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Housing Market Conditions and Neighborhood Concentrated Disadvantage: Impacts on Crime Victimization in Knoxville, Tennessee

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Housing Market Conditions and Neighborhood Concentrated Disadvantage: Impacts on Crime Victimization in Knoxville, Tennessee

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ABSTRACT

Neighborhood concentrated disadvantage is a composite social factor that quantifies the quality of neighborhoods in urban areas. Criminal activity and victimization are more prevalent in disadvantaged neighborhoods. However, whether housing market factors (e.g., eviction, foreclosure, and subprime lending) represent an unrecognized dimension of neighborhood concentrated disadvantage remains unknown. I contribute to the neighborhood disadvantage literature by assessing whether three housing market factors (eviction, foreclosure, and subprime lending) are a neglected part of neighborhood concentrated disadvantaged that explains criminal activity and victimization. Furthermore, I investigate whether housing market factors mediate the relationship between concentrated disadvantage and crime. Last, using spatial analysis techniques, I examine the spatial patterns of neighborhood concentrated disadvantage and crime in terms of three housing market factors in the city of Knoxville, Tennessee.

Data are collected from different agencies: the Knoxville Police Department, the Census Bureau’s American Community Survey, Knox County Civil Sessions Court, the Knox County Register of Deeds, and federal filings as part of the FFIEC Home Mortgage Disclosure Act. My results indicate that eviction, foreclosure, and subprime loan have a complex relationship to neighborhood concentrated disadvantage as it predicts crime. Moreover, although housing market factors are not mediating the relationship between concentrated disadvantage and crime, concentrated disadvantage mediates the relationship between eviction and crime.

I find there are spatial differences in crime rates across 86 census tracts in Knoxville. Crime rates in Knoxville are spatially interdependent, suggesting that for crime increase in a census tract, it leads to crimes occurring in neighboring census tracts. Eviction and foreclosure are spatially clustered, while subprime loan shows a spatial dissimilar pattern across the city. High eviction and foreclosure census tracts are surrounded by high crime census tracts, but low subprime loan census tracts are surrounded by high crime census tracts. These neighborhoods are mainly in the downtown Knoxville and its outer areas.

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CHAPTER ONE

INTRODUCTION

Objective of this Dissertation

My dissertation examines concentrated disadvantage and crime at the neighborhood level. Concentrated disadvantage is “the degree to which poverty and other disadvantages are confined to a limited number of neighborhoods within a city” (Krivo et al. 1998:62) and it is “a synergistic composite of social factors that mark the qualitative aspects of neighborhoods as an ecological unit of analysis” (Sampson 2012:100). Concentrated disadvantage matters because people who live in disadvantaged neighborhoods experience a range of poor outcomes related to health (Lantos et al. 2018; Ludwig et al. 2011), education (Levy, Owens, and Sampson 2019; Wodtke, Harding, and Elwert 2011), crime (Kubrin and Weitzer 2003; Papachristos, Brazil, and Cheng 2018), and unemployment (Sampson 2012).

Need for this Study

Most work on concentrated disadvantage uses Sampson’s (2012) concentrated disadvantage index to predict crime and victimization. This work has been of great value to criminologists and sociologists, but it ignores important housing market conditions. Eviction, foreclosure, and subprime loans are significant factors in the concentration of neighborhood poverty (Rugh and Massey 2010; Squires 2009; Desmond 2016). Housing conditions are also significant factors predicting neighborhood crime and victimization (Alm 2018; Alm and Bäckman 2020; Boessen and Chamberlain 2017; Chen and Rafail 2020; Cui and Walsh 2015;

Ellen, Lacoe, and Sharygin 2013; Jones and Pridemore 2012; Katz, Wallace, and Hedberg 2013). Thus, here I examine the role of eviction, foreclosure, and subprime lending on neighborhood disadvantage as it is related to crime victimization. Additionally, because the concentrated disadvantage model has been used to examine crime and victimization in large metropolitan areas such as Chicago, Illinois (Papachristos et al. 2018; Sampson 2012); Columbus, Ohio (Peterson, Krivo, and Harris 2000); Washington, D.C. (Johnson and Kane 2018); and Los Angeles, California (Hipp and Kubrin 2017), I examine these linkages in a mid-sized city, which some scholars have noted are important and overlooked (Gau et al. 2012).

My research is motivated by wondering whether housing markets are a neglected part of concentrated disadvantage regarding crime and victimization. If so, my dissertation explores what characteristic(s) of the housing market is (are) most appropriate to include in the concentrated disadvantage index (or as a separate predictor in addition to the concentrated disadvantage index) to predict crime victimization. I examine the relationship between reported crimes at the neighborhood level and foreclosure, eviction, and predatory lending (and the various ways that these factors can be included in a crime model) in Knoxville, Tennessee. Using spatial analysis techniques, I investigate census tract-level crime victimization when housing market variables (evictions, foreclosures, and subprime lending) are added to the model as mediators, moderators, and as a modification of Sampson's index.

The study area is the city of Knoxville, Tennessee. Knoxville is located in eastern Tennessee and is the state's third largest city after Nashville and Memphis. As of July 1, 2019, the total population of Knoxville city was 187,603 (Census Bureau, Population and Housing Units Estimates, 2010-2019). Knoxville is 72.4% White, 17% Black or African American, 5.3%

Hispanic or Latino, and 1.8% Asian (Census Bureau, QuickFacts 2019). Knoxville is an ideal site for studying mid-sized cities because Tennessee state laws require that all public data (including crime data and eviction data) be made public upon request. What makes the City of Knoxville unusual in the study of crime is that Knoxville is home to the University of Tennessee, Knoxville (UT). As of Fall 2020, there were a total of 30,559 students enrolled at UT, with 24,254 undergraduate and 6,305 graduate and professional students (University of Tennessee, Quick Facts 2020). University students suffer economic stress as they are not socially and economic independent. Most college students are temporarily poor, and the few who have mortgages are typically homeowning on the short run to complete their degree for their tuition. Also, according to the university, about 45 percent of the total college population is male, which could potentially increase crime in and around the campus as young men are more likely to commit criminal acts (Smith 2014).

Research Questions and Hypotheses

My dissertation answers three broad research questions and six sub-questions related to crime, neighborhood disadvantage, and housing conditions (see a summary in Table 3-4 in Chapter 3) by testing relative hypotheses.

Q1. Should housing market conditions be added to a concentrated disadvantage index used to predict crime?

Q1a. Does concentrated disadvantage better predict crime when eviction is added to the concentrated disadvantage index?

H_{1a}: Concentrated disadvantage predicts crime better when eviction is added to the concentrated disadvantage index.

Q1b. Does concentrated disadvantage better predict crime when foreclosure is added to the concentrated disadvantage index?

H_{1b}: Concentrated disadvantage predicts crime better when foreclosure is added to the concentrated disadvantage index.

Q1c. Does concentrated disadvantage better predict crime when subprime lending is added to the concentrated disadvantage index?

H_{1c}: Concentrated disadvantage predicts crime better when subprime lending is added to the concentrated disadvantage index.

Q2. Do housing market characteristics mediate Sampson's model of concentrated disadvantage and crime?

Q2a. Does eviction mediate Sampson's model of concentrated disadvantage as it predicts crime?

H_{2a}: Eviction mediates Sampson's model of concentrated disadvantage and crime.

Q2b. Does foreclosure mediate Sampson's model of concentrated disadvantage as it predicts crime?

H_{2b}: Foreclosure mediates Sampson's model of concentrated disadvantage and crime.

Q2c. Does subprime lending mediate Sampson's model of concentrated disadvantage as it predicts crime?

H_{3c}: Subprime lending mediates Sampson's model of concentrated disadvantage and crime.

Q3. Is there spatial correlation between housing market characteristics and crime across census tracts?

Q3a. If evictions in a neighborhood increase, in which neighborhoods (if any) do crime rates change?

H_{3a}: When evictions in a neighborhood increase, crime in adjacent neighborhoods will increase (i.e., eviction and crime rates are spatially clustered).

Q3b. If foreclosures in a neighborhood increase, in which neighborhoods (if any) do crime rates change?

H_{3b}: When foreclosures in a neighborhood increase, crime in adjacent neighborhoods will increase (i.e., foreclosure and crime rates are spatially clustered).

Q3c. If subprime lending in a neighborhood increase, in which neighborhoods (if any) do crime rates change?

H_{3c}: When subprime lending in a neighborhood increase, crime in adjacent neighborhoods will increase (i.e., foreclosure and crime rates are spatially clustered).

CHAPTER TWO

LITERATURE REVIEW

Neighborhood has constituted a fundamental unit of interest for sociologists and criminologists for many years. The Chicago School conceptualized an ecological model in which the neighborhood was constituted as a context impacting people's lives (Park and Burgess 1921; Shaw and McKay 1942). In the latter part of the twentieth century, the "neighborhood effect" literature has examined the consequences of neighborhood characteristics on different social outcomes. This dissertation lies under the broad topic of "neighborhood effects" as conceived by the Chicago School, as the subject field of this dissertation is the neighborhood.

Neighborhood has been broadly defined as people and institutions occupying a spatially defined area that is conditioned by a set of ecological, cultural, and political forces (Park and Burgess, 1925:147). Although this conceptualization is nearly a century old, there are two aspects of Park and Burgess's definition that is applicable today and relevant to my dissertation. First, neighborhoods are spatial units with differential organizational characteristics; second, neighborhoods are nested within larger communities categorized into various social aspects (Sampson, 2012:54). Beyond this, Suttles identifies neighborhood from a cultural perspective, and argues that "residential groups are defined in contradistinction to one another" (Suttles 1972:8). The conceptualization is also relevant here. The neighborhood, as a concept, is unique to itself, and residents sort themselves into different groups (e.g., race, ethnicity, class) depending on the neighborhood they live in. Thus, neighborhoods are similar, and simultaneously unique. The similarity of neighborhood is that a group of neighborhoods reside within the larger social, political, economic, and cultural contexts. The uniqueness of neighborhood is centered around the idea that each neighborhood is comprised of individuals with complementary organizational networks, institutional features, solidarity, collectivity, and the like.

Despite these clear conceptualizations, neighborhoods are challenging to measure because they are not politically bounded like a county or city is. In essence, your neighborhood is whatever you think it is. This conception does not lend itself to large-scale research projects, however. Research studying neighborhood disadvantage thus uses different types of geographical units of analysis to measure neighborhoods (typically Census Bureau defined). Sampson (2012) measures neighborhood using a neighborhood cluster–a group of two or three census tracts that contain approximately eight thousand people so that they are relatively homogeneous with respect to racial/ethnic mix, socioeconomic status, housing density, and family structure. Hipp and Boessen (2013:289) propose using egohoods to measure neighborhoods. The essence for egohoods is to “move away from the focus on discrete, exclusive, nonoverlapping geographic units that characterizes nearly all of the existing literature on neighborhood effects and processes” because “residents are not part of a single neighborhood but of many neighborhoods” (Hipp and Boessen 2013:290). Other previous studies on neighborhood effect use census tracts (Benson et al. 2004), block groups (Tillyer, Wilcox, and Walter 2020; Wo 2019), and zip codes as units of analyses to measure neighborhoods. In my dissertation, I operationalize neighborhoods as Census Tracts, because there are common proxies for neighborhoods and there are enough within a single city to conduct a statistical analysis with sufficient power, but I acknowledge the limitations of doing so.

The number of neighborhoods (i.e., tracts) with a high poverty rate (30% or higher) doubled from 1980 to 2010 and has remained high in the past 10 years (Benzow & Fikri 2020). According to a recent study, of 3617 US urban neighborhoods, 732 are described as experiencing concentrated disadvantage (Poverty Solutions 2019). Concentrated poverty—one aspect of concentrated disadvantage—is most common in Black neighborhoods. Black people are five times as likely as Whites to live in an extremely economically disadvantaged neighborhood (Kneebone and Holmes 2015). This matters because people who live in disadvantaged neighborhoods experience poor child development (Brooks-Gunn and Duncan 1993; Sampson, Sharkey, and Raudenbush 2008) and high secondary school and college attrition (Levy et al. 2019; Sampson, Morenoff, and Gannon-Rowley 2002). Those living in disadvantaged neighborhoods are more likely to experience health issues, such as high rates of diabetes and cytomegalovirus seroprevalence in pregnancy (Lantos et al. 2018; Ludwig et al. 2011). And disadvantaged neighborhoods tend to have high crime and violence, such as retaliatory homicide (Kubrin and Weitzer 2003) and other forms of violent crime (Papachristos et al. 2018).

As noted above, where one lives has an impact on individual lives, and living in concentrated disadvantage is one social context that matters. The concentrated disadvantage index was first fully developed by Robert, J. Sampson, a professor at Harvard University (1997, 2012). Neighborhood concentrated disadvantage is defined as “a synergistic composite of social factors that mark the qualitative aspects of neighborhood as an ecological unit of analysis” (Sampson 2012:100). Concentrated disadvantage epitomizes the neighborhood inequality within which the neighborhood effect draws. Sampson considers that many sources of social problems tend to cluster together. Unemployment, poverty, family disruption, and segregation can cluster spatially from block group to larger geographic and ecological unit of analysis, such as the metropolitan area or state. Concentrated disadvantage is neighborhood level comprehensive characteristics of social and economic inequality, representing a degree of vulnerability of individuals in a neighborhood. The index includes 6 variables: poverty, unemployment, female-headed households, welfare receipt, racial composition, and density of children (Sampson 2012:100). These variables are typically taken from the Census Bureau’s American Community Survey five-year estimates (Sampson, Morenoff, and Earls 1999; Wodtke et al. 2011). A principal component analysis is usually conducted to generate a composite score of neighborhood disadvantage. Although studies use various units of analysis to study concentrated disadvantage (i.e., neighborhood cluster, census tracts, block group, county etc.), they all represent a neighborhood-level social and economic vulnerability (for more details, see Chapter 3).

Concentrated disadvantage can intensify subsequent inequalities in ways that systematically produce less favorable outcomes for certain individuals or groups in society (Kurlychek and Johnson 2019). Several studies have focused on the effect of concentrated disadvantage on various significant social outcomes, such as health issues, impaired child development, and environmental issues. Ludwig and colleagues (Ludwig et al. 2011) investigated the effect of neighborhood environment on the development of obesity and diabetes. They found that residents moving from a neighborhood with a high level of poverty to a low level of poverty see a modest but important reduction in the prevalence of extreme obesity and diabetes. Lanto et al. (2018) studied the relationship between neighborhood disadvantage and cytomegalovirus seroprevalence (CMV) in pregnancy among women. They found that the likelihood of CMV is significantly associated with Area Deprivation Index (ADI), a neighborhood-level measure of socioeconomic contextual disadvantage. Levy et al. (2019) studied neighborhood effects on educational attainment. They found that children living in a disadvantaged neighborhood held reduced educational expectations in terms of the probability of bachelor's attainment. Given the link between educational expectations and educational attainment, the completion of a bachelor's degree may depend more on the quality of neighborhood high schools, local networks from whom children can learn about college options, and the desire to pursue high-status careers by observing neighbors' lifestyles.

Across a variety of environmental components, including proximity to hazardous waste sites and exposure to air and water pollution, neighborhoods with a high concentration of disadvantaged and vulnerable people faced consistent exposure to higher levels of environmental risk (Chakraborty, Tobin, and Montz 2005; Cutter 2006). Neighborhoods with the poor, and especially non-White poor, "bear a disproportionate burden of exposure to suboptimal and unhealthy conditions in the United States" (Evans and Kantrowitz 2002:323). Those living in disadvantaged neighborhoods are exposed to risky substances use behaviors and disorders, especially among racial minorities and the poor (Mennis, Stahler, and Mason 2016). Those living in urban neighborhoods or "city places" are disproportionately exposed to and contaminated by risky social and environmental hazards, thus, residents are perpetuated by risky substance use (Galea, Rudenstine, and Vlahov 2005; Mason et al. 2009). The environmental hazards experienced by those living in disadvantaged and vulnerable neighborhoods not only influence people's substance use, but ultimately their health conditions. Winter and Sampson (2017) investigated lead exposure in early childhood to adolescent health. They find that exposure to lead is unevenly distributed with children who are minorities and poor experiencing higher rates of exposure than children who are White and less poor. Exposure to lead poses long-term consequences for health and cognitive development.

