8206***	-6.3729***	-4.6178***	-3.4578***	-2.2486***
	(0.6942)	(0.6015)	(0.7439)	(0.6399)	(0.8440)	(0.7248)	(0.8727)	(0.7015)
Han	0.7071	0.9005	3.1772	3.1982	7.7723**	7.4204***	3.9680	1.1602
	(2.6833)	(2.2981)	(3.0137)	(2.5646)	(3.2314)	(2.7807)	(3.3228)	(2.6589)
Hui	-4.0176	-2.3989	-2.0564	-0.6054	5.4147	5.8652*	2.7880	-0.1014
	(2.9877)	(2.5643)	(3.3451)	(2.8538)	(3.5588)	(3.0705)	(3.7480)	(3.0021)
Kazakh	-6.9227**	-4.8238**	-5.9359*	-4.2668*	6.0041*	5.9670**	3.1493	1.1692
	(2.7841)	(2.3751)	(3.0348)	(2.5934)	(3.2125)	(2.7713)	(3.3476)	(2.6914)
Family Financial Difficulties	1.5257	0.1852	1.0143	-0.6809	0.6375	-0.1953	-1.5844	-1.0147
(Yes)	(1.5504)	(1.3387)	(1.6752)	(1.4401)	(1.6131)	(1.3899)	(1.5472)	(1.2440)
Parents Occupation (Farmer)	------	------	-3.5120*	-1.3042	-2.0595	-0.3487	-2.1689	-0.4809
			(1.9648)	(1.6892)	(2.0142)	(1.7428)	(1.8227)	(1.4750)
In City	-2.8154**	-2.8709***	-3.4871***	-3.5605***	-5.9779***	-4.8031***	-4.0169***	-3.5474***
	(1.1130)	(0.9774)	(1.1834)	(1.0334)	(1.3147)	(1.1383)	(1.2832)	(1.0326)
Rural	-1.8609	-1.2192	-2.2792*	-1.5114	-3.3979**	-2.8315**	-4.7918***	-4.4226***
	(1.1595)	(1.0100)	(1.2986)	(1.1300)	(1.3963)	(1.1952)	(1.5726)	(1.2710)
Head of Household (Mother)	-0.5622	-1.5756	1.1479	-0.0002	1.5090	0.7467	2.8369*	2.0488
	(1.7848)	(1.5376)	(2.0942)	(1.7981)	(1.8405)	(1.5828)	(1.7194)	(1.3712)
ρ	0.5417***	0.5173***	0.5315***	0.4660***	0.7128***	0.6898***	0.6927***	0.7842***
	(0.1207)	(0.1189)	(0.1128)	(0.1201)	(0.0955)	(0.1035)	(0.1031)	(0.0595)
λ	0.2395	0.1845	0.2179	0.1977	-1.0000	-1.0000	-1.0000	-1.0000*
	(0.2100)	(0.2120)	(0.2018)	(0.1956)	(0.6639)	(0.6665)	(0.6794)	(0.5729)
σ^2	260.8847***	195.4451***	254.9976***	188.5760***	273.6545***	203.5663***	229.1119***	148.3465***
	(7.9819)	(6.3325)	(8.7910)	(6.8363)	(13.0587)	(10.4403)	(11.9045)	(8.0166)
Likelihood value	-6053.9771	-5738.0102	-5119.4940	-4837.7694	-4476.9907	-4240.5597	-3386.0705	-3126.4227
R-squared	0.3030	0.2666	0.3433	0.2895	0.2004	0.1888	0.1501	0.2681
Rbar-squared	0.3005	0.2639	0.3401	0.2860	0.1958	0.1842	0.1438	0.2627
Sample Size	2170	2170	1843	1843	1582	1582	1236	1236

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2b: Summary Results of Dormitory Peer Effects in Model (5)

Explanatory Variable	Grade 1		Grade 2			
	(1) AVGCM_g1	(2) AVG_g1	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g2	(4) AVG_g2
ρ	0.0571	0.0978	**0.6075*** **	**0.5456*** **	**0.6669*** **	**0.6645*** **
	(0.6287)	(0.5238)	**(0.1015)**	**(0.1227)**	**(0.1372)**	**(0.1324)**
λ	-0.1059	-0.0872	**-0.7538** **	**-0.6913* **	-1.0000	**-0.9866* **
	(0.7182)	(0.6141)	**(0.3750)**	**(0.3848)**	(0.6246)	**(0.5995)**
Likelihood value	-907.5043	-871.3266	-1800.9496	-1702.1273	-995.7145	-933.9431
R-squared	0.0258	0.0357	0.5270	0.4711	0.2808	0.2867
Rbar-squared	0.0013	0.0114	0.5203	0.4637	0.2630	0.2691
Sample Size	327	327	646	646	374	374

Grade 3

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g2	(4) AVG_g2	(5) AVGCM_g3	(6) AVG_g3
ρ	**0.6592*** **	**0.6609*** **	**0.4933*** **	**0.6409*** **	0.3735	0.4221
	(0.0650)	**(0.0699)**	**(0.1277)**	**(0.0857)**	(0.3022)	(0.2633)
λ	**-1.0000*** **	**-1.0000*** **	-0.3788	**-0.8995*** **	-0.4937	-0.5679
	(0.2709)	**(0.2929)**	(0.3084)	**(0.3422)**	(0.6143)	(0.5936)
Likelihood value	-1619.2806	-1551.1535	-1649.3221	-1545.8951	-1427.3029	-1308.1890
R-squared	0.4556	0.4265	0.3185	0.3883	0.0756	0.0908
Rbar-squared	0.4470	0.4175	0.3079	0.3788	0.0611	0.0766
Sample Size	579	579	587	587	585	585