Despite numerous studies on the topic (Kubrin and Weitzer 2003; Lantos et al. 2018; Levy et al. 2019; Ludwig et al. 2011; Wodtke et al. 2011; Papachristos et al. 2018), neighborhood concentrated disadvantage research suffers limitations. It is possible that housing market conditions are also important when examining concentrated of disadvantage in urban neighborhoods.

First, for renters, eviction has a perpetually cumulative effect that channels the inner-city poor from one place to another and leads to increased residential mobility, homeless, and a relocation to a disadvantaged neighborhood and/or substandard housing (Desmond 2012). Eviction is defined as a process whereby the landlord files a detainer warrant to renters due to non-payment of rental fees (although illegal evictions can also occur but are challenging to document). Landlords are less likely to rent to those with eviction records, which can lead to homelessness (Kleysteuber 2007). Many low-income families experience forced moves (involuntary displacement) at a higher rate than wealthier families, and they often experience subsequent mobility due to dilapidated housing conditions (Desmond, Gershenson, and Kiviat 2015). Housing evictions can destabilize communities, both the communities from which the residents are evicted and the ones to which the residents are relocated (Desmond 2016). Researchers find that exploitation of tenants is the highest in poor neighborhoods and landlords tend to extract higher profits from housing units in these neighborhoods (Desmond et al. 2015, Desmond and Wilmers 2019). Thus, neighborhoods stay disadvantaged because they consistently receive a disproportionate share of poor, previously evicted residents who are potentially exploited by local landlords.

Second, housing foreclosure negatively impacts urban neighborhoods. Foreclosed properties lose resale value in the housing market (Sumell 2009; Campbell, Stefanon, and Parag 2011) because sellers are willing to accept a lower price in order to sell faster to avoid holding costs (Frame 2010) and because those who cannot afford to make their house payments often cannot afford or are not motivated to keep up the maintenance of their home (Chan et al. 2013). The lower sales value of one home will then reduce the value of neighboring properties (Lin, Rosenbaltt, and Yao 2009). Sumell (2009) estimates a 50 percent foreclosure discount for property sales in Cuyahoga County, Ohio between 2004 and 2006. Campbell and colleagues (2011) report a 22 percent foreclosure discount for single-family properties in Massachusetts during 1987-2007.

Because of the linked values of homes, studies suggest that foreclosures have contagion effects (Immergluck and Smith 2006; Rogers and Winter 2009; Towe and Lawley 2013). Immergluck and Smith (2006) find that foreclosures had a statistically significant impact on property values within a 1/8 mile radius of the foreclosed property, a 0.9% decline for each foreclosure. Rogers and Winter (2009) obtain similar results. They find that foreclosures have a larger negative impact on the houses closest to them. When property prices go down, neighbors can find themselves "upside down" on their mortgage (i.e., they now owe more than the house is worth) putting them at a higher risk of being in foreclosure. Like with evictions, the loss of a home through foreclosure typically funnels people from better neighborhoods to worse ones and potentially the addition of new poor or disadvantaged people to a neighborhood potentially makes a neighborhood more disadvantaged.

Third, subprime loans and predatory lending are potentially mechanisms through which the housing market concentrates residents into disadvantaged neighborhoods. Although there are no official definitions for subprime lending, scholars conceptualize subprime loans as loans to borrowers with blemishes on their credit records who could not qualify for conventional loans. They are higher priced loans, involving higher interest rates or fees–presumably to compensate lenders for the higher risk involved (Squires 2009). Subprime and predatory lending has skyrocketed since the 2000s, especially in minority and low-income areas, as these areas show an increase of high poverty and in-migration of disadvantaged residents (Squires 2009). Due to the fact that mainstream banks and mortgage lenders are reluctant to open branches in minority and disadvantaged neighborhoods (Faber 2013), the urban disadvantaged population are most vulnerable to predation from risky financial institutions. Many borrowers in disadvantaged neighborhoods are steered into subprime mortgages when they could have qualified for prime mortgages because predatory financial institutions geographically settle their branches in disadvantaged neighborhoods and intentionally target disadvantaged people to buy their loan products (Brooks and Simon 2007; Mayer, Pence, and Sherlund 2009). Thus, the poorest people end up paying the most for loans—loans they can ill-afford to pay back, and they are less likely to pay off their loans due to high monthly interest.

The presence of subprime lenders in a neighborhood is already a signal that a neighborhood is disadvantaged (but not necessarily poor), because it is a neighborhood that mainstream banks and mortgage lenders are avoiding (Turner and Skidmore 1999).

Neighborhoods without mainstream banks are typically neighborhoods that also lack grocery stores, drug stores, and other good places to buy goods and services at a reasonable price (Bonacich 1980). This lends itself to two possibilities that can be connected to crime. First, mainstream institutions (such as chain drug stores) can afford surveillance such as store detectives and private security, which may reduce crime. Owners of bodegas and similar locally owned business likely cannot afford these measures. Second, risky subprime loans put residents at high risk for foreclosure (Faber 2013; Haupert 2019), which weakens collective efficacy and social ties, thus increasing the probability of actual crime and victimization.

Although subprime lending is strongly linked to foreclosure, the two factors should be examined differently for two reasons. First, the impact of foreclosures on neighborhood disadvantage could be felt even if those experiencing foreclosure did not have subprime loans. Second, there may be impacts of subprime lending that magnify neighborhood disadvantage over and above what is typically seen in foreclosure. For example, if much of a neighborhood was established by subprime loans, the potential for foreclosure contagion would be much higher. Additionally, those paying the higher price of subprime loans may have fewer funds to invest in repairs or basic maintenance for their homes, which may drive down housing values for the entire neighborhood.

Although research investigating the association between housing market conditions and crime is limited, high levels of eviction, foreclosure and subprime loans potentially create conditions for neighborhood crime. An insecure housing market will have a greater impact on some neighborhoods than others, and the most disadvantaged neighborhoods might become even more unstable and socially vulnerable. As Desmond and his colleagues (Desmond 2012;

Desmond et al. 2015) argue, eviction creates residential flows from one neighborhood to another. Semenza and colleagues (Semenza et al. 2022) argue that neighborhood crime is likely to be influenced by the residential instability (i.e., eviction) that is characterized by involuntary displacement. The hypermobility has precarious consequences on the urban poor, leading to worse living conditions and repeated moving. Some evicted residents also experience prolonged periods of homelessness (Burt 2001; Crane and Warnes 2000).

Evictions not only disadvantage the evicted, but also disadvantage the neighborhoods where the eviction is taking place. In work using classical strain theory, general strain theory, and a resource perspective (Alm 2018; Alm and Bäckman 2020), it is argued that criminality after eviction can become “a ‘conditional survival strategy’ in a severely exposed life situation, when all alternative courses of action are blocked” (Alm and Bäckman 2020; MaCarthy and Hagan 1991). Also, when neighborhoods constantly experience high eviction rates, their residents experience the deterioration of collective efficacy and loosening of informal social control because social networks and ties among residents are become severed (Morenoff and Sampson 1997; Sampson 2012), thus increasing crime and victimization of local neighborhoods. Additionally, it is possible that evictions (and foreclosures) disadvantage nearby neighborhoods, because those who cannot pay their rent or mortgage are driven to less costly housing available within a short distance.

Foreclosures also lend themselves to crime. The social disorganization approach suggests that foreclosure and house vacancy are both linked to the residential instability (defined as churning, meaning people moving in and out) of a neighborhood, which have consequences for neighborhood crime (Boessen and Chamberlain 2017; Jones and Pridemore 2012). High rates of foreclosure weaken collective efficacy and social ties because the foreclosed resident is cut off from their neighbors during the foreclosure process, and neighborhoods with less efficacy and weaker ties are associated with higher rates of crime.

Broken window theory suggests another link between home foreclosure and crime, because homes in foreclosure may be less well taken care of during the foreclosure process (Kingsley, Smith and Price 2009). Once the homeowners realize that they face foreclosure, the property may be poorly maintained due to lack of motivation or funds and start to show signs of disrepair (Cui and Walsh 2015). This might signal to potential criminals a lack of surveillance and increase crime and victimization around the foreclosed properties. As the number of foreclosures in a neighborhood reaches a critical tipping point, the start of decline emerges, and neighborhood levels of crime increase (Katz et al. 2013).

Routine activity theory also suggests a relationship between foreclosure and crime. Ellen and colleagues (Ellen et al. 2013) propose that foreclosure changes the benefits and costs of committing a crime through the availability of suitable targets for criminal activity and the perceived presence (or absence) of capable guardians against crime. The vacant properties due to foreclosure provide good opportunities for motivated offenders to engage in illicit activities such as drug dealing and prostitution (Chen and Rafail 2020). The lack of homeowners means a reduced number of guardians and police officers who may be less motivated to monitor vacant properties, thus offering opportunity for criminal behavior and victimization.

In neighborhoods with high eviction and foreclosure rates, crime could also be driven up because of over-policing. Although few studies have focused on the relationship between eviction, foreclosure and over-policing, a neighborhood with high rates of eviction is suggested to be accommodating residents with low socio-economic status and poverty (Desmond 2016), thus potentially leading to the police presence in these neighborhoods. Researchers found that disadvantaged neighborhoods have a greater police presence than their wealthier counterparts (Bloch 1974; Kane 2007). Since disadvantaged neighborhoods are potentially the site of greater policy surveillance, this will increase the crime reports even if no more actual crimes occur.

Some researchers have focused on the relationship between concentrated disadvantage and crime in large metropolitan areas, including Columbus, Ohio; Chicago, Illinois; Los Angeles, California; Washington, D. C. and St. Louis, Missouri (Hipp and Kubrin 2017; Hipp and Yates 2011; Johnson and Kane 2018; Krivo and Peterson 1996; Papachristos et al. 2018; Peterson and Krivo 1999; Sampson, Raudenbush and Earls 1997). In these places, scholars find that extremely disadvantaged neighborhoods have a higher level of crime than less disadvantaged neighborhoods (Krivo and Peterson 1996; Kubrin and Weitzer 2003). This is because either disadvantaged people are crime-prone, disadvantaged people are more likely to be crime victims, disadvantaged neighborhoods are over-policed, or some combination of these effects are occurring. Despite a handful of studies focusing on the disadvantage-crime relationship in large metropolitan areas, crime in mid-sized cities is an important and understudied area (Gau et al. 2012). It is important because neighborhood effects may be less (or more) important in mid-sized cities than in larger urban areas. I will investigate the relationship between neighborhood disadvantage and crime in a mid-sized city—Knoxville, Tennessee. Thus, research present here is novel in that it examines the possibility of adding housing market dimensions to traditional measures of neighborhood disadvantage. It also examines these conditions in a mid-sized city—an urban environment that is understudied but one in which most people in the United States live.

CHAPTER THREE

DATA AND METHODS

Scope of the Study

The study area is the city of Knoxville, Tennessee. Knoxville is located in East Tennessee and is the state's third largest city after Nashville and Memphis (see Figure 3-1). As of July 1, 2019, the total population of Knoxville City is 187,603 (Census Bureau, Population and Housing Units Estimates, 2010-2019). It is 72.4 percent White, 17 percent Black or African American, 5.3 percent Hispanic or Latino, and 1.8 percent Asian (Census Bureau, QuickFacts, 2019).

The unit of analysis of this research is neighborhoods within the Knoxville city limits, as proxied by census tracts. A census tract is small relative permanent statistical subdivisions of a county, uniquely numbered in each county with a numeric code, A census tract ideally contains about 4,000 people and 1,600 housing units (Glossary of Census Bureau, 2022). Within the city limit were a total of 90 census tracts drawn from the 2010 census (Knoxville-Knox County Planning 2020). With the launch of the 2020 census, new tract boundaries were drawn (Press Release of Census Bureau, 2021), but the 2010 boundaries more closely align with the data used for this study (see below), so it was those tract boundaries that were used. It should be noted that census tracts 103.01 and 104 are in the City of Knoxville, but they fall in Anderson County (adjacent to Knox County). As most of the available data for this project are associated with Knox County, I omitted tracts 103.01 and 104 from this study. To clarify, although demographic data for all tracts can be obtained directly from the Census Bureau, eviction and foreclosure data are restricted to tracts within Knox County, and they do not include information about the two Anderson County tracts. In the end, this study includes 88 census tracts that lie within the

Figure 3-1. Map of Tennessee.
Source: https://www.nationsonline.org/oneworld/map/USA/tennessee_map.htm

Knoxville city limits in Knox County.

It is worth noting that using census tracts as a proxy for neighborhoods as the unit of analysis for contexts where actual crime take place raises potential concerns about the modifiable area unit problem (MAUP). The MAUP is the problem that pertains to the fact that statistical measures for data are “sensitive to the ways in which spatial units are organized” (Anselin 1988: 26). This occurs because data change according to different geographic boundaries, thus yielding different results when analyzing these data at different geographies (Openshaw and Taylor 1979; Wong 2004). There are two mechanisms in spatial analysis that can create the MAUP. First, when smaller spatial units are aggregated into larger spatial units, inherent heterogeneity and structural instability will arise from the aggregation scheme. In other words, there is no homogeneous spatial process underlying the new aggregated units (Anselin 1988; Dark and Bram 2007). So crime report data are cases that are aggregated at the neighborhood (tract) level from the individual and household level and it may not make sense to consider these data at the neighborhood level because the contexts that create actual crime may not be the neighborhood (as proxied by tracts). The same logic happens to the eviction and foreclosure data since these data are originally individual cases and aggregated into the tract level.

The second mechanism pertains to the proper identification of the structure of spatial dependence. As the observations are re-arranged into “zones”, several statistics changes in value, such as correlation coefficients and measures of spatial autocorrelation (Anselin 1999). This leads to insufficient information in the data to allow for the full specification of the simultaneous interactions over space.

Besides MAUP, Modifiable Temporal Unit Problem (MTUP) is an issue majorly focusing on temporal aggregation and its effects on statistical inference (Alt, King, and Signorino 2000). MTUP includes temporal aggregation effect, temporal segmentation effect, and temporal boundary effect. The temporal aggregation is a process that converts the observations from a fine interval into a coarse interval. The number of events with each time interval is summed and reported as a single value. Averaging or taking the maximum of the number of the events within the original intervals could also be a form of aggregation (Cheng and Adepeju 2014). By aggregating the data from one temporal scale to another, the basic statistical estimates such as variance and correlation coefficients are affected due to the change in the number of resulting intervals (Rossana and Seater 1995). Most data collected and used in this dissertation was originally formatted as the exact day per case (i.e., crime, eviction, and foreclosure). In order to align these data with other data formats (i.e., subprime and demographic data, which are formatted by year internals). I aggregate data with day intervals into year intervals. As of now, it is uncertain to what extent the temporal aggregation might impact the statistical results, but the results of this dissertation should be interpreted with caution due to temporal aggregation effect of MTUP.

In addition to the MAUP and MTUP, there is question of whether census tracts are a good proxy for neighborhoods and whether the information captured at the census tract level is appropriately allocated to the neighborhoods in which they belong. In this research, there is a chance that actual crime maybe identified as occurring outside of one’s home neighborhood when one has simply crossed a tract boundary that is not truly socially meaningful. Or, put more simply, what the Census Bureau considers to be your neighborhood and what you consider to be your neighborhood may be different, so to the extent that there are neighborhood effects, it makes more sense that those effects would come from the neighborhood to which you feel you are a part rather than some externally imposed idea of your neighborhood. Nonetheless, we see enduring effects of neighborhood disadvantage when using tracts as proxies in other contexts (Diez Roux and Mair 2010).

Scholars have investigated the disadvantage and crime relationship at different geographical levels (Sampson 2012; Hipp and Boessen 2013; Tillyer, Wilcox, and Walter 2020), such as neighborhood cluster, egohood, census tract, and block group. Sampson (2012) argues that there is a need for spatial flexibility when it comes to measuring contextual influences. Moreover, Anerson and Malmberg (2015) argue that there is not a correct or best operational definition of neighborhood or a perfect measurement. In this research, I use census tracts as the geographic unit of analysis to represent neighborhoods because census tracts are widely used in previous research on neighborhood disadvantage and crime (Hipp 2010; Krivo and Peterson 1996; Krivo, Peterson, and Kuhl 2009), making my findings comparable to other studies. Also, since the Census Bureau restricts information at smaller unit of analysis data (i.e., block, block group), much of the information needed for this study is not available at units smaller than tracts. Larger levels of aggregation (e.g., county level data) fall outside of my theoretical application. Finally, data on crime and housing conditions are available at prescribed units of analysis that are not amenable to placement in self-identified neighborhoods.

Dependent Variable

Crime report data are taken from the Knoxville Police Department's records made available to me on March 3, 2021, by public records request pursuant to the Tennessee Public

Records Act. These data detail each recorded crime report incident that occurred from 2016 to 2019 in the City of Knoxville and include exact addresses of each incident. It should be noted that the crime report data include all types of crime that is recorded by the police officer (e.g., homicide, robbery, simple/aggravated assault, shoplifting, motor vehicle theft, and theft from buildings) and I do not differentiate between types of crime in this study. Crimes are geolocated and aggregated at the census tract level for the purpose of this study.

The problem of underreporting crime is a well-known issue with criminological research, especially for crime report data taken from official sources (Xie and Baumer 2019). Previous studies have investigated the underreporting of various types of crime (Gove, Hughes, and Geerken 1985; Hindelang 1978; Rennison 2001; Zhang, Messner, and Liu 2007). However, few studies have done so examining the relationship between neighborhood disadvantage and crime (Baumer 2002; Goudriaan, Wittebrood, and Nieuwbeerta 2006). In one of the few studies that examines this, Baumer (2002) found no evidence that underreporting of serious violent crimes (i.e., aggravated assault and robbery) are systematically related to the level of disadvantage in the neighborhood. However, we do not know yet whether underreporting for more minor types of crime (e.g., property crime) negatively impacts the study of neighborhood disadvantage.

Another major issue of official crime records to study neighborhood disadvantage concerns the extent to which official crime data reflect ecological biases in official reactions to criminal behavior (Hagan, Gillis, and Chan 1978; Sampson and Groves 1989). Disadvantaged neighborhoods may have higher crime report rates in part because these neighborhoods are over-policed and because police departments concentrate spending on policing actual crime in presumed “bad” neighborhoods compared with neighborhoods that are less intensely policed

(Kappeler and Potter 2018; Bohon and Ortiz 2021) rather than because there is some real association between disadvantage and actual crime. The type of neighborhood in which police-resident encounters occur may also influence the actions taken by police (Hagan et al. 1978; Sampson 1986). In other words, police may look for more crime in disadvantaged neighborhoods, so they are likely to find it. This may create an indirect relationship between neighborhood disadvantage and crime rates, mediated by over-policing. Unfortunately, I do not have the data to test this at this time.

Smith (1986) demonstrated that the probability of arrest across neighborhoods declines with increased socioeconomic status. Moreover, the politics of policing influences crime report statistics. Police administrators can use crime report statistics to demonstrate the efficiency of one's operation or to argue for a serious need for further funding (Alpert et al. 2015). Police policies directly affect the publicized crime rate, which in turn, affect police policies and budgets (Kappeler and Potter 2018). Therefore, crime data should be interpreted with caution. In this dissertation, I analyze and interpret data directly collected from Knoxville Police Department, and it is likely to be biased, but the direction of the bias is unknown.

Independent Variables

I am interested in accessing the relationship between concentrated disadvantage and crime at the census tract level in the City of Knoxville, Tennessee, and in examining whether housing market factors, including eviction, foreclosure and subprime lending are needed to improve the measure of concentrated disadvantage (or not) that explains crime and victimization. Thus, in all models Sampson's index of concentrated disadvantage is a key independent variable; variables measuring eviction, foreclosure, and subprime lending are also important predictors.

In this research, I use six variables in an index of concentrated disadvantage that builds on Sampson's theoretical framework (Morenoff and Sampson 1997, Sampson 2012). Concentrated disadvantage is an index representing economic disadvantage in racially segregated urban neighborhoods (Sampson, Morenoff and Earls, 1999). The index includes tract level measures of percent of population below 125 percent of the poverty line, percent of residents in the labor force who are unemployed, percent of households that are female-headed, percent of children living in households receiving government welfare, percent Black, and percent of children living in single-parent households under 18 years old. These six variables are taken from the U.S. Census Bureau's American Community Survey (American Community Survey 5-Year Estimates), 2016-2019 at the tract level for the city of Knoxville, Tennessee. To construct an index of concentrated disadvantage, I follow the approach outlined by Sampson, Morenoff and Earls (1999). Principal component analysis was conducted to confirm that the variables used are part of a single underlying construct (presumably of concentrated disadvantage). Table 3-1 shows the rotated factor loadings (oblique rotated) of Sampson's concentrated disadvantage variables. All variables load high on a single factor (factor 1). Therefore, I incorporate these variables and create a z-score transformed index, which is referred to in this dissertation as the concentrated disadvantage index. Concentrated disadvantage is a z-score and thus has a mean of approximately 0 and standard deviation of 0.88. The minimum value is -0.97, which indicates the least disadvantaged census tract and maximum value is 2.70 indicating the most disadvantaged tract. Thus, the most disadvantaged neighborhoods are more than two standard deviations above the mean composite of the six variables.

Table 3-1. Rotated Factor Loadings of Variables Used in the Concentrated Disadvantage Index

Variables	Factor 1
Percent poverty	0.89
Prevent female-headed household	0.88
Precent government assistance	0.92
Percent unemployment	0.77
Percent people under 18 years	0.89
Percent black	0.81

NOTE: Data are taken from the American Community Survey 2016-2019 Five-Year Estimates

To give an overview of tract level concentrated disadvantage in Knoxville, I create a customized map of concentrated disadvantage in three groups using Geoda software (Anselin 2020). The first group is the least disadvantaged census tracts with value from -0.97 to 0 because these census tracts have concentrated disadvantaged value below the mean, indicating that these neighborhoods are not disadvantaged. The second group is somewhat disadvantaged census tracts with value from 0 to 1.34. These census tracts have values up to about one standard deviation above the mean of the concentrated disadvantage index. The third group is the most disadvantaged census tracts with value from 1.34 to 2.70 meaning more than one standard deviation to more than two standard deviations above the mean of the concentrated disadvantage index.

Figure 3-2. shows the customized map of concentrated disadvantage by census tract. Light yellow represents the least disadvantaged tracts, the darker yellow represent somewhat disadvantaged census tracts, and orange represents the most disadvantaged census tracts. Table 3-2 shows descriptive statistics for the index variables for the five most disadvantage tracts in Knoxville and the five least disadvantaged tracts. Among the most disadvantaged tracts are the neighborhoods known as Arlington, Lonsdale, and Marble City. These set of tracts are adjacent to one another. Another cluster of most disadvantaged tracts are neighborhoods of Old North Knoxville, Parkridge, Mabry's Hill and Burlington. Both tracts 19 and 20 are adjacent to tract 32, in which is bounded by Asheville Highway, Holston River, and the Tennessee River.

Eviction data were obtained from the Knox County Civil Sessions Court on July 1, 2021. The civil sessions court clerk's office provides Detainer Possession Reports, which show only properties where the landlord prevailed in an eviction case. It is worth noting that according to

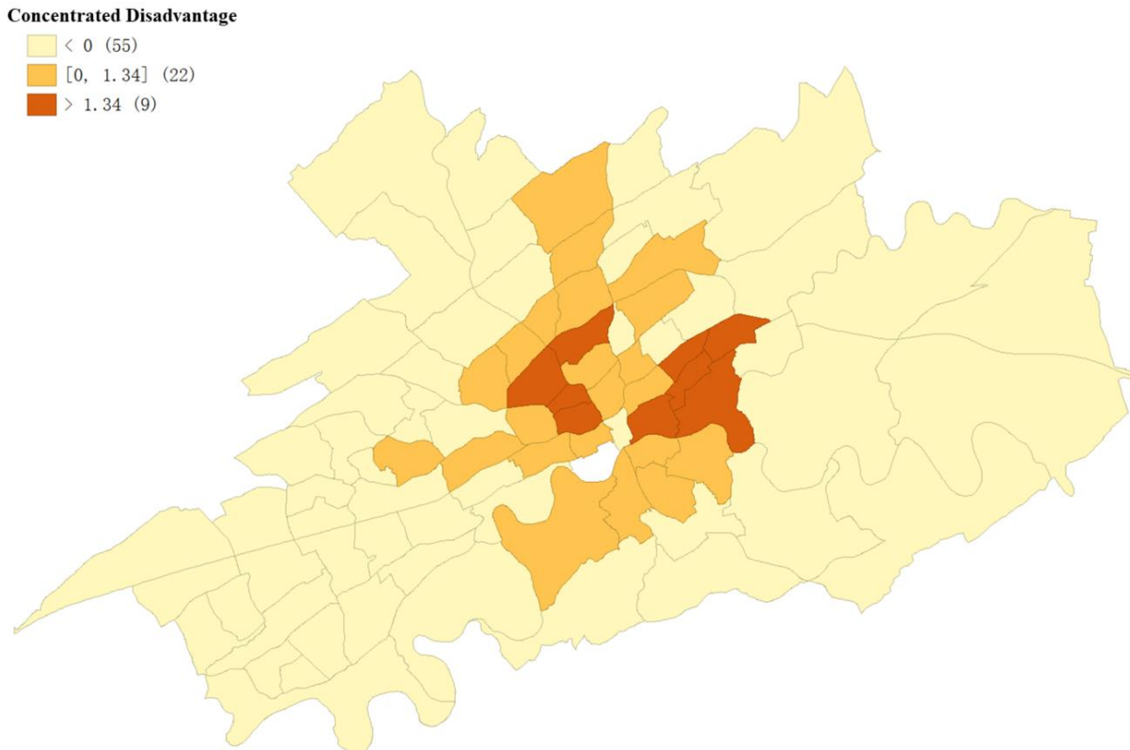

Figure 3-2. Concentrated Disadvantage by Census Tract, 2016-2019: Knoxville, TN

Tennessee Law regarding the required steps of eviction, when the landlord prevails in the hearing, the judge orders the tenants to move within 10 calendar days. If the tenant posts one year's worth of rent as a bond with the appeal, the tenant may be allowed to stay in possession of the rental unit (Renter Resource Center 2022). Therefore, these records included every rental property that was involved in a detainer possession for eviction from January 2016 to December 2019 with the exact address of the rental property. Whether the residents were finally evicted remains unknown in these data because according to the steps of eviction, after judge orders the tenant to move within 10 calendar days, if tenant posts one year's worth as a bond with the appeal, the tenant may be allowed to stay in possession of the rental unit. However, that is unlikely. Thus, the detainer process captures most of those evicted legally, and even for those who ultimately were not evicted after a court order, the data still represents local disadvantage since the tenant has not paid the rent within 14 days after a landlord issued a notice to vacate. The data used in my dissertation undoubtedly undercount the true level of evictions, because they are limited only to court-ordered evictions and do not include (unknowable) cases where residents voluntarily vacate due to their inability to pay the rent or illegal evictions where the landlord simply locks out residents who do not have the resources to sue (Desmond 2016). Each eviction case was geocoded into the tract level.

Foreclosure data were obtained from the Knox County Register of Deeds. The Register of Deeds is the official record keeper of legal documents pertaining to real property established by the Tennessee State Constitution. The data include all the legal records of properties that have been foreclosed with information about the property address, owner company agency, sale price, agency responsible for payments. etc. The year range of foreclosure data used are from January

2016 to December 2019. Again, each foreclosure case was geocoded to the tract level in the final dataset.

Subprime loan data are collected from the Federal Financial Institutions Examination Council. The Home Mortgage Disclosure Act (HMDA) was passed in 1975 to shed light on the mortgage industry. The law requires that most lending institutions report information regarding home loan applications on a yearly basis. The dataset provided by the Federal Financial Institutions Examination Council (FFIEC 2020) includes information on the name of the lender; loan purpose; loan type; the final disposition of the application (i.e., approved or denied); the census tract in which the desired property is located; and the income, race, and gender of the borrower. I use HMDA data from 2018 and 2019 because there are only three years of data available for public use (2018, 2019 and 2020) and this time frame is in accordance with my other data sources. Although the HMDA platform does not specifically flag subprime loans, nor does it separate out any prime loans made by specialized lenders, other researchers have used these data to classify loans as subprime (Been, Ellen, and Madar 2009; Faber 2013, 2018; Williams, Nesiba, and McConnell 2005).

In order to obtain a subprime loan sample from the HMDA dataset, I created the following measures that are consistent with previous research (Been et al. 2009; Kingsley and Pettit 2009; Faber 2013; Assadi 2017; Simon 2020). First, a primary loan was defined as subprime if it had an interest rate three or more points above the federal treasury rate (Been et al. 2009; Kingsley and Pettit 2009; Faber 2013). The federal treasury rate (FTR) data come from the U.S. Department of the Treasury 2018 and 2019 (Resource Center, U.S. Department of the Treasury). Therefore, I classify any primary loan that has an interest rate 3 or more points as

Table 3-2. Characteristics of 5 Most Disadvantaged and 5 Least Disadvantaged Census Tracts in the City of Knoxville

Concentrated Disadvantage Group	Tract	Places	Concentrated Disadvantage Index	Percent Poverty	Percent Female-Headed Household	Percent Government Welfare	Percent Unemployment	Density of Children	Percent Black
Most Disadvantaged Census Tracts	68	Mabry's Hill (Mabry-Hazen House)	2.70	63.69	23.61	81.73	19.27	88.14	63.84
	70	Mechanicsville East	2.30	60.83	27.11	77.01	16.15	60.10	55.89
	14	College Hills	2.22	70.64	29.37	82.40	17.38	55.21	27.32
	19	Chilhowee Park; Lake Ottosee; Zoo Knoxville	2.10	52.27	19.59	57.01	15.77	82.07	62.61
	20	Burlington	2.01	49.67	21.02	78.10	5.13	89.64	75.78
Least Disadvantaged Census Tracts	71	Sequoyah Hills; Lyons View	-0.97	11.08	2.16	0.75	2.53	5.80	0.75
	57.12	Farrington; Kensington	-0.96	5.22	4.49	3.20	1.89	5.87	2.16
	57.01	Westminister Ridge; Mockingbird Hill; Riverbend;	-0.93	8.56	3.21	5.97	1.36	11.71	0.31
	57.08	Garland	-0.92	2.76	5.14	1.71	2.27	10.66	1.78
	58.07	Lovell Heights; Tan Rara Oesta	-0.89	9.23	4.76	0.81	1.32	12.18	3.20

subprime or predatory. Second, since I focus on homeownership in neighborhoods and their associated loan status, I choose home purchase loans as the loan purpose, excluding business and other loans. Third, it is proposed that home refinance loans could potentially also be subprime (Simon 2020). Researchers suggest that refinance loans are subprime if the interest rate is 5 or more points higher than federal treasury rate (Been et al. 2009). Therefore, I classify home refinance loans with 5 or more points higher than FTR as subprime. Fourth, I also include the second lien mortgage because compared to first lien mortgage, second lien mortgage's priority is subsequent to the first mortgage, and interest rates are often higher on the loan due to the higher risk of default (Assadi 2017). Thus, second lien mortgages could potentially be subprime or predatory. Fifth, I only include conventional loans for the loan type. The reason is that conventional loans are not backed by the Federal Housing Administration, Veterans Affairs and USDA Rural Housing Service or Farm Service Agency which are unlikely to fall into subprime. Sixth, I include only loans originated and purchased and omit those not accepted, denied, and withdrawn since no predatory lending occurred.