Grade 3 (Graduates)

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g2	(4) AVG_g2	(5) AVGCM_g3	(6) AVG_g3
ρ	0.2954	**0.4131** **	-0.2778	**-0.6938* **	**0.3920** **	**0.4652** **
	(0.2080)	**(0.1901)**	(0.3644)	**(0.3775)**	**(0.1999)**	**(0.1870)**
λ	-0.2365	-0.4034	**0.3980** **	**0.5573*** **	-0.2356	-0.3856
	(0.3371)	(0.3926)	**(0.1995)**	**(0.1299)**	(0.3711)	(0.4230)
Likelihood value	-1673.1452	-1552.3010	-1783.8283	-1705.2279	-1863.9789	-1716.6039
R-squared	0.2011	0.1949	0.1550	0.2116	0.1927	0.1943
Rbar-squared	0.1893	0.1829	0.1426	0.2000	0.1814	0.1830
Sample Size	618	618	621	621	651	651

Whole Sample

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g1	(4) AVG_g1	(5) AVGCM_g2	(6) AVG_g2	(7) AVGCM_g3	(8) AVG_g3
ρ	**0.6331*** **	**0.5974*** **	**0.6307*** **	**0.5108*** **	**0.6272*** **	**0.6772*** **	**0.6485*** **	**0.7203*** **
	(0.0547)	**(0.0641)**	**(0.0615)**	**(0.0924)**	**(0.0690)**	**(0.0539)**	**(0.0686)**	**(0.0470)**
λ	**-0.6759*** **	**-0.6098*** **	**-0.7090*** **	**-0.4149* **	**-0.7538*** **	**-1.0000*** **	**-0.8650*** **	**-1.0000*** **
	(0.1956)	**(0.2056)**	**(0.2236)**	**(0.2301)**	**(0.2512)**	**(0.2394)**	**(0.2752)**	**(0.2459)**
Likelihood value	-6111.3865	-5776.2045	-5162.1831	-4864.4266	-4456.3515	-4215.5275	-3374.9709	-3125.0717
R-squared	0.3740	0.3363	0.4161	0.3239	0.3135	0.3598	0.2956	0.4191
Rbar-squared	0.3717	0.3339	0.4133	0.3206	0.3096	0.3561	0.2904	0.4149
Sample Size	2170	2170	1843	1843	1579	1579	1236	1236

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3b: Results of Dormitory Peer Effects in Model (5)

Explanatory Variable	(1) AVGCM_g1	(2) AVG_g1	(3) AVGCM_g1	(4) AVG_g1	(5) AVGCM_g2	(6) AVG_g2	(7) AVGCM_g3	(8) AVG_g3
Age	-0.2258	**-0.8643*** **	0.1338	**-0.6199** **	**-0.5001* **	**-0.6706*** **	**-1.4732*** **	**-1.9076*** **
	(0.2266)	**(0.2283)**	(0.2790)	**(0.2837)**	**(0.3023)**	**(0.2435)**	**(0.3632)**	**(0.3363)**
Gender	**-2.0002*** **	**-1.8266*** **	**-2.2427*** **	**-2.4821*** **	**-2.4974*** **	**-1.5471*** **	**-1.1892** **	**-0.5671* **
(Male)	**(0.5027)**	**(0.4634)**	**(0.5515)**	**(0.6352)**	**(0.6348)**	**(0.4127)**	**(0.4918)**	**(0.3327)**
Han	1.0452	0.9555	2.8065	2.8821	**7.6975*** **	**6.4157*** **	**4.9863* **	2.1959
	(2.3996)	(2.0961)	(2.6617)	(2.4425)	**(2.8976)**	**(2.3333)**	**(2.9085)**	(2.2367)
Hui	-3.6265	-2.3541	-2.4219	-1.0671	**5.4915* **	**4.9729** **	4.3788	1.6647
	(2.6393)	(2.3105)	(2.8930)	(2.6678)	**(3.1491)**	**(2.5234)**	(3.2550)	(2.5119)
Kazakh	**-5.8656** **	**-4.2864** **	**-5.0057* **	**-4.3649* **	**5.1344* **	**4.7267** **	3.7524	1.9538
	(2.4723)	**(2.1538)**	**(2.7196)**	**(2.5024)**	**(2.8595)**	**(2.3058)**	(2.9218)	(2.2683)
Family Financial Difficulties	**3.3174** **	1.2404	1.9082	-0.6329	0.8221	0.1233	-1.2370	-1.2959
(Yes)	**(1.3663)**	(1.1877)	(1.4753)	(1.3566)	(1.4968)	(1.1910)	(1.3779)	(1.0687)
Parents Occupation (Farmer)	------	------	**-3.6523** **	-1.2645	-1.1707	0.4739	-0.9471	0.5121
			(1.7869)	(1.6202)	(1.8224)	(1.4559)	(1.5950)	(1.2347)
In City	**-1.8378* **	**-1.9563** **	**-2.3346** **	**-2.9018*** **	**-5.1364*** **	**-3.6301*** **	**-3.3130*** **	**-2.7053*** **
	(0.9645)	**(0.8582)**	**(1.0296)**	**(0.9735)**	**(1.2182)**	**(0.9597)**	**(1.1394)**	**(0.8830)**
Rural	-0.8125	-0.8284	-0.8894	-1.2458	-1.8886	-1.5506	**-4.0186*** **	**-3.6579*** **
	(0.9907)	(0.8690)	(1.0710)	(0.9988)	(1.2096)	(0.9496)	**(1.4575)**	**(1.1255)**
Head of Household (Mother)	-0.8114	-1.3876	-0.5652	-0.7808	1.3438	0.6534	**2.6554* **	**1.9902* **
	(1.4431)	(1.2806)	(1.6669)	(1.5951)	(1.7107)	(1.3260)	**(1.5297)**	**(1.1582)**
ρ	**0.6331*** **	**0.5974*** **	**0.6307*** **	**0.5108*** **	**0.6272*** **	**0.6772*** **	**0.6485*** **	**0.7203*** **
	(0.0547)	**(0.0641)**	**(0.0615)**	**(0.0924)**	**(0.0690)**	**(0.0539)**	**(0.0686)**	**(0.0470)**
λ	**-0.6759*** **	**-0.6098*** **	**-0.7090*** **	**-0.4149* **	**-0.7538*** **	**-1.0000*** **	**-0.8650*** **	**-1.0000*** **
	(0.1956)	**(0.2056)**	**(0.2236)**	**(0.2301)**	**(0.2512)**	**(0.2394)**	**(0.2752)**	**(0.2459)**
σ^2	**234.3236*** **	**176.8682*** **	**226.7182*** **	**179.4414*** **	**234.8918*** **	**160.5165*** **	**189.8928*** **	**117.7287*** **
	(15.5537)	**(11.8268)**	**(17.1029)**	**(11.6360)**	**(20.0313)**	**(14.9284)**	**(18.6929)**	**(11.6898)**
Likelihood value	-6111.3865	-5776.2045	-5162.1831	-4864.4266	-4456.3515	-4215.5275	-3374.9709	-3125.0717
R-squared	0.3740	0.3363	0.4161	0.3239	0.3135	0.3598	0.2956	0.4191
Rbar-squared	0.3717	0.3339	0.4133	0.3206	0.3096	0.3561	0.2904	0.4149
Sample Size	2170	2170	1843	1843	1579	1579	1236	1236

Standard errors are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4a: Summary Results of Classroom Peer Effects in Model (6)

Explanatory Variable	Grade 1		Grade 2						
	(1) Chinese_g1	(2) Math_g1	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g1_g2	(6) Math_g1_g2	(7) AVG_g1_g2
γ	-0.0910	0.0165	**0.1075****	**0.1026*****	**0.0957****	0.0054	0.0016	0.0068	0.0310
	(0.1475)	(0.0780)	**(0.0438)**	**(0.0346)**	**(0.0470)**	(0.0413)	(0.0417)	(0.0504)	(0.0474)
ρ	**-2.3376***	-0.0561	**-0.1340***	**-0.2528****	0.1183	0.0929	-0.0713	-0.1009	-0.1082
	(1.3828)	(0.4677)	**(0.0695)**	**(0.1177)**	(0.1392)	(0.1829)	(0.1014)	(0.1003)	(0.1114)
λ	0.0001	0.0001	**0.4980*****	**0.6550*****	**0.3020***	**0.3860*****	**0.3820*****	**0.3820*****	**0.3580****
	(0.2192)	(0.2151)	**(0.0793)**	**(0.0553)**	**(0.1549)**	**(0.1351)**	**(0.1373)**	**(0.1328)**	**(0.1399)**
Sample Size	327	327	646	646	384	384	384	384	378
Grade 3									
Explanatory Variable	(1) Chinese	(2) Math	(3) Chinese_g1_g2	(4) Math_g1_g2	(5) Chinese_g1_g3	(6) Math_g1_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	-0.0068	0.0001	**0.8546*****	**0.8238*****	-0.0031	0.0158	**0.7915*****	-0.0010	0.0151
	(0.0234)	(0.0265)	**(0.0285)**	**(0.0210)**	(0.0231)	(0.0351)	**(0.0227)**	(0.0274)	(0.0283)
ρ	0.0265	-0.0793	**-0.3388*****	-0.1066	0.0430	0.0401	-0.1094	0.0383	0.0357
	(0.1047)	(0.1202)	**(0.1153)**	(0.1345)	(0.0705)	(0.0899)	(0.1287)	(0.0741)	(0.0752)
λ	**0.5020*****	**0.5320*****	**0.5089*****	**0.2980****	**0.2290***	0.0001	**0.2570****	0.0001	0.0000
	(0.0839)	**(0.0748)**	**(0.0780)**	**(0.1219)**	**(0.1348)**	(0.1732)	**(0.1275)**	(0.1732)	(0.1735)
Sample Size	585	585	574	574	572	572	574	572	585
Grade 3 (Graduates)									
Explanatory Variable	(1) Chinese	(2) Math	(3) Chinese_g1_g2	(4) Math_g1_g2	(5) Chinese_g1_g3	(6) Math_g1_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	-0.0448	-0.0299	**0.7799*****	**0.7612*****	**0.6135*****	**0.7640*****	**0.8436*****	**0.6942*****	**0.6885*****
	(0.0316)	(0.0535)	**(0.0387)**	**(0.0323)**	**(0.0384)**	**(0.0362)**	**(0.0380)**	**(0.0366)**	**(0.0231)**
ρ	0.0593	0.1031	0.2031	**-0.4650*****	**0.4690****	**-0.4382*****	-0.2946	-0.1522	-0.1424
	(0.0633)	(0.1281)	(0.2430)	**(0.1253)**	**(0.2379)**	**(0.1347)**	(0.2165)	(0.2127)	(0.1956)
λ	**0.2590****	0.0780	0.0500	0.1830	0.0001	0.1800	0.0001	0.0190	0.1510
	(0.1206)	(0.1325)	(0.1540)	(0.1334)	(0.1513)	(0.1314)	(0.1631)	(0.1556)	(0.1346)
Sample Size	654	654	609	609	614	614	609	615	618
Whole Sample									
Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	0.0160	**0.0519****	-0.0048	0.0133	-0.0284	-0.0322	**0.6126*****	**0.2962*****	**0.4077*****
	(0.0193)	**(0.0224)**	(0.0220)	(0.0253)	(0.0189)	(0.0309)	**(0.0220)**	**(0.0253)**	**(0.0208)**
ρ	-0.0246	0.0178	0.0456	-0.0003	**0.0815****	0.0534	**-0.4181*****	**-0.2559*****	**-0.2621*****
	(0.0340)	(0.0594)	(0.0476)	(0.0714)	**(0.0416)**	(0.0777)	**(0.0579)**	**(0.0760)**	**(0.0697)**
λ	**0.5960*****	**0.6620*****	**0.4440*****	**0.5040*****	**0.3870*****	**0.4620*****	**0.4720*****	**0.6670*****	**0.6870*****
	(0.0357)	**(0.0294)**	**(0.0576)**	**(0.0491)**	**(0.0719)**	**(0.0629)**	**(0.0551)**	**(0.0396)**	**(0.0376)**
Sample Size	2170	2170	1592	1592	1235	1235	1561	1187	1203