Control Variables

Three control variables are used in my analysis. These control variables are selected based on previous studies of crime and literature on concentrated disadvantage, eviction, foreclosure, and subprime loan more broadly (Roncek 1981; Roncek and Maier 1991; Immergluck and Smith 2006; Hipp 2010; Baumer, Wolff and Arnio 2012; Desmond 2016; Passley 2019)

First, all models in this project control for percentage of residential units that are unoccupied, given that unoccupied residential units may increase crime opportunities (Roncek

1981; Roncek and Maier 1991; Hipp 2010). Percent of residential units that are unoccupied is obtained from the American Community Survey (ACS 5-year estimates) from 2016-2019. It is calculated as the number of vacant housing units divided by the total number of housing units at the census tract level.

Second, I control for median gross rent in all models as home rental fees are suggested to have positive effect on local crime rates (Passley 2019). Also, Desmond (2016) suggests that the rental fee would be higher for those families who are in possession of housing voucher. The local Department of Housing and Urban Development sets a Fair Market Rent (FMR), which is the most landlord can charge a family in possession of a housing vouchers. Because the rents are higher in the suburbs than in the inner city, the FMR may exceed market rent in disadvantaged neighborhoods. When voucher holders live in those neighborhoods, landlords "could charge them more than what the apartment would fetch on the private market" (Desmond 2016:148). Therefore, I expect that higher rent would lead not only to high possibility of being evicted, but also greater actual crime due to the lack of rents. Median gross rent is collected from American Community Survey (ACS 5-year estimates) from 2016-2019 at the tract level.

Third, I control for house sale value in all models. Previous research on the relationship between foreclosure and crime have investigated the effect of a city housing affordability index on crime (Baumer et al. 2012). The housing affordability index is calculated as median family income divided by median price single-family home. They found that HAI is negatively significantly related to burglary in the United States. Researchers also found that in Chicago, every additional foreclosure within an eighth of a mile reduced a home's value by 0.9 percent (Immergluck and Smith 2006). In this research, I use median home value to represent the house sale value, and I obtain these data from American Community Survey (ACS 5-year estimates) from 2016-2019 at the tract level.

Determining Models

Before creating models to test my hypothesis, it was necessary to determine what type of regression model would be used to model crime. Potentially the dependent variables could be measured two different ways—as crime rates and as crime counts. Depending on which dependent variable was used, there are two different categories of methods for regression modeling in terms of the type of dependent variable. First, to model crime rates, an ordinary least-squares (OLS) regression model should be used. However, it should be noted here that often criminologists measure crime rate as the number of crime events per 100,000 people. In the cases of small geographic units of analysis with small populations (e.g., a census tract with 5,000 residents), it is not easy to comprehend the scope of crime if you calculate crimes per 100,000 people. To make crime rates more easily comprehensible, I used 100 as my base rate, so that the crime rate is crimes per 100 people. Therefore, I calculate crime rate as:

$$Crime\ Rate = \left(\frac{Number\ of\ Crime\ Events}{Total\ Population}\right) \cdot 100$$

Second, to model crime count, Poisson or negative binomial approaches should be used. Poisson regression model requires that the dependent variable not be over-dispersed, meaning that the variance equals the mean of the dependent variable, an assumption that often does not hold for most crime data (Bohon and Ortiz 2021; Holmes et al. 2018; Osgood 2000). Table 3-3 shows the variance and mean of averaged four-year (2016-2019) crime counts. The average number of crimes at the tract level is 289, and the variance is over 80,000. That is, the variance is

Table 3-3. Mean and Variance of Averaged Crime Counts (2016-2019) at Tract Level

	Observations	Mean	Variance
Crime Count	88	289.49	86069.14

considerably larger than the mean of crime. When the variances are larger than the mean, negative binomial models are often employed as these models allow for over-dispersion by directly estimating this over-dispersion with a dispersion parameter (Osgood 2000). (For more details in choosing between Poisson and negative binomial models, see Appendix A).

A concern with count models is excess zeros, which may occur if you have many census tracts without any crime at all and if these zeros crime counts derive from different sources (e.g., no actual crimes occurred versus no crimes were reported). Crime is a relatively rare event, so depending on the level of geography, large numbers of zero cases could occur (c.f. Ortiz 2020), which leads to concern of whether it is better to model non-adjusted or zero-inflated negative binomial models. Table 3-4 displays the percent of census tracts without any crime report event at the tract level. It shows that there are only three census tracts that have zero crime report events in 2017, which account for only 3.49 percent of all tracts across time. In 2018, there are only two census tracts that contain zero crime report event. In 2016 and 2019, there is only 1 tract with zero crime report events. Although many zeros are not the same as excess zero, the presence of few zeros indicates that an excess zero problem is not a concern. Since the zero-crime report event is relatively small in the city of Knoxville across 2016-2019, I do not fit the zero-inflated model (For more details in choosing between non-adjusted negative binomial regression, and zero-inflated negative binomial regression using AIC, see Appendix B).

Overall, the data do not violate the assumption of OLS modeling when using crime rates as a dependent variable and the results are easier to understand, so I present OLS regression for analysis of research question 1 and 2. Similar models using negative binomial regression models are in Appendix C.

Table 3-4. Frequency and Percent of Knoxville City Tracts Reporting No Crime

Variable	Frequency	Percent
Crime Count 2016	1	1.16 percent
Crime Count 2017	3	3.49 percent
Crime Count 2018	2	2.33 percent
Crime Count 2019	1	1.16 percent
Crime Count Four Year All	0	0 percent
Crime Count Four Year Average	0	0 percent

Third, as I tested for spatial autocorrelation in models of crime and concentrated disadvantage, and the results show spatial clustering occurs in the city of Knoxville across tracts. So, the spatial lag model is appropriate for parameter estimates in this context (For more details on choosing spatial lag mode, see Appendix D). Therefore, a spatial lag model is used to answer my third research question. The spatial lag model is expressed as:

$$y = \rho W_y + X\beta + \varepsilon$$

where y is a N by 1 vector of observations on the dependent variable. W_y is the corresponding spatially lagged dependent variable for weight matrix W, X is a N by K matrix of observations on the explanatory (exogenous) variables, ε is a N by I vector of error terms of normally distributed random error terms with mean equal to 0 and constant variances. ρ is a spatial autoregressive parameter, and β is K by I vector of regression coefficients (Anselin and Bera 1998). The spatial lag model is chosen because it is appropriate for my theoretical approach. Moreover, the spatial lag model outperformed the corresponding spatial error models in a variety of diagnostic tests (Details of the diagnostic tests will be discussed in Chapters 4, 5, and 6.).

Model Diagnostics

Before moving on to further analysis, it is necessary to perform diagnostic tests for the presence of multicollinearity of influential cases. Multicollinearity generally refers to a set of highly correlated predictors in a model. The consequences of multicollinearity will bias the magnitude and signs of regression coefficients that are not consistent with true effects (Thomson et al. 2017). A method to check multicollinearity is to estimate variance inflation factors (VIFs). It is suggested that a VIF greater than 10 indicates the presence of multicollinearity (Midi and Bagheri 2010). Others argue that the cutoff point should be more subjective (Graham 2003;

Obrien 2007). Another method to check multicollinearity is to estimate tolerance. Tolerance is the degree to which independent variables are correlated to a degree that the model can tolerate (or that does not violate the assumption of independence). Tolerance is calculated based on VIF so that

$$Tolerance = 1/VIF$$

Research suggest that multicollinearity may not be negatively impact models when tolerance values are above 0.5 (Bohon and Nagle 2022). Shrestha (2020) argues that there will be multicollinearity if the tolerance is less than 0.2. Table 3-5 displays the results of VIFs and tolerance of OLS regression model. Concentrated disadvantage, eviction and median home value have VIFs more than 2. Since the VIFs are below 10, I conclude that there is not enough multicollinearity to reduce the validity of my models.

Moreover, I assess whether there are influential cases in my dataset that would bias the regression results. One way to examine influential cases is to calculate the Cook's distance (D) for all 88 census tracts. The result shows that six tracts (census tracts 1, 19, 48, 71, 9.01 and 9.02) of Cook's D values are greater than 4/88, which is one means by which influence can be detected. However, only the tracts 9.01 and 9.02 exceed the value of Cook's D that equals 1 (Weisberg 1985). Therefore, I eliminate two census tracts 9.01 and 9.02, and the final dataset includes 86 census tracts (observations) in total.

Descriptive Statistics

Table 3-6 displays the descriptive statistics from the variables used to address the research questions listed above. In all cases, the variables represent averages across time. Values by year are shown in Appendix E. The dependent variable, crime rate, has a mean of

Table 3-5. VIFs and Tolerance of Independence for OLS Regression Model

Variable	VIF	1/VIF(Tolerance)
Concentrated Disadvantage	3.34	0.30
Eviction	2.16	0.46
Foreclosure	1.49	0.67
Subprime Loan	1.21	0.82
Unoccupied Housing Unit	1.61	0.62
Median Gross Rent	1.75	0.57
Median Home Value	2.38	0.42

Table 3-6. Descriptive Statistics

Variables	Mean	SD
Dependent Variable		
Crime Rate (2016-2019) Average	8.37	9.32
Independent Variables		
Eviction Count (2016-2019) Average	16.47	15.82
Foreclosure Count (2016-2019) Average	3.72	2.47
Subprime Loan Count (2018-2019) Average	3.89	2.55
Concentrated Disadvantage (2016-2019) Average	0.00	0.88
Percent Poverty (2016-2019) Average	23.75	17.22
Percent Female-Headed Household (2010 Decennial)	8.37	6.03
Percent of Government Welfare (2016-2019) Average	29.79	23.67
Percent Unemployment (2016-2019) Average	5.71	4.01
Ave. % of Children under 18 Years (2016-2019)	32.20	20.75
Percent Black (2016-2019) Average	12.47	16.45
Control Variables		
Ave. % of Unoccupied Housing Units (2016-2019)	9.45	4.74
Median Gross Rent (*100) (2016-2019) Average	8.89	2.28
Median Home Value (*1000) (2016-2019) Average	170.744	88.84

approximately 8 crimes per 100 people across 86 census tracts for the four years 2016-2019. Over time, the crime rate has dropped from 8.59 in 2016 to 7.79 in 2019 in the City of Knoxville.

For the independent variables, the mean of eviction counts is 16 across 86 tracts for the four-year (2016-2019) period. In 2016, eviction has a mean of 17, and it dropped to 15, on average, in 2019. The mean of foreclosure counts is approximately 4 across 86 tracts in the four-year (2016-2019) period. In 2016, mean foreclosures had a value of 5, while in 2019, the average foreclosure counts in each tract in Knoxville went down to 2. The count of subprime loans has a mean of 4 across 86 tracts in the two-year (2018-2019) period. In 2018, there were an average of 3 subprime loans in each tract, but in the year 2019, the subprime loan count increased to approximately 5 on average in each tract.

The concentrated disadvantage index is a z-score, which means that the mean is standardized at 0. For greater clarity, Table 3-6 also shows the variables that comprise the concentrated disadvantage index. First, on average, 24 percent of population live under 125 percent of the poverty line in Knoxville. Only 8 percent of the households are female-headed. On average, 30 percent of the population are receiving government welfare across 86 census tracts in Knoxville. Only 6 percent of the population on average are unemployed across 86 tracts. About 32 percent of the population on average are children under 18 years old. Blacks comprises 12 percent of the total population on average across 86 census tracts. These statistics show that in Knoxville, nearly one third of the population is living in poverty and receiving government welfare. Less than 10 percent of the households are female headed. Meanwhile, few people are unemployed for the population unemployment is six percent. The percent of Black population living within the Knoxville city limit is 12, which is in accordance with the Black population at the national level of 13 percent in 2019 (Census Bureau 2019)

For control variables, there are, on average, 9 percent of the housing unit that are unoccupied across 86 tracts in Knoxville. From 2016 to 2019, the median gross rent in Knoxville has a mean of $889, and it has increased year by year from 2016 to 2019. This is also true for median owner-occupied home values, which are increased from 2016 to 2019, has a mean of $170744.

Analytic Strategy

In order to answer my research questions, I develop strategies to address whether crime victimization and criminal behavior is explained by concentrated disadvantage or housing market factors in the City of Knoxville, Tennessee. Table 3-7 outlines the detailed research questions and the corresponding regression model being used to test the question. Since I have tested different types of models in Appendix A and Appendix B, I use OLS regression to model crime rates. Negative binomial regression is discussed to model crime count in Appendix C. Broadly, there are three general questions to be resolved in this dissertation. I ask: RQ1. Are housing markets characteristics a neglected part of concentrated disadvantage with regard to crime? RQ2. Do housing market characteristics mediate Sampson's model of concentrated disadvantage and crime? RQ3. Is there spatial correlation between housing market characteristics and crime across census tracts?

To answer the first research question, first, three housing market variables are separately added to the concentrated disadvantage index to recreate a single, new, concentrated disadvantage index. To do this, I ran factor analysis for concentrated disadvantage with each of

Table 3-7. Research Questions and Corresponding Method

Research Question	Sub-questions	Model and Method
Q1. Are housing market characteristics neglected part of concentrated disadvantage with regard to crime?	Q1a. Does concentrated disadvantage better predict crime when eviction is added to the concentrated disadvantage index?	OLS regression
	Q1b. Does concentrated disadvantage better predict crime when foreclosure is added to the concentrated disadvantage index?	OLS regression
	Q1c. Does concentrated disadvantage better predict crime when subprime loan is added to the concentrated disadvantage index?	OLS regression
Q2. Do housing market characteristics mediate Sampson's model of concentrated disadvantage and crime?	Q2a. Do evictions mediate Sampson's model of concentrated disadvantage and crime?	OLS regression
	Q2b. Do foreclosures mediate Sampson's model of concentrated disadvantage and crime?	OLS regression
	Q2c. Do subprime loans mediate Sampson's model of concentrated disadvantage and crime?	OLS regression
Q3. Is there spatial correlation between housing market characteristics and crime across census tracts?	Q3a, If evictions in a neighborhood increase, in which neighborhood (if any) do crime rates change?	Global and Local Moran's I Test Spatial Lag Model
	Q3b, If foreclosures in a neighborhood increase, in which neighborhood (if any) do crime rates change?	Global and Local Moran's I Test Spatial Lag Model
	Q3c, If subprime lending in a neighborhood increases, which neighborhood (if any) do crime rates change?	Global and Local Moran's I Test Spatial Lag Model

the house market variables to examine whether they are measuring the same underlying construct. Second, I created a new variable for each housing market factor with concentrated disadvantage and created a z-score transformation. Third, I ran two models; one model is crime rates regressed on concentrated disadvantage with control variables, another is crime rates regressed on the new concentrated disadvantage index that includes each housing market variable. I compare the Akaike Information Criteria (AIC) between these two models. The model with the lowest AIC provides the best fitting model (Wagenmakers and Farrel 2004).

The second research question is whether housing market variables are mediators of concentrated disadvantage as it predicts the crime relationship. To test this, I use a method developed by Baron and Kenny (1986) to provide greater evidence for the possibility of mediation. The first step of Baron and Kenny’s method is to determine the total effect of the variable of interest on the outcome by testing a simple regression model and determining that the regression coefficient is different from zero (i.e., the *t*-test is significant at the $p<.05$ level). In this dissertation, I run a simple regression between concentrated disadvantage and the crime rate. The second step to Baron and Kenny’s approach is to produce a simple regression model regressing the potential mediator on the variable of interest. In this step, each housing market variable will be regressed on the concentrated disadvantage index. The third step is to create a full model that includes the variable of interest and the mediator as predictors of the dependent variable. This step allows me to begin to establish if there is a significant (or non-zero) relationship between the mediator and the dependent variable. For this step, I establish a model with both concentrated disadvantage and each housing market variable as the predictors, and the crime rate as the dependent variable to examine if the housing market variables significantly predict crime rate. The fourth and final step is to examine the model created in the third step to establish that the relationship between the independent variable (concentrated disadvantage) and outcome (crime rate) is now zero or non-significant in the presence of the mediator (each housing market variable).