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5a: Results of Classroom Peer Effects in Model (6)

Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	0.0160	0.0519**	-0.0048	0.0133	-0.0284	-0.0322	0.6126***	0.2962***	0.4077***
	(0.0193)	(0.0224)	(0.0220)	(0.0253)	(0.0189)	(0.0309)	(0.0220)	(0.0253)	(0.0208)
ρ	-0.0246	0.0178	0.0456	-0.0003	0.0815**	0.0534	-0.4181***	-0.2559***	-0.2621***
	(0.0340)	(0.0594)	(0.0476)	(0.0714)	(0.0416)	(0.0777)	(0.0579)	(0.0760)	(0.0697)
Age	-0.2405	-1.0089**	-0.5831	-0.9648*	-0.9331***	-1.9040***	-0.2998	-1.1604***	-0.8415***
	(0.2816)	(0.3985)	(0.3875)	(0.5122)	(0.3618)	(0.6012)	(0.2919)	(0.3387)	(0.3127)
Gender (Male)	-6.6727***	-2.7489***	-9.0502***	-4.0181***	-4.9770***	-2.2615*	-1.2696**	-0.5129	0.4919
	(0.6243)	(0.8996)	(0.7850)	(1.0476)	(0.7227)	(1.2015)	(0.6100)	(0.6990)	(0.6373)
Han	0.1127	-0.0508	4.6564	9.9938**	2.4433	6.3121	5.3231**	1.6355	-1.0428
	(2.3381)	(3.3733)	(3.0155)	(4.0530)	(2.7622)	(4.6126)	(2.3353)	(2.7971)	(2.4809)
Hui	-2.2109	-7.3541*	3.6713	6.0890	3.2232	3.4089	5.7444**	1.5542	-1.3324
	(2.6155)	(3.7737)	(3.3716)	(4.5311)	(3.1138)	(5.1978)	(2.5952)	(3.0964)	(2.7750)
Kazakh	-3.4812	-8.9281***	6.1399**	1.8168	1.5522	2.6979	5.2112**	1.5096	-0.7816
	(2.3585)	(3.4051)	(3.0311)	(4.0634)	(2.7757)	(4.6186)	(2.3557)	(2.7787)	(2.4777)
Family Financial	-0.0490	3.8193*	-0.3308	2.9660	-1.9980	1.2096	0.8847	0.0638	0.0369
Difficulties (Yes)	(1.3748)	(1.9780)	(1.6367)	(2.1642)	(1.3719)	(2.2616)	(1.2330)	(1.2890)	(1.1746)
Parents Occupation	------	------	-0.2768	-1.3177	-0.7392	-1.9157	1.2436	0.0359	-0.1783
(Farmer)			(1.9503)	(2.6020)	(1.5624)	(2.5983)	(1.4747)	(1.4976)	(1.3776)
In City	-2.6669***	-2.4999*	-5.0770***	-8.0566***	-3.5391***	-4.8928***	-2.8814***	-2.9782***	-1.6941*
	(0.9723)	(1.3932)	(1.2206)	(1.6354)	(1.0802)	(1.7971)	(0.9537)	(1.0745)	(0.9658)
Rural	-1.3542	-2.3173	-3.2841**	-2.0074	-3.3814**	-5.9791**	-0.0591	-3.7029**	-3.3307**
	(1.0194)	(1.4598)	(1.4094)	(1.9005)	(1.7109)	(2.8357)	(1.1123)	(1.7335)	(1.5109)
Head of Household	-1.4257	-0.1658	1.1471	2.4640	0.9117	6.1169**	0.2703	2.2866	2.2474
(Mother)	(1.5641)	(2.2524)	(2.0212)	(2.6931)	(1.6422)	(2.7282)	(1.5283)	(1.5287)	(1.4075)
λ	0.5960***	0.6620***	0.4440***	0.5040***	0.3870***	0.4620***	0.4720***	0.6670***	0.6870***
	(0.0357)	(0.0294)	(0.0576)	(0.0491)	(0.0719)	(0.0629)	(0.0551)	(0.0396)	(0.0376)
σ^2	209.8740***	435.1111***	243.9868***	434.5894***	160.1968***	443.0804***	139.5241***	138.6084***	115.9678***
	(9.6022)	(13.7857)	(11.4429)	(13.5863)	(11.4569)	(14.6994)	(7.3992)	(8.2090)	(7.0266)
Sample Size	2170	2170	1592	1592	1235	1235	1561	1187	1203