The theoretical implication of the third research question is that crime is not only determined by concentrated disadvantage and the housing market of that neighborhood, but also neighborhoods adjacent or nearby. Methodologically, this leads to a model of spatial dependence in which neighborhood observations are interdependent and are characterized by a "functional relationship between what happens at one place and what happens elsewhere" (Anselin 1988:11). Spatial dependence might also arise due to the correspondence between neighborhood boundaries imposed by census tracts and the ecological patterning of social interactions (Sampson et al. 1999). To answer this question, I first investigate if there is a spatial effect across census tracts in Knoxville in terms of crime and concentrated disadvantage by using a global Moran's I statistic (Cliff and Ord 1973; Moran 1948). Second, once the global Moran's I statistics are tested, I test the local Moran's I statistics using a local indicator of spatial association (LISA) (Anselin 1995). Third, if the spatial patterns are detected, then I use a spatial lag model to examine the relationship between concentrated disadvantage, housing markets, and crime.

Spatial weights are essential elements in the construction of spatial autocorrelation statistics. The spatial weights express the neighbor structure between the observations as a $n \times n$ matrix W in which the elements w_{ij} of the matrix are the spatial weights (Figure 3-3). In its simplest form, the spatial weights matrix expresses the existence of a neighbor relation as a

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix}.$$

Figure 3-3. Basic Spatial Weights Matrix simplest form, the spatial weights matrix expresses the existence of a neighbor relation as a binary relationship, with weights 1 and 0. Formally, each spatial unit is represented in the matrix by a row i, and the potential neighbors by the columns j, with $j \neq i$. The existence of a neighbor relation between the spatial unit corresponding to row i and the one matching column j follows then as $w_{ij} = w_{i,j} = 1$ (Anselin and Rey 2014; Anselin 2020).

The spatial weights include different forms (Anselin and Arribas-Bel 2012; Anselin and Rey 20140). There are Continuity Spatial Weights (rock, bishop, and quees), Distance-Based Spatial Weights, and K-Nearest Neighbor Weights. The continuity means that two spatial units share a common border of non-zero length. The distance-based spatial weights measure the distance of two spatial points $i \; and \; j$ with respective coordinates $(x_i, y_i) \; and \; (x_j, y_j)$. In this dissertation, I use continuity spatial weights as the continuity spatial weights are based on the common shared borders of different spatial units. As is shown in Figure 3-2, the unit of analysis of this dissertation are 86 census tracts in the city of Knoxville. This spatial form is in accordance with the continuity weight character. The differences among rock continuity, bishop continuity and queen continuity are that rock continuity is based on common edges between spatial units, not the diagonal, and bishop continuity is based on the common corners between spatial units. Queen continuity is based on both common edges and corners among spatial units. The queen continuity spatial weights are in accordance with the spatial characteristics of 86 census tracts under study as the census tracts are not quadrate, which are not easily to identify the edge and corner.

Moran's I statistic is the most used indicator of global spatial autocorrelation. Fundamentally, it is a cross-product statistic between a variable and its spatial lag, with the variable expressed in deviations from its mean. For a variable x with observation of location i, this is expressed as:

$$z_i = x_i - \bar{x}$$

where $\bar{x}$ is the mean of variable x. Moran's I statistic is then:

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j / S_0}{\sum_i z_i^2 / n}$$

with w_{ij} as the elements of the spatial weights matrix, $S_0 = \sum_i \sum_j w_{ij}$ as the sum of all the weights, and *n* as the number of observations.

Moran scatter plot was first outlined in Anselin (1996) and consists of a plot with the spatially lagged variable on the y-axis and the original variable on the x-axis. The slope of the linear fit to the scatter plot equals Moran's I. The principle underlying the Moran scatter plot lies in two aspects that I am using. First, let's consider the Moran's I statistic:

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j / S_0}{\sum_i z_i^2 / n}$$

I consider the variable z, given in deviations from the mean. With row-standardized weights, the sum of all the weights S_0 equals the number of observations n. As a result, the expression for Moran's I simplifies to:

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j}{\sum_i z_i^2} = \frac{\sum_i \left(z_i \cdot \sum_j w_{ij} z_j\right)}{\sum_i z_i^2}$$

Upon closer examination, this turns out to be the slope of a regression of $\sum_j w_{ij} z_j$ on z_i^3. This is the first principle of Moran's scatter plot.

Second, the visualization of Moran's scatter plot is the classification of the nature of spatial autocorrelation into four categories (Luc Anselin 2022). Since the plot is centered on the mean of zero, all points to the right of the mean are $z_i > 0$, and all points to the left are $z_i < 0$. O I refer to these values, respectively, as high and low, in the limited sense of higher and lower than average. The scatter plot is easily decomposed into four quadrants. The upper-right quadrant and the lower-left quadrant correspond with positive spatial autocorrelation (similar values at neighboring locations). I refer to them, respectively as high-high and low-low spatial autocorrelation. In contrast, the lower-right and upper-left quadrant correspond to negative spatial autocorrelation (dissimilar values at neighboring locations). I refer to them as respectively high-low and low-high spatial autocorrelation. It is important to note that the classification does not imply significance, and it only tells the spatial patterns of all tracts in the city of Knoxville in terms of variable concerned.

Figure 3-4 shows the test statistic result of global Moran's I for the four-year average crime rate. The green line shows the value of the statistic for the actual data, placed at 0.5452, well to the right of the reference distribution. The z-score that correspond to computed Moran's I (0.5452) is 9.2498. This suggest a strong rejection of the null hypothesis that there is spatial randomness (no spatial autocorrelation) and I conclude that crimes across census tract in Knoxville are spatially clustered, meaning that crime and victimization in Knoxville occurs more often in some census tracts, while in others census tracts, it does not occur very often (for more details, see local Moran's I analysis).

Figure 3-5 shows the result of Moran's scatter plot of variable crime rate four-year average. The slope of the line is the value of global Moran's I as I have indicated in the above formula. The upper-right and lower-left quadrants are census tracts that display positive spatial autocorrelation to crime. These census tracts are similar to each other in terms of crime patterns,

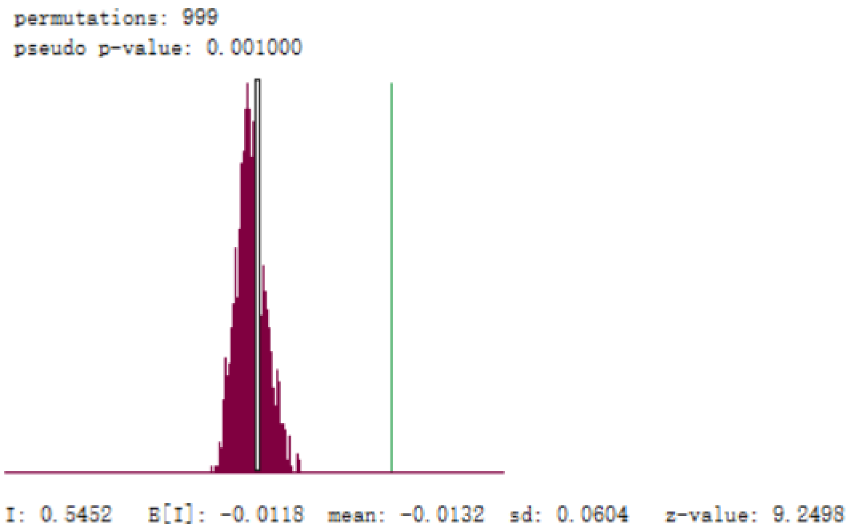

Figure 3-4. Test Statistics of Global Moran's I of Crime Rate Four-Year Average

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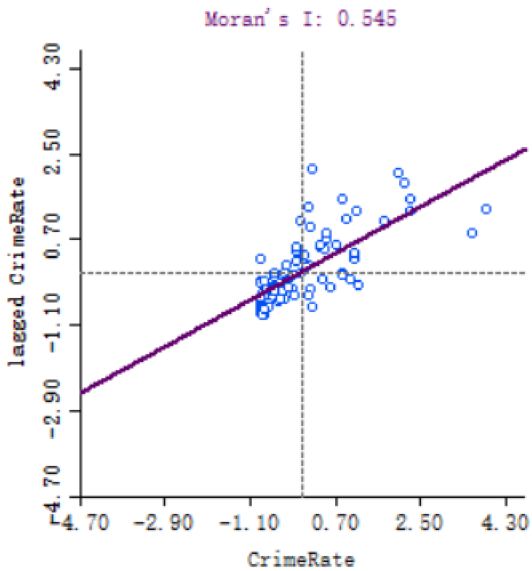

Figure 3-5. Moran Scatter Plot of Crime Rate Four-Year Average

while the lower right and upper left quadrant are tracts that are negative spatial correlation, these census tracts are different (dissimilar) from their neighboring tracts in terms of crime cases. Out of 88 census tracts, there are more tracts that crime and victimization occur that are positively autocorrelated (i.e., crime cases are more spatially clustered) because more dots are in the upper-right and lower-left quadrants, and less dots are in the lower-right and upper-left quadrants, which is a sign of spatially heterogeneous crime.

Figures 3-6 and 3-7 show the test statistic of global Moran's I and Moran's scatter plot of the main independent variable, concentrated disadvantage (other independent variables will be shown in the following chapters). The Moran's I value is 0.542 and the green line is well to the right of the reference distribution. The z-score that correspond to the computed Moran's I (0.542) is 8.621. This also suggests a strong rejection of the null hypothesis, and I conclude that concentrated disadvantage across census tract in Knoxville are spatially autocorrelated.
Figure 3-6 displays Moran's scatter plot of concentrated disadvantage. The scatter pattern is similar to that of crime in the sense that most tracts are located in the upper-right and lower-left quadrant, which display positive spatial autocorrelation. It is clear that several tracts lie within the upper-left quadrant, which are negatively autocorrelated. In general, like crime, concentrated disadvantage has more tracts that are spatially clustered from their neighboring tracts than those that are spatially heterogeneous (dissimilar) from neighboring tracts.

Bivariate global Moran scatter plot extends univariate Moran scatter plot used above with a variable on the x-axis and its spatial lag on y-axis to a bivariate context. The bivariate spatial correlation measures the degree to which the value for a given variable at a location is correlated with its neighbors for a different variable (Anselin, Syabri and Smirnov 2002; Lee 2001; Luc

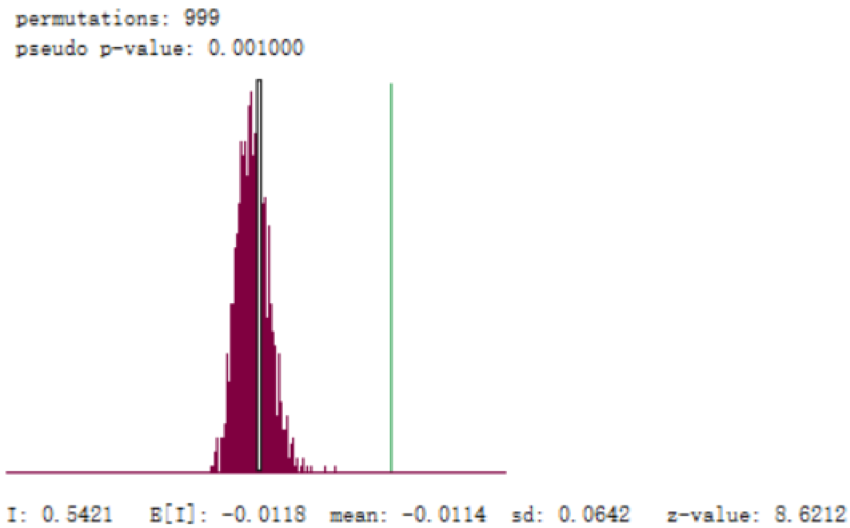

Figure 3-6. Test Statistics of Global Moran's I of Concentrated Disadvantage Four-Year Average

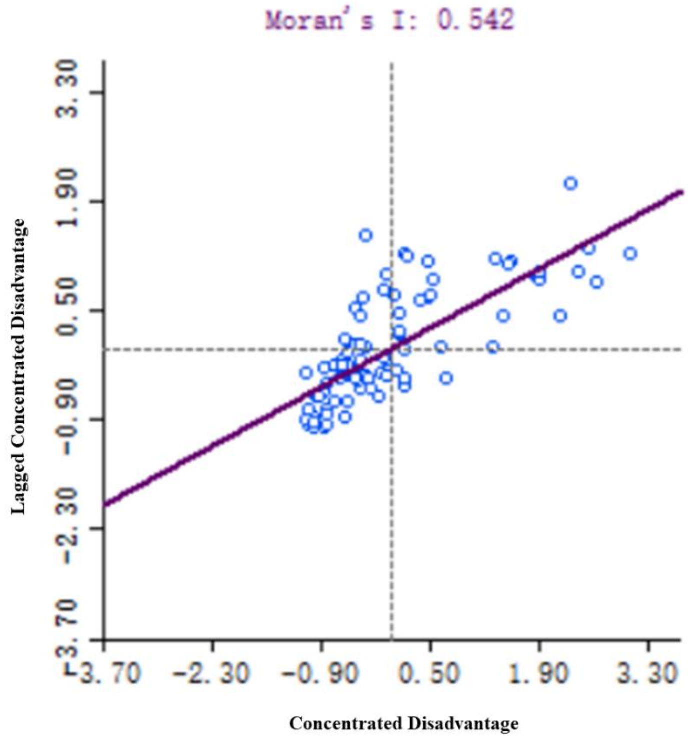

Figure 3-7. Moran Scatter Plot of Concentrated Disadvantage Four-Year Average

Anselin 2020). Figures 3-8 and 3-9 show the bivariate Moran's I test and Moran's scatter plot of concentrated disadvantage and lagged crime. The pseudo p-value indicates that the association between concentrated disadvantage and lagged crime is significant. The bivariate Moran's I is 0.505. As we can see from the Moran scatter plot, most tracts (dots) are located in the upper-right and lower-left quadrants, which are most spatially clustered. Therefore, concentrated disadvantage in a census tract generally has significant associations with crime in a neighboring tract.

A local indicator of spatial association (LISA) was proposed by Luc Anselin (Anselin 1995). Global spatial autocorrelation aims to reject the null hypothesis of spatial randomness in favor of an alternative hypothesis of spatial patterning, which is either spatial clustering or spatial heterogeneity. However, global spatial autocorrelation does not provide the locations of the cluster or outliner. LISA amends this method with two important characteristics. First, it provides a statistic for each location with an assessment of significance. Second, it provides a proportional relationship between the sum of local statistics and a corresponding global statistic. Different from global spatial autocorrelation, which is expressed as a double sum over i and j indices, such that $\sum_i \sum_j g_{ij}$, the local form of such a statistic would be, for each observation (location) i, the sum of the relevant expression over the j index, such that $\sum_g g_{ij}$.