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4b: Summary Results of Dormitory Peer Effects in Model (6)

Explanatory Variable	Grade 1		Grade 2						
	(1) Chinese_g1	(2) Math_g1	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g1_g2	(6) Math_g1_g2	(7) AVG_g1_g2
γ	0.0157	0.0153	**0.0995****	**0.0889****	**0.0997****	0.0196	-0.0206	0.0051	0.0067
	(0.1479)	(0.0792)	**(0.0425)**	**(0.0359)**	**(0.0472)**	(0.0404)	(0.0410)	(0.0470)	(0.0450)
ρ	-0.2925	0.0202	-0.0952	**-0.1395***	0.0268	-0.0484	0.0198	-0.0905	-0.0119
	(0.3005)	(0.1911)	(0.0614)	**(0.0760)**	(0.0887)	(0.0908)	(0.0772)	(0.0787)	(0.0830)
λ	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****
	(0.0610)	**(0.0607)**	**(0.0449)**	**(0.0441)**	**(0.0602)**	**(0.0598)**	**(0.0602)**	**(0.0596)**	**(0.0599)**
Sample Size	327	327	646	646	381	381	381	381	375
Grade 3									
Explanatory Variable	(1) Chinese	(2) Math	(3) Chinese_g1_g2	(4) Math_g1_g2	(5) Chinese_g1_g3	(6) Math_g1_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	-0.0037	-0.0056	**0.8616*****	**0.8232*****	0.0014	0.0121	**0.7914*****	0.0047	0.0200
	(0.0233)	(0.0265)	**(0.0289)**	**(0.0211)**	(0.0233)	(0.0351)	**(0.0227)**	(0.0274)	(0.0283)
ρ	0.0051	0.0375	**-0.2952*****	**-0.2383*****	-0.0002	0.0229	**-0.2604*****	-0.0009	-0.0051
	(0.0536)	(0.0618)	**(0.0664)**	**(0.0568)**	(0.0416)	(0.0606)	**(0.0561)**	(0.0476)	(0.0500)
λ	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****
	(0.0462)	**(0.0451)**	**(0.0454)**	**(0.0466)**	**(0.0467)**	**(0.0468)**	**(0.0467)**	**(0.0468)**	**(0.0468)**
Sample Size	585	585	574	574	572	572	574	572	585
Grade 3 (Graduates)									
Explanatory Variable	(1) Chinese	(2) Math	(3) Chinese_g1_g2	(4) Math_g1_g2	(5) Chinese_g1_g3	(6) Math_g1_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	-0.0276	-0.0204	**0.7608*****	**0.7346*****	**0.5957*****	**0.7279*****	**0.8320*****	**0.6672*****	**0.6719*****
	(0.0301)	(0.0503)	**(0.0388)**	**(0.0320)**	**(0.0387)**	**(0.0357)**	**(0.0382)**	**(0.0366)**	**(0.0232)**
ρ	0.0078	0.0128	**-0.1529***	**-0.2524*****	-0.0361	**-0.2146*****	**-0.2752*****	**-0.1439***	**-0.1844*****
	(0.0509)	(0.0910)	**(0.0928)**	**(0.0702)**	(0.0904)	**(0.0766)**	**(0.0856)**	**(0.0810)**	**(0.0570)**
λ	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****
	(0.0443)	**(0.0435)**	**(0.0444)**	**(0.0443)**	**(0.0440)**	**(0.0440)**	**(0.0444)**	**(0.0442)**	**(0.0441)**
Sample Size	654	654	609	609	614	614	609	615	618
Whole Sample									
Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	0.0186	**0.0589*****	0.0038	0.0184	-0.0195	-0.0388	**0.5834*****	**0.2789*****	**0.3938*****
	(0.0187)	**(0.0226)**	(0.0212)	(0.0245)	(0.0180)	(0.0295)	**(0.0216)**	**(0.0256)**	**(0.0214)**
ρ	-0.0227	0.0314	0.0189	-0.0168	0.0436	0.0743	**-0.2454*****	**-0.1081****	**-0.0965****
	(0.0288)	(0.0437)	(0.0367)	(0.0485)	(0.0316)	(0.0561)	**(0.0407)**	**(0.0468)**	**(0.0420)**
λ	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****	**0.3820*****
	(0.0240)	**(0.0236)**	**(0.0282)**	**(0.0277)**	**(0.0321)**	**(0.0319)**	**(0.0283)**	**(0.0317)**	**(0.0318)**
Sample Size	2170	2170	1589	1589	1235	1235	1558	1187	1203

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5b: Results of Dormitory Peer Effects in Model (6)

Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3	(7) AVG_g1_g2	(8) AVG_g1_g3	(9) AVG_g2_g3
γ	0.0186	**0.0589*** **	0.0038	0.0184	-0.0195	-0.0388	**0.5834*** **	**0.2789*** **	**0.3938*** **
	(0.0187)	**(0.0226)**	(0.0212)	(0.0245)	(0.0180)	(0.0295)	**(0.0216)**	**(0.0256)**	**(0.0214)**
ρ	-0.0227	0.0314	0.0189	-0.0168	0.0436	0.0743	**-0.2454*** **	**-0.1081** **	**-0.0965** **
	(0.0288)	(0.0437)	(0.0367)	(0.0485)	(0.0316)	(0.0561)	**(0.0407)**	**(0.0468)**	**(0.0420)**
Age	-0.1116	**-1.0076** **	**-0.6332***	**-0.9378***	**-0.9967*** **	**-2.0808*** **	-0.3271	**-2.0824*** **	**-1.7134*** **
	(0.2838)	**(0.4104)**	**(0.3828)**	**(0.5023)**	**(0.3542)**	**(0.5871)**	(0.2900)	**(0.3418)**	**(0.3161)**
Gender (Male)	**-4.3590*** **	**-1.9027** **	**-5.8192*** **	**-2.6449** **	**-3.2965*** **	-1.4926	**-1.0871***	-0.3782	0.6462
	(0.6470)	**(0.9314)**	**(0.8193)**	**(1.0418)**	**(0.7310)**	(1.1870)	**(0.6249)**	(0.7341)	(0.6804)
Han	0.5988	3.3032	4.8176	**11.4096*** **	1.8901	4.8721	**4.7509** **	-0.3250	-2.4607
	(2.3646)	(3.4852)	(2.9901)	**(3.9925)**	(2.7116)	(4.5366)	**(2.3146)**	(2.7999)	(2.5091)
Hui	-1.9367	-4.4603	4.2684	**8.0939***	2.6868	1.6927	**5.5029** **	-0.4347	-2.8582
	(2.6461)	(3.9005)	(3.3439)	**(4.4695)**	(3.0579)	(5.1193)	**(2.5742)**	(3.1060)	(2.8096)
Kazakh	**-4.5673***	**-12.0889*** **	**6.5295** **	1.3654	0.9210	0.9446	**6.0680*** **	0.2830	-1.8483
	(2.3843)	**(3.5096)**	**(3.0074)**	(4.0012)	(2.7272)	(4.5477)	**(2.3315)**	(2.8035)	(2.5189)
Family Financial	-0.0175	**4.6170** **	-1.0256	2.0842	**-2.6943** **	0.3710	0.5564	-1.1170	-1.1517
Difficulties (Yes)	(1.3922)	**(2.0443)**	(1.6143)	(2.1371)	**(1.3415)**	(2.2282)	(1.2255)	(1.2989)	(1.1900)
Parents Occupation	------	------	-0.6700	-2.4531	-0.9517	-2.8375	0.9130	0.2657	-0.0643
(Farmer)			(1.9346)	(2.5710)	(1.5350)	(2.5621)	(1.4664)	(1.5110)	(1.4009)
In City	**-3.0366*** **	**-2.7617***	**-5.2050*** **	**-8.6843*** **	**-3.3987*** **	**-4.6191*** **	**-2.9443*** **	**-3.1767*** **	**-1.8777***
	(0.9831)	**(1.4398)**	**(1.2117)**	**(1.6139)**	**(1.0617)**	**(1.7711)**	**(0.9471)**	**(1.0856)**	**(0.9812)**
Rural	-1.1298	-2.1472	**-3.3241** **	-1.2484	**-3.4426** **	**-5.9303** **	-0.2327	**-5.4371*** **	**-5.1365*** **
	(1.0299)	(1.5088)	**(1.3970)**	(1.8604)	**(1.6771)**	**(2.7932)**	(1.0914)	**(1.7150)**	**(1.5138)**
Head of Household	-1.5532	-0.1879	1.4052	2.6851	0.6321	**6.2320** **	0.7250	**2.6090***	**2.4140***
(Mother)	(1.5838)	(2.3278)	(2.0041)	(2.6636)	(1.6129)	**(2.6917)**	(1.5190)	**(1.5440)**	**(1.4300)**
λ	**0.3820*** **	**0.3820*** **	**0.3820*** **	**0.3820*** **	**0.3820*** **	**0.3820*** **	**0.3820*** **	**0.3820*** **	**0.3820*** **
	(0.0240)	**(0.0236)**	**(0.0282)**	**(0.0277)**	**(0.0321)**	**(0.0319)**	**(0.0283)**	**(0.0317)**	**(0.0318)**
σ^2	**215.1569*** **	**464.8931*** **	**240.1830*** **	**424.1702*** **	**154.7372*** **	**430.5111*** **	**137.9145*** **	**141.4427*** **	**119.7492*** **
	(9.5277)	**(13.3179)**	**(11.6910)**	**(14.0204)**	**(11.6131)**	**(15.2163)**	**(7.5135)**	**(8.2719)**	**(7.0629)**
Sample Size	2170	2170	1589	1589	1235	1235	1558	1187	1203