Spatial autocorrelation consists of a combination of a measure of attribute similarity between a pair of observations, $f(x_i, x_j)$, with an indicator for geographical or locational similarity, in the form of spatial weights, w_{ij}. For a global statistic, it takes on the form $\sum_i \sum_j w_{ij} f(x_i, x_j)$. A generic form for a local indicator of spatial association is:

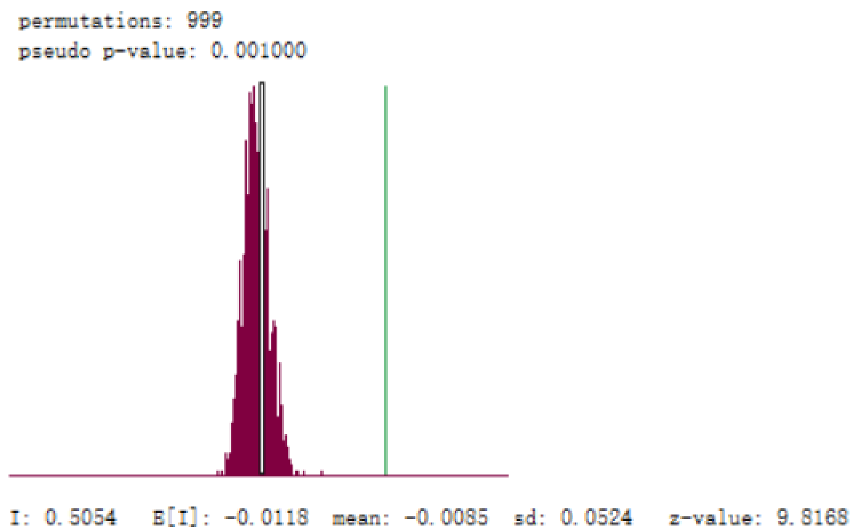

Figure 3-8. Test Statistic of Bivariate Global Moran's I of Concentrated Disadvantage and Lagged Crime Rate

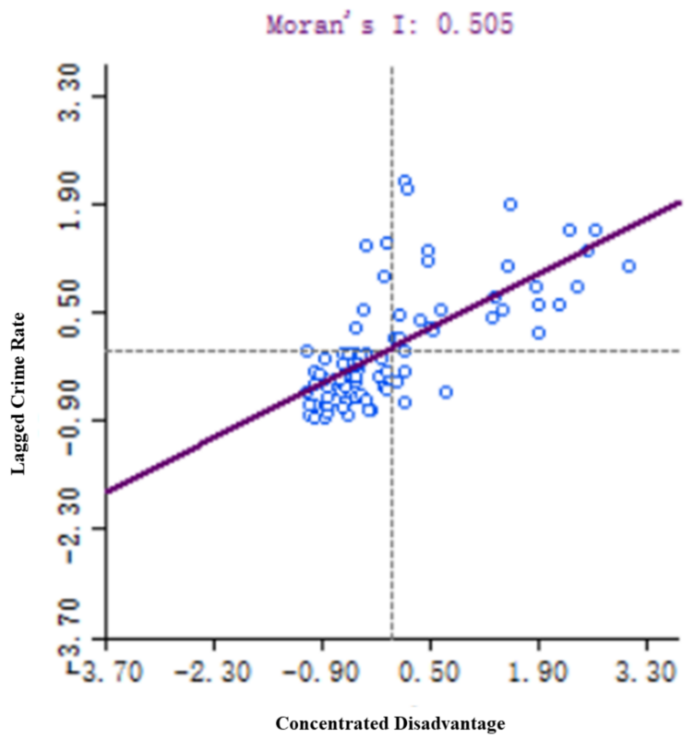

Figure 3-9. Bivariate Moran Scatter Plot of Concentrated Disadvantage and Lagged Crime Rate

$$\sum_j w_{ij} f(x_i, x_j)$$

The local Moran's I statistic is a way to identify local clusters and local spatial outliners. Following the logic of Global Moran's I (2) and LISA (5). The Local Moran's I is expressed as:

$$I_i = \frac{\sum_j w_{ij} z_i z_j}{\sum_i z_i^2}$$

where i represents the observation of the data (For details, see Anselin 1995).

Figures 3-10, 3-11 and 3-12 show the local Moran's I scatter plot, LISA significance map, and LISA cluster map for crime rate. Table 3-8 shows the geographic information of tracts and the corresponding spatial pattern for crime rate. As I have already interpreted the Moran scatter plot and its significant value, we now turn to the cluster map. In the left panel of the cluster map, there are five categories. The colored four categories dark red, dark blue, light red and light blue are significant tracts, and the grey category are non-significant tracts for all other four spatial patterns. High-High, Low-Low, Low-High and High-Low represent the spatial patterns of the tracts that located correspondingly in the upper-right, lower-left, upper-left and low-right quadrant. These are the values relative to the mean, which is the center of the plot. High-High and Low-Low represent positive spatial autocorrelation and spatial clustering (spatial similarity). Low-High and High-Low represent negative spatial autocorrelation and spatial heterogeneity (spatial dissimilarity).

From Figure 3-12, there are 16 tracts of crime significantly clustered (dark red) in the center of Knoxville. These large areas include the neighborhoods of College Hills, Coster Yards, Cecil Ave, Plantation Hills, Zoo Knoxville, Burlington, Richmond Hill, Happy Holler, Parkridge, Mabry's Hill, Fort Sanders and Malcolm Martin Park. Also, there are four large areas

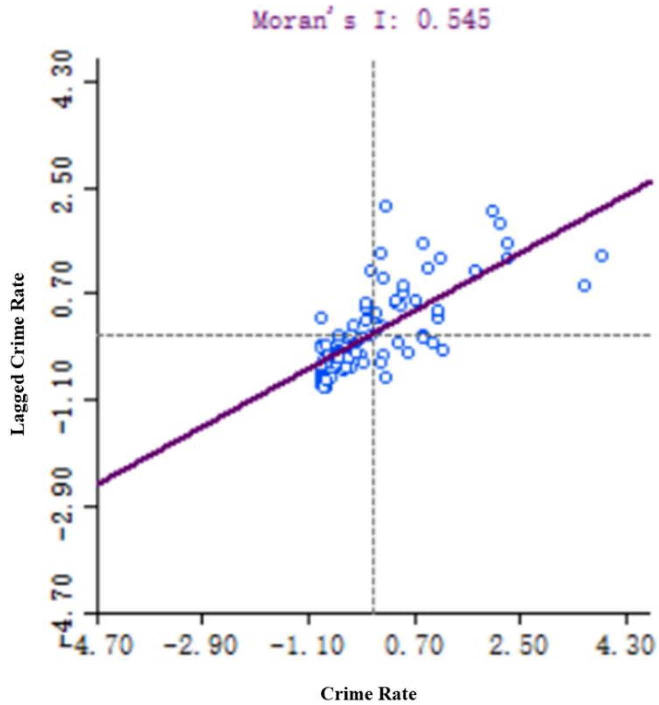

Figure 3-10. Local Moran Scatter Plot for Crime Rate Four-Year Average

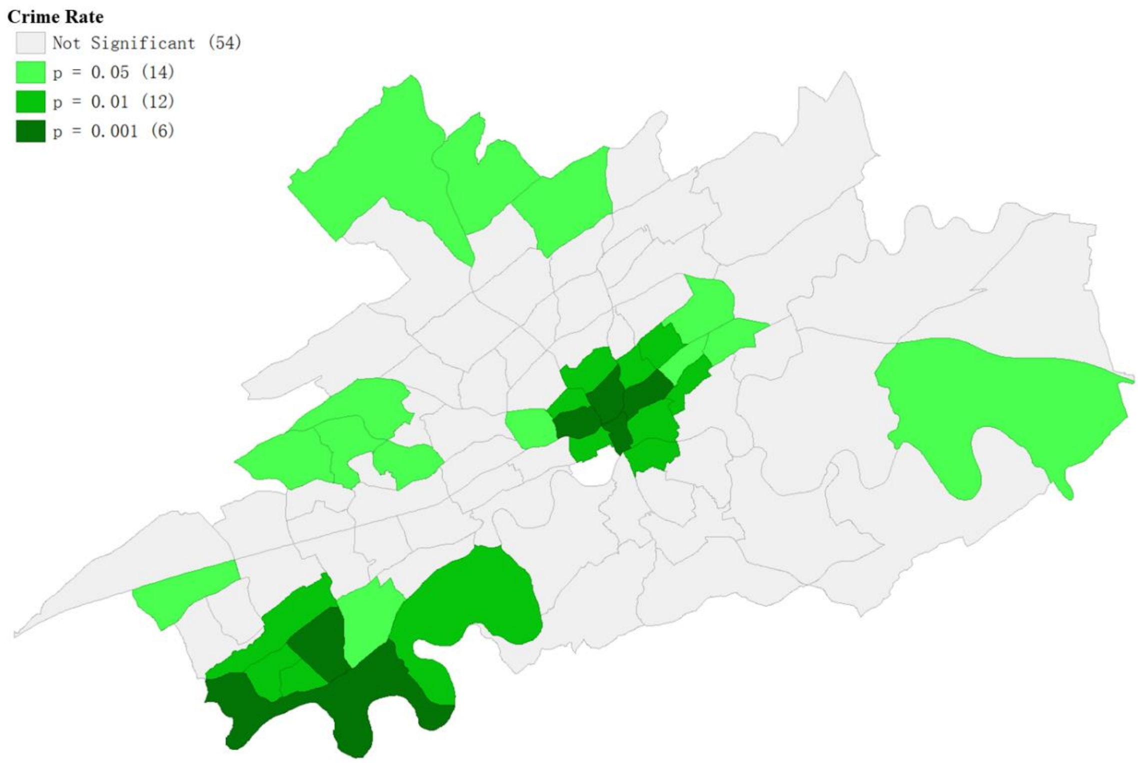

Figure 3-11. Local Moran Significance Map for Crime Rate Four-Year Average

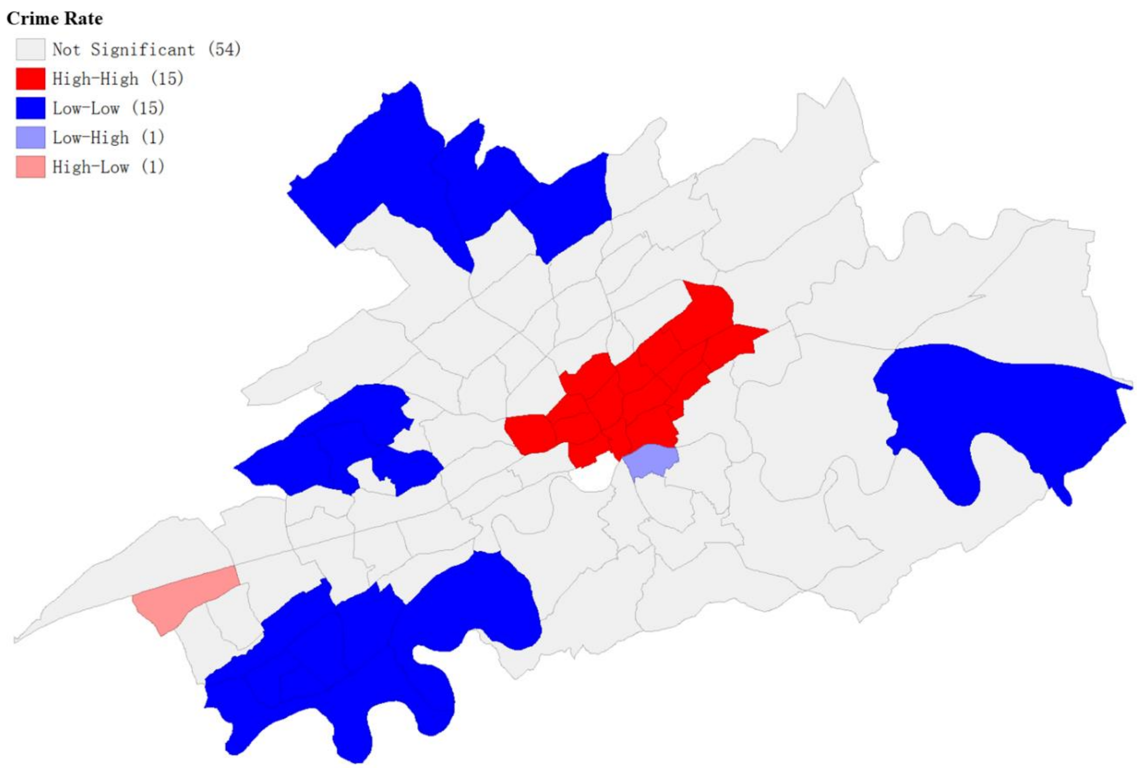

Figure 3-12. Local Moran Cluster Map for Crime Rate Four-Year Average

Table 3-8. Geographic Information of Tracts and Corresponding Spatial Patterns for Crime Rate

Spatial Patterns	Census Tract	Places	Crime Rate
High-high Spatial Pattern	1	Cumberland Ave; Summit Hill	44.36
	14	College Hills; Western Hights	29.42
	15	Coster Yards; Oakwood-Lincoln Park	17.13
	17	Cecil Ave; Michell Street; Coker Ave	19.05
	18	Plantation Hills	9.65
	19	Zoo Knoxville	41.94
	20	Burlington	16.22
	27	Richmond Hill; West View	13.14
	66	Happy Holler; Old Grey Cemetery; 4th and Gill	27.19
	67	Parkridge	28.41
	68	Mabry’s Hill	24.35
	69	Fort Sanders	10.34
	70	Malcolm Martin Park	29.54
Low-low Spatial Pattern	46.06	Brentwood; Trails End; Glen Arden	0.05
	46.07	Fair Oaks; Hidden Hills	1.53
	46.13	Meadowbrookl; Hunting Hills West;	0.64
	46.15	Amherst	5.00
	54.02	Stony Point; Midway; Peters Mill; Riverdale	0.91
	57.01	Riverbend; Westminister Ridge	0.55
	57.07	Lakewood; Ebenezer	0.08
	57.08	Garland	0.01
	57.09	Scenic Valley-Poplar Hill-Tierra Verde	1.07

Table 3-8 (Continued)

Spatial Patterns	Census Tract	Places	Crime Rate
	57.10	Blue Grass	0.52
	57.11	Pine Springs; Farmington	0.30
	57.12	Kensington; Farrington	0.05
	61.02	Heiskell	0.35
	62.06	Cedar Crest North; Whispering Hills	0.23
	62.08	Fieldview; Fountaincrest;	0.03
Low-high Spatial Pattern	8	Flagship Kerns; Suttree Landing Park; Lincoln Street	7.97
High-low Spatial Pattern	58.03	Boxwood Hills; SweetBriar	10.34

(dark blue) that are also significantly clustered, but with a low crime rate relative to the mean. They are tracts 61.02, 62.06 and 62.08, which represent the neighborhoods of Heiskell, Cedar Crest North, Fieldview and Fountaincrest in the north of the city; tracts 54.01, 54.02, and 53.02, which are the neighborhoods of Marbledale, Stony Point and Peters Mill, these neighborhoods are located in the southeast of Knoxville; tracts 46.06, 46.07, 46.13 and 46.15 are the places of Berkshire Wood, Meadowbrook, Canby Hills and Amherst neighborhoods; tracts 57.01, 57.07, 57.08, 57.09, 57.10, 57.11 and 57.12, includes neighborhoods of Riverbend, Lakewood, Garland, Scenic Valley-Poplar Hill-Tierra Verde, Blue Grass, Famington and Kensington. The cluster map also shows one tract that are significantly spatially outliners (light blue). This tract has a low crime rate and a high lagged crime rate in their adjacent tracts, which is already shown in dark red. This is tract 8, it is the neighborhood surrounded by the Chapman Hwy, South Heaven Rd, East Moody Ave and the Tennessee River. There is also one tract having a significantly high-low spatial pattern. This tract is 58.03, located in the west of Knoxville, which is the neighborhood of Boxwood Hills and Sweet Briar.