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 1a: Summary Statistics of Grade 1 and Grade 2

Variable	Grade 1				Grade 2			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Chinese	68.8838	5.0941	47	75	53.9895	19.3062	4	98
Mathematics	59.0031	15.4552	23	87	53.8872	23.2235	0	96
AvgCM0	63.9434	9.2665	42	80.5	53.9384	16.2987	6.5	91
AvgC	62.7994	13.2874	15.4167	89.5833	64.5510	14.8616	4.1667	89.7219
AvgM	57.9683	21.8320	9.1667	99.5833	46.0893	23.3031	2.5000	98.8885
AvgCM	60.3839	16.2576	17.7083	92.5	55.4908	17.1720	5.1389	94.3052
AVG	64.1113	14.6249	19.2917	90.8571	58.7241	14.3580	15.1805	92.2112
Age	12.8593	0.7862	7	16	13.6246	0.7360	10	19
Male	0.5688	0.4960	0	1	0.5489	0.4980	0	1
(Female)	0.4312	0.4960	0	1	0.4511	0.4980	0	1
Han	0.5749	0.4951	0	1	0.4977	0.5004	0	1
Hui	0.0795	0.2709	0	1	0.0586	0.2351	0	1
Kazakh	0.3211	0.4676	0	1	0.4226	0.4943	0	1
(Other Minorities)	0.0245	0.1547	0	1	0.0211	0.1437	0	1
Financial Difficulties	0.0642	0.2455	0	1	0.0123	0.1104	0	1
(No Financial Difficulties)	0.9358	0.2455	0	1	0.9877	0.1104	0	1
Parents Occupation: Farmer	---	---	---	---	0.9940	0.0774	0	1
(Other Occupations: Officials, Teacher, Doctor)	---	---	---	---	0.0060	0.0774	0	1
In City	0.2202	0.4150	0	1	0.0451	0.2077	0	1
Rural	0.6177	0.4867	0	1	0.7789	0.4153	0	1
(Other Cities)	0.1621	0.3691	0	1	0.1759	0.3811	0	1
Head of Household: Mother	0.0795	0.2709	0	1	0.0015	0.0389	0	1
(Head of Household: Father or Grandparents)	0.9205	0.2709	0	1	0.9985	0.0389	0	1

Note: Grade 2 includes students who have incomplete information but valid grades.

Table 1b: Summary Statistics of Grade 3 and Grade 3 (Graduates)

Variable	Grade 3				Grade 3 (Graduates)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Chinese	63.8345	17.9040	2	98	56.1918	23.3334	6	96
Mathematics	52.0186	23.4985	3	100	57.5738	18.3056	2	96
AvgCM0	57.9265	18.7744	2.5	96	56.8828	16.3738	4	94.5
AvgC	62.7730	12.8280	15.1852	85.1853	63.9641	14.6140	10.9697	90.6667
AvgM	44.3981	20.1232	4.7917	93.4816	45.7551	21.8586	5.8636	94.0606
AvgCM	54.7106	13.7283	11.0417	88.5117	54.7263	16.6517	8.6435	91.0949
AVG	58.8707	11.4711	17.3716	87.3808	53.4530	13.5306	14.3168	80.9964
Age	14.6660	0.7890	12	18	15.6683	0.9833	12	29
Male	0.5118	0.5003	0	1	0.5175	0.5001	0	1
(Female)	0.4882	0.5003	0	1	0.4825	0.5001	0	1
Han	0.5101	0.5003	0	1	0.5601	0.4968	0	1
Hui	0.0541	0.2263	0	1	0.0609	0.2393	0	1
Kazakh	0.4189	0.4938	0	1	0.3607	0.4806	0	1
(Other Minorities)	0.0169	0.1290	0	1	0.0183	0.1340	0	1
Financial Difficulties	0.0338	0.1808	0	1	0.1191	0.3241	0	1
(No Financial Difficulties)	0.9662	0.1808	0	1	0.8809	0.3241	0	1
Parents Occupation: Farmer	0.9679	0.1764	0	1	0.9209	0.2702	0	1
(Other Occupations: Officials, Teacher, Doctor)	0.0321	0.1764	0	1	0.0791	0.2702	0	1
In City	0.7939	0.4048	0	1	0.7915	0.4066	0	1
Rural	0.0709	0.2570	0	1	0.0731	0.2604	0	1
(Other Cities)	0.1351	0.3422	0	1	0.1355	0.3425	0	1
Head of Household: Mother	0.0422	0.2013	0	1	0.0611	0.2396	0	1
(Head of Household: Father or Grandparents)	0.9578	0.2013	0	1	0.9389	0.2396	0	1

Note: Grade 3 (Graduates) includes students who have incomplete information but valid grades.

Table 4c: Summary Results of Classroom Peer Effects in Model (6)

Grade 3						
Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3
γ	0.0053	0.0175	-0.0039	0.0250	-0.0162	-0.0244
	(0.0328)	(0.0376)	(0.0352)	(0.0359)	(0.0178)	(0.0313)
ρ	0.0234	-0.1361	0.1012	-0.1329	-0.1048	-0.0623
	(0.1475)	(0.1729)	(0.1591)	(0.1645)	(0.0818)	(0.1422)
λ	**0.4060***	**0.5190***	**0.5450***	**0.5740***	0.1809	0.0001
	(0.0950)	**(0.0764)**	**(0.0737)**	**(0.0671)**	(0.1428)	(0.1719)
Sample Size	579	579	587	587	585	585

Grade 3 (Graduates)						
Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3
γ	-0.0194	0.0022	-0.0215	-0.0020	-0.0346	-0.0331
	(0.0274)	(0.0533)	(0.0342)	(0.0584)	(0.0301)	(0.0615)
ρ	0.0552	0.1924	-0.0056	0.0496	0.0355	-0.0050
	(0.0542)	(0.1311)	(0.0669)	(0.1388)	(0.0604)	(0.1431)
λ	0.2010	**0.2939***	0.1970	0.0000	**0.2840**	0.1790
	(0.1305)	**(0.1044)**	(0.1302)	(0.1502)	**(0.1131)**	(0.1238)
Sample Size	618	618	621	621	650	650

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4d: Summary Results of Dormitory Peer Effects in Model (6)

			Grade 3			
Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3
γ	0.0078	0.0158	0.0087	0.0223	-0.0210	-0.0389
	(0.0326)	(0.0379)	(0.0354)	(0.0362)	(0.0179)	(0.0314)
ρ	0.0082	-0.0297	0.0003	-0.0139	0.0088	**0.1326***
	(0.0744)	(0.0871)	(0.0815)	(0.0845)	(0.0411)	**(0.0732)**
λ	**0.3820***	**0.3820***	**0.3820***	**0.3820***	**0.3820***	**0.3820***
	(0.0455)	**(0.0449)**	**(0.0456)**	**(0.0447)**	**(0.0468)**	**(0.0468)**
Sample Size	579	579	587	587	585	585
			Grade 3 (Graduates)			
Explanatory Variable	(1) Chinese_g1	(2) Math_g1	(3) Chinese_g2	(4) Math_g2	(5) Chinese_g3	(6) Math_g3
γ	-0.0110	0.0131	-0.0262	-0.0003	-0.0292	-0.0203
	(0.0261)	(0.0510)	(0.0325)	(0.0549)	(0.0285)	(0.0576)
ρ	0.0213	0.1011	0.0203	0.0140	0.0224	-0.0337
	(0.0441)	(0.0927)	(0.0541)	(0.0989)	(0.0483)	(0.1042)
λ	**0.3820***	**0.3820***	**0.3820***	**0.3820***	**0.3820***	**0.3820***
	(0.0443)	**(0.0432)**	**(0.0441)**	**(0.0439)**	**(0.0440)**	**(0.0436)**
Sample Size	618	618	621	621	650	650

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

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ABSTRACT

ESSAYS ON APPLICATIONS OF SPATIAL ECONOMETRIC MODEL

by

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Degree: Doctor of Philosophy

Since the infamous riot of 1967, high crime rates and negative media reports have labeled the city of Detroit as one of the most dangerous cities in the U.S. For a better understanding of crime situation in Detroit, we discuss the spatial interactions of crime rates among block groups as well as the impact of socioeconomic variables on crime by using spatial autoregressive models, crime data, and socioeconomic data. In particular, we introduced a geographical methodology: inverse distance weighting (IDW), which is mainly used to estimate distance based weighting from a scattered set of points. This paper is an essential and policy-relevant topic that has seldom been studied in the past. The study not only enhances our understanding of spatial interactions in regional criminal activities but also provides implications for policymaking, especially for re-allocation of police resource in a certain patrol area based on the fact of spatial interactions of different types of crime. Strong spatial interactions are found in this paper except for weapons offenses. Considerable significant parameters of the socioeconomic variables on crime are discussed as well.

The evidence of the existence of peer effects is scarce for endogeneity issues like selection bias. This study analyzes peer effects in student academic performance of a junior high school in Xinjiang Province, China where students were randomly selected to each classroom and dormitory. Based on unique data from a remote area of China, we find that both positive and negative peer effects exist and are also significant in both classroom and dormitory analyses, which provide new insight and implications for educational policy making. According to two comparable SAR models, this paper provides relatively rational and considerable empirical results and shows more accurate interdependence results. In particular, consistent and unique dormitory peer effect coefficients are presented in our model. It also empirically confirms and supports the theoretical work of previous studies in SAR modeling. Limited but considerable exogenous variables are discussed in this paper as well.

AUTOBIOGRAPHICAL STATEMENT

My name is Jihu Zhang, and I was born in China. Our family made up of my mother and father. When I was in elementary school and high school, I was good at math and was always curious about the truth behind those numbers. As time goes by, two years after I entered college, I found econometrics was what I really want to focus on in my future career. In 2011, I came to the U.S. as an international student. Thanks to the department of economics at Wayne State University, I got opportunities to continue my graduate studies in economics and teach undergraduate and graduate courses as an independent instructor as well.

In the economics department at Wayne State University, I was trained to have an ability to design and to carry out independent research not only in economics, but also in a wide variety of applied fields. Through years of graduate studies, I start to know how to be a scholar and how to do research in applied econometrics progressively. The empirical study is not as easy as what we think and what we see. When the time you really dig into it, you will find another world, a really amazing world.

In addition, I really like to teach and enjoy my teaching experiences. “Teaching, more accurately education, is to use your life to influence lives”. I like this quote and definitely will use it as my faith for my future career in education. My ultimate goal is to be a sophisticated scholar in economics as well as a university professor who would use his life to influence lives.