Concentrated disadvantage’s local Moran’s I scatter plot, LISA significance map, and LISA cluster map are shown in Figures 3-13, 3-14 and 3-15. Table 3-9 displays the geographic information of tracts and the corresponding spatial pattern for concentrated disadvantage. The cluster map in Figure 3-15 shows that concentrated disadvantage is significantly spatially autocorrelated in 36 census tracts in Knoxville. Of which 33 tracts are significantly spatially clustered (dark blue and dark red). The dark red areas, which are high disadvantaged tracts significantly correlated to lagged high disadvantaged in their adjacent tracts. These neighborhoods are Flagship Kerns, College Hills, Coster Yards, Zoo Knoxville, Marble Hill,

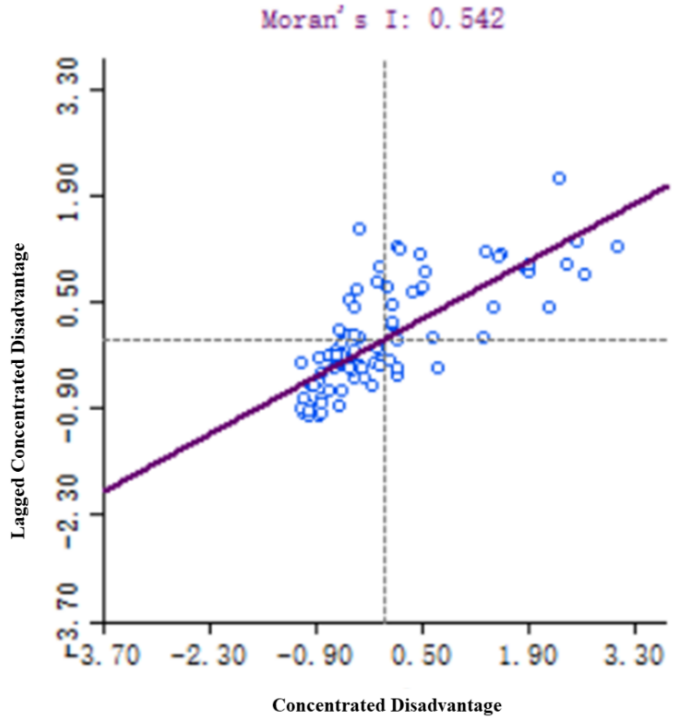

Figure 3-13. Local Moran Scatter Plot for Concentrated Disadvantage Four-Year Average

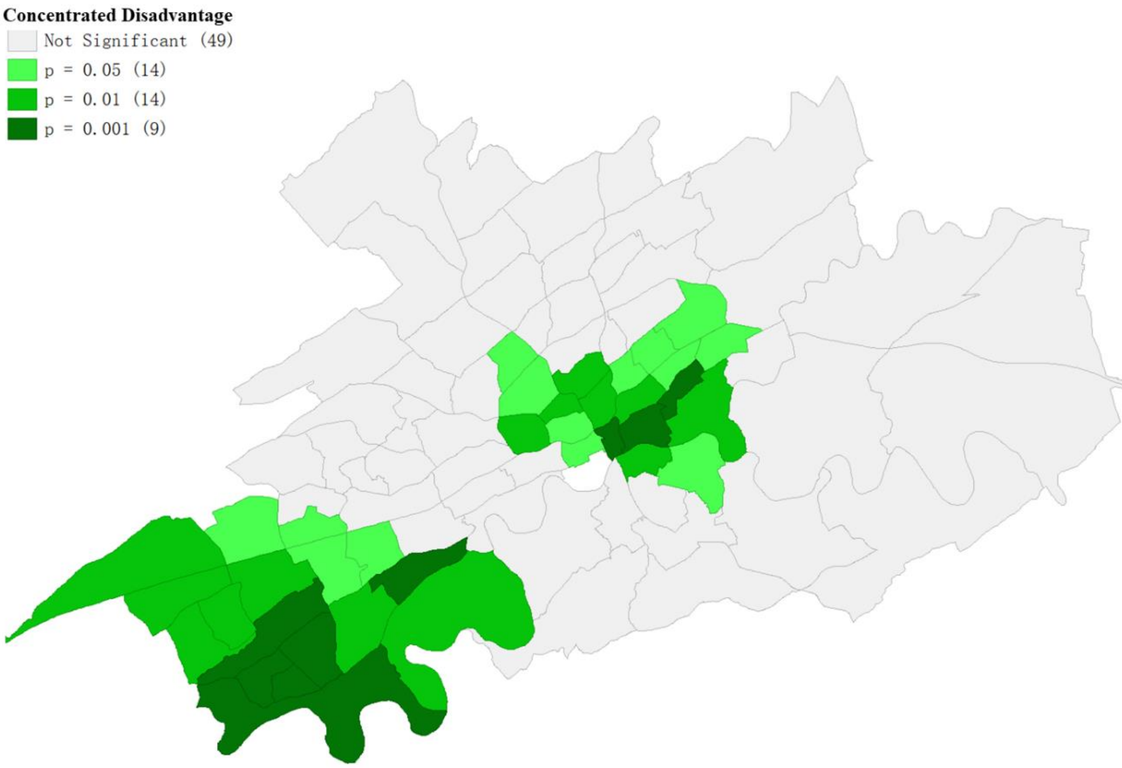

Figure 3-14. Local Moran Significance Map for Concentrated Disadvantage Four-Year Average

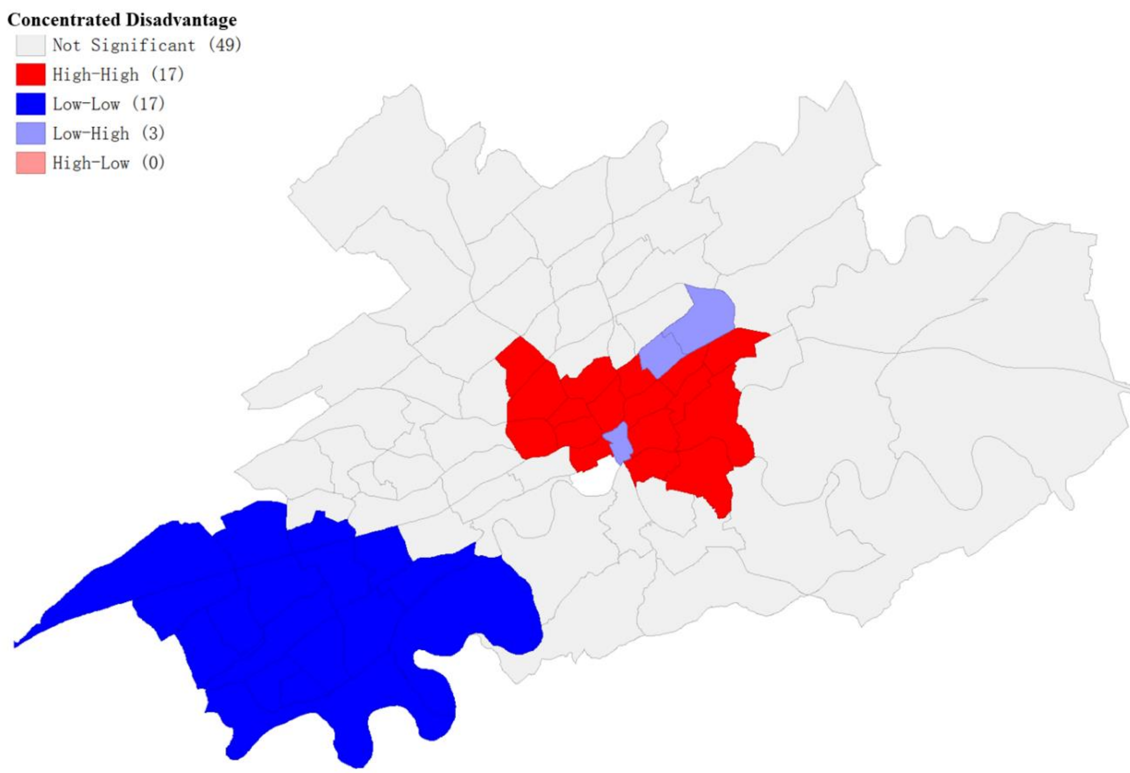

Figure 3-15. Local Moran Cluster Map for Concentrated Disadvantage Four-Year Average

Table 3-9. Geographic Information of Tracts and Corresponding Spatial Patterns for Concentrated Disadvantage

Spatial Patterns	Census Tract	Places	Concentrated Disadvantage
High-high Spatial Pattern	8	Flagship Kerns; Suttree Landing Park; Lincoln Street	1.32
	14	College Hills; Western Hights	2.21
	15	Coster Yards; Oakwood-Lincoln Park	0.40
	17	Cecil Ave	0.41
	19	Zoo Knoxville	2.10
	20	Burlington	2.01
	21	Marble Hill; Holston Park	1.67
	22	Island Home	0.48
	27	Richmond Hill; West View	1.17
	28	Lonsdale	1.67
	32	Chilhowee Hill	1.63
	39.02	Norwood	0.45
	66	Happy Holler; Old Grey Cemetery; 4th and Gill	0.17
	67	Parkridge	1.33
	68	Mabry’s Hill	2.70
	69	Fort Sanders	0.13
	70	Malcolm Martin Park	2.30
Low-low Spatial Pattern	44.01	Hickory Hills	-0.87
	44.03	Montuve	-0.50
	46.10	Crestwood Hills	-0.16
	46.11	Rennbore; Belmont West	-0.83
	57.01	Riverbend; Westminister Ridge	-0.93
	57.04	Suburban Hills; Echo Valley	-0.64
	57.06	Ashley Oaks; Sevenoaks	-0.74

Table 3-9 (Continued)

Spatial Patterns	Census Tract	Places	Concentrated Disadvantage
	57.07	Lakewood; Ebenezer	-0.87
	57.08	Garland	-0.92
	57.09	Scenic Valley-Poplar Hill-Tierra Verde	-0.76
	57.10	Blue Grass	-0.87
	57.11	Pine Springs; Farmington	-0.88
	57.12	Farrington; Kensington; Fox Fire	-0.96
	58.03	Boxwood Hills; Sweet Briar; Woodland Trace	-0.73
	58.07	Lovell Heights; Tan Rara Oesta	-0.89
	58.08	Farragut; Concord Woods	-0.74
	59.04	Amber Meadows; Twin Springs	-0.52
Low-high Spatial Pattern	1	Cumberland Ave; Summit Hill	-0.29
	18	Plantation Hills	-0.05
	31	Loveland	-0.08

West View, Lonsdale, Chilhowee Hill, Parkridge, Mabry's Hills, Malcolm Martin Park, Norwood and Island Home. This large, clustered area is located in the center of the city (mostly south of downtown), as is indicated in the cluster map. The dark blue areas are largely clustered in west Knoxville, these tracts significantly have low disadvantage correlated with the lagged low disadvantage in adjacent tracts. These neighborhoods are Hickory Hills, Montuve, Crestwood Hills, Riverbend, Suburban Hills, Ashley Oaks, Lakewood, Garland, Scenic Valley-Poplar Hill-Tierra Verde, Rennbore, Blue Grass, Pine Springs, Farrington, Boxwood Hills, Lovell Heights, Farragut and Amber Meadows. The light blue tracts are significantly low disadvantage correlated with lagged high disadvantage in their adjacent tracts. These neighborhoods are downtown Knoxville, Plantation Hills, and Loveland.

Bivariate local Moran of spatial patterns between concentrated disadvantage and lagged crime is shown in Figures 3-16, 3-17 and 3-18. Table 3-10 displays the geographic information of tracts and the corresponding spatial pattern for concentrated disadvantage and lagged crime rate. The cluster map in Figure 3-18 shows that There are 35 census tracts that are significantly associated in terms of the spatial patterns between concentrated disadvantage in a tract and crime in the neighboring tracts. Of which, 29 census tracts have positive association (dark red and dark blue). The dark red shows the highly concentrated disadvantage tracts that are significantly associated with high crime in its neighboring tracts. These tracts include neighborhoods of Flagship Kerns, College Hills, Coster Yards, Zoo Knoxville, Burlington, West View, Happy Holler, Parkridge, Fort Sanders, Mabry's Hill and Malcolm Martin Park. Dark blue are the tracts that have a significantly low disadvantage and low crime in its adjacent tracts. These neighborhoods are Glen Arden, Fair Oaks, Meadowbrook, Moshina Heights, Stony Point,

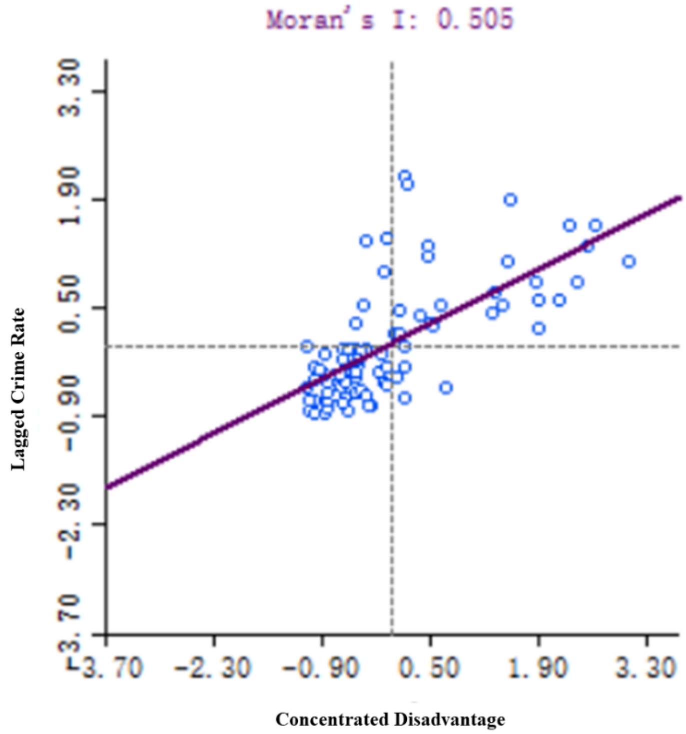

Figure 3-16. Bivariate Local Moran Scatter Plot of Concentrated Disadvantage and Lagged Crime

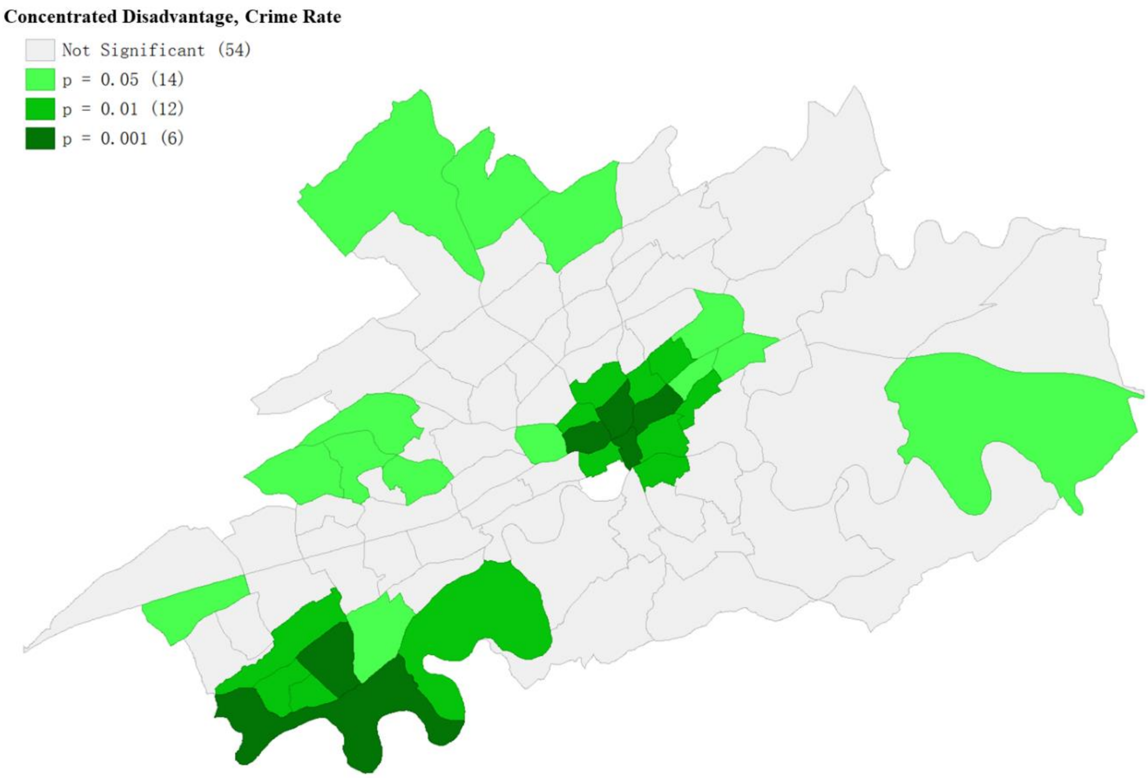

Figure 3-17. Bivariate Local Moran Significance Map of Concentrated Disadvantage and Lagged Crime

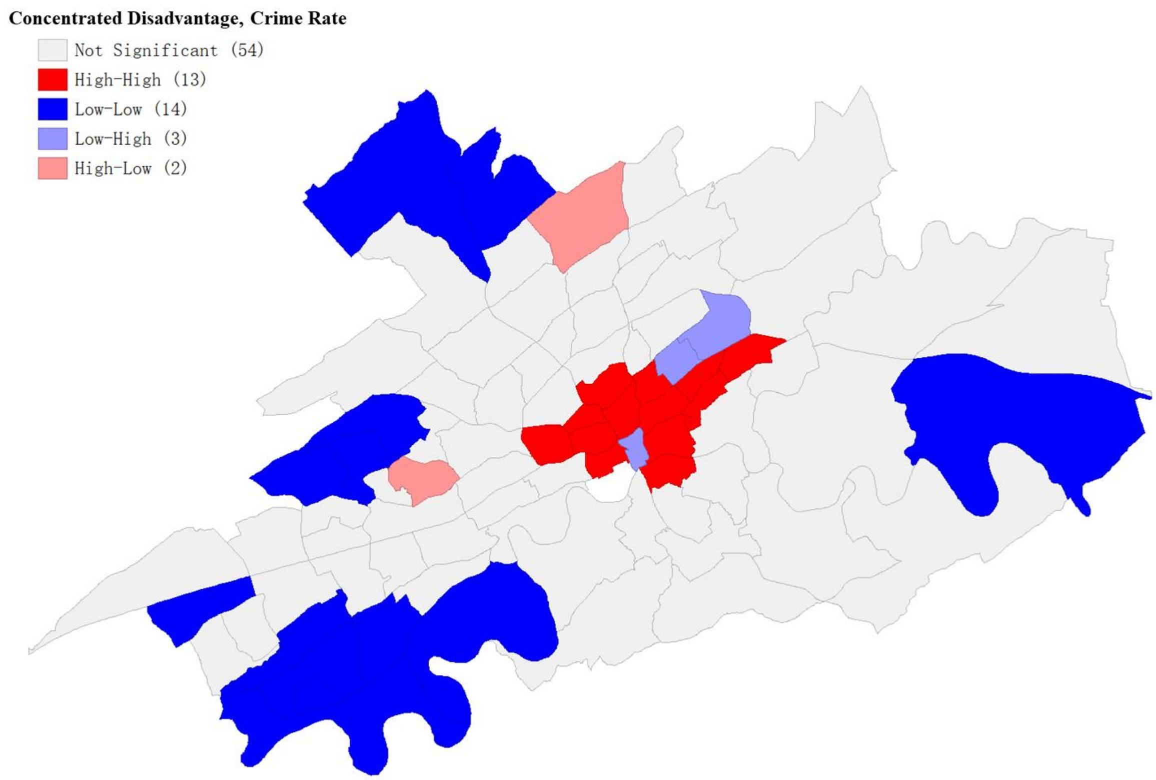

Figure 3-18. Bivariate Local Moran Cluster Map of Concentrated Disadvantage and Lagged Crime

Table 3-10. Geographic Information of Tracts and Corresponding Spatial Patterns for Concentrated Disadvantage and Lagged Crime Rate

Spatial Patterns	Census Tract	Places
High-high Spatial Pattern	8	Flagship Kerns; Suttree Landing Park; Lincoln Street
	14	College Hills; Western Hights
	15	Coster Yards; Oakwood-Lincoln Park
	17	Cecil Ave; Michell Street; Coker Ave
	19	Zoo Knoxville
	20	Burlington
	27	Richmond Hill; West View
	32	Chilhowee Hills
	66	Happy Holler; Old Grey Cemetery; 4th and Gill
	67	Parkridge
	68	Mabry’s Hill
	69	Fort Sanders
	70	Malcolm Martin Park
Low-low Spatial Pattern	46.06	Brentwood; Trails End; Glen Arden
	46.07	Fair Oaks; Hidden Hills
	46.13	Meadowbrookl; Hunting Hills West;
	54.02	Stony Point; Midway; Peters Mill; Riverdale
	57.01	Riverbend; Westminister Ridge
	57.07	Lakewood; Ebenezer
	57.08	Garland
	57.09	Scenic Valley-Poplar Hill-Tierra Verde
	57.10	Blue Grass
	57.11	Pine Springs; Farmington
	57.12	Kensington; Farrington
	58.03	Boxwood Hills; Sweet Briar; Woodland Trace
	61.02	Heiskell
	62.06	Cedar Crest North; Whispering Hills
Low-high Spatial Pattern	1	Cumberland Ave; Summit Hill
	18	Plantation Hills
	31	Loveland

Table 3-10 (Continued)

Spatial Patterns	Census Tract	Places
High-low Spatial Pattern	46.15	Amherst
	62.08	Fieldview; Fountaincrest;

Riverbend, Lakewood, Garland, Blue Grass, Pine Springs, Kensington, Boxwood Hills, Heiskell and Whispering Hills. There are 4 light blue tracts showing a low concentrated disadvantage significantly associated with high crime in their neighboring tracts. They are downtown Knoxville, Plantation Hills, and Loveland. There are two light red tract (tracts 46.15 and 62.08) that have significantly high concentrated disadvantage and low crime rate in its adjacent tracts, which is the neighborhoods of Amherst, Fieldview and Fountaincrest. Overall, more neighborhoods of concentrated disadvantage and crime are spatially clustered, while only 6 neighborhoods are spatial outliners on this relationship in Knoxville.

CHAPTER FOUR

EVICTION ANALYSIS

Based on the analytic strategy from the previous chapter, in this chapter I focus on eviction and its role in the relationship between concentrated disadvantage and crime at the tract level in Knoxville. Specifically, I ask:

RQ1a. Does concentrated disadvantage better predict crime when eviction is added to the concentrated disadvantage index?

RQ2a. Do evictions mediate Sampson's model of concentrated disadvantage and crime?

RQ3a. If evictions in a neighborhood increase, in which neighborhood (if any) do crime rates change?

Research Question 1a

To answer my first research question (Q1a), it is necessary to conduct factor analysis with the six concentrated disadvantage variables in Sampson's index and include eviction. Table 4-1 shows rotated factor loadings of these seven variables, which loaded on a single factor. Since they load together with factor loadings on all variables of at least 0.7, it is reasonable to assume that they are all measuring the same underlying construct. Therefore, I create a new concentrated disadvantage index that includes eviction and make it z-score transformed. The Cronbach's alpha of concentrated disadvantage that includes the eviction variable is 0.91. Table 4-2 displays the regression results for the crime rate regressed on both the old and new concentrated disadvantage index. From the AIC, Model 1 has an AIC value of 576.60, which is smaller than the AIC of Model 2 at 577.06. Burnham and Anderson (2002) suggest smaller differences in AICs provide

Table 4-1. Rotated Factor Loadings for Concentrated Disadvantage Variables and Eviction

Variables	Factor 1
Percent poverty	0.89
Prevent female-headed household	0.87
Precent government assistance	0.93
Percent unemployment	0.77
Percent people under 18 years	0.89
Percent Black	0.80
Eviction	0.73

Table 4-2. Regression Results for Concentrated Disadvantage and Eviction Index on Crime Rate

	Model 1		Model 2	
	Coef/se	*Beta*	*Coef/se*	*Beta*
Sampson's concentrated disadvantage index	4.86*** (1.30)	0.46	N/A	N/A
Disadvantage index including eviction	N/A	N/A	4.94*** (1.35)	0.46
Percent of unoccupied housing units	0.59** (0.19)	0.30	0.59** (0.19)	0.30
Median gross rent	-0.74 (0.41)	-0.18	-0.69 (0.41)	-0.17
Median home value	0.02 (0.01)	0.15	0.01 (0.01)	0.14
Constant	6.82 (4.07)	N/A	6.47 (4.10)	N/A
F (4,81)	20.63***		20.41***	
R-squared	0.50		0.50	
AIC	576.60		577.06	
N	86		86	

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

more support for selecting the model with the smallest AIC. Differences in AIC are considered "substantial" if differences in AICs between models are between 0 and 2, "considerably less" if the differences are between 4 and 7, and "essentially" not different if the differences are greater than 10. The difference in AIC between Model 1 and Model 2 is 0.46, with Model 1 exhibiting the smaller AIC. Therefore, I conclude that Model 1 is the better model, and the new concentrated disadvantage index has not improved the prediction of crime in Knoxville compared to simply using Sampson's concentrated disadvantage index.

From the results of Model 1, with a one standard deviation increase in Sampson's concentrated disadvantage index, the crime rate significantly increased approximately 5 per 100 people, controlling for percent of unoccupied housing units, median gross rent, and median home value ($t=3.74$, $p<0.001$). For each one percent increases in unoccupied housing units, the crime rate significantly increased 0.59 per 100 people, holding all other variables constant ($t=3.05$, $p<0.01$). Median gross rent and median home value are not significantly associated with crime rate in Model 1, but it is worth noting that a non-significant p-value is weak evidence for the absence of an effect when creating OLS regression models with a small sample size ($N=86$ in this research; Jenkins and Quintana-Ascencio 2020; Bohon and Nagle 2022). Controls that are marginally significant ($p<.10$) should not be simply dismissed. For every $100 increase in the median gross rent, the crime rate dropped 0.74 per 100 people ($t=-1.82$, $p=0.07$), controlling for all other variables. In Model 1, concentrated disadvantage index, percent of unoccupied housing units, median gross rent, and median home value together explain 50 percent of the variance in crime rates across census tracts in Knoxville.

Model 2 is the less well-fitting of the two models bur it is worth discussing to better understand the relationship (or lack thereof) between eviction, concentrated disadvantage, and crime. From the results of Model 2, for one standard deviation increase in the new concentrated disadvantage index, the crime rate significantly increases about 5 units per 100 people, controlling for percent of unoccupied housing units, median gross rent, and median home values ($t=3.67$, $p<0.001$). For each one percent increases in unoccupied housing units, the crime rate significantly increased 0.59 per 100 people across tracts in Knoxville, holding all other variables constant ($t=3.05$, $p<0.01$). Neither median gross rent, nor median home value are not significantly or marginally associated with crime rate in Model 2, but median gross rent is close. For $100 increase in the median gross rent, the crime rate dropped 0.69 per 100 people ($t=-1.67$, $p=0.1$), controlling for all other variables. In Model 2, new concentrated disadvantage index, percent of unoccupied housing units, median gross rent, and median house value together explain 50 percent of the variance in crime rate across census tracts in Knoxville.

The new concentrated disadvantage index produces a larger coefficient than Sampson's, but such comparison should not be made on their face. To compare the relative strength of coefficients between Model 1 and Model 2, it is necessary to standardize the regression coefficient so that they are on the same metric. From Table 4-2, both Sampson's concentrated disadvantage index and the new concentrated disadvantage index have the same beta coefficient of 0.46, followed by a percent of unoccupied housing units of 0.30 in both models. Therefore, this information along with the AIC suggests that the contributions of Sampson's concentrated disadvantage index and the new concentrated disadvantage index have the most impact on models of crime rate, but adding eviction is not improving Sampson's concentrated disadvantage index.

Research Question 2a

The strategy for answering the second research question (Q2a) is to add eviction to the crime rate regressed on concentrated disadvantage model to look for possible mediation. It is worth considering that when adding a variable into a model, the coefficient value or sign of the main effect (in this case, the crime rate regressed on concentrated disadvantage), or the significance value of the main effect might change (Allison 1977; Baron and Kenny 1986). In the following section, I will use the method developed by Baron and Kenny (1986) to provide initial evidence for the possibility of mediation, as is outlined in Chapter 3.

Table 4-3 illustrates Baron and Kenny's steps for mediation. In Model 1 (first step), crime is regressed on concentrated disadvantage. For a one standard deviation increase in Sampson's concentrated disadvantage index, crime rates significantly increase about 6.68 crimes per 100 people ($t=7.47$, $p<0.001$). In Model 2 (second step), concentrated disadvantage is regressed on eviction, and the results show that concentrated disadvantage is significantly and positively associated with eviction. For every one standard deviation increase in Sampson's concentrated disadvantage index, eviction counts significantly increase by about 13 evictions ($t=9.18$, $p<0.001$). In Model 3 (third step), when concentrated disadvantage and eviction are both included to predict crime rate, concentrated disadvantage remains significant and positive, and the coefficient of concentrated disadvantage slightly decreased from 6.68 in step 1 to 6.04 in step 3. However, eviction is non-significant. For a one standard deviation increase in Sampson's concentrated disadvantage index, crime rates significantly increased 6.04 crimes per 100 people

Table 4-3. Baron and Kenny Steps for Mediation of Eviction

	Model 1 (step1) Crime Rate *Coef/se*	Model 2 (step2) Eviction *Coef/se*	Model 3 (step3) Crime Rate *Coef/se*
Concentrated disadvantage	6.68***	12.69***	6.04***
	(0.89)	(1.38)	(1.27)
Eviction	N/A	N/A	0.05
			(0.07)
Constant	8.37***	16.47***	7.55***
	(0.78)	(1.21)	(1.41)
F (1,84)/F (2,83)	55.87***	84.29***	28.02***
R-squared	0.40	0.50	0.40
N	86	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

(t=4.76, p<0.001), holding eviction constant. For one eviction count increase, crime rate increased 0.05 per 100 people (t=0.71, p=0.48). Given that the strength of the coefficient of concentrated disadvantage is not greatly reduced from step 1 to step 3, and the potential mediator eviction is not significant in step 3. This suggests that eviction is not mediating the relationship between concentrated disadvantage and the crime rate.

However, the result made me wonder if I was thinking about the direction of causality wrongly; concentrated disadvantage might be mediating the relationship between eviction and the crime rate. Table 4-4 displays Baron and Kenny's steps for mediation of concentrated disadvantage on the potential relationship between eviction and crime rate. In Model 1 (first step), crime is regressed on eviction. For every one eviction count increase, the crime rate significantly increased about 0.29 per 100 people (t=5.15, p<0.001). In Model 2 (second step), eviction is significantly associated with concentrated disadvantage. For one eviction count increase, concentrated disadvantage increased approximately 0.04 standard deviations (t=9.18, p<0.001). In Model 3 (third step), when eviction and concentrated disadvantage are both included to predict crime rate, eviction became non-significant, and concentrated disadvantage, the potential mediator, remains significant. For one eviction count increase, crime rate increased 0.05 per 100 people (t=0.71, p=0.48), controlling for concentrated disadvantage. For one standard deviation increase in Sampson's concentrated disadvantage index, the crime rate significantly increased 6.04 per 100 people (t=4.76, p<0.001), holding eviction constant. These results strongly suggest that the concentrated disadvantage mediates the relationship between eviction and crime. In other words, the relationship between eviction and crime rates are indirect. More evictions potentially increase concentrated disadvantage which increases the presence of

Table 4-4. Baron and Kenny Steps for Concentrated Disadvantage Mediating the Relationship between the Crime Rate and Eviction

	Model 1 (step1) Crime Rate *Coef/se*	Model 2 (step2) Concentrated Disadvantage *Coef/se*	Model 3 (step3) Crime Rate *Coef/se*
Eviction	0.29*** (0.06)	0.04*** (0.00)	0.05 (0.07)
Concentrated Disadvantage	N/A	N/A	6.04*** (1.27)
Constant	3.62** (1.28)	-0.65*** (0.10)	7.55*** (1.41)
F (1,84)/F (2,83)	26.51***	84.29***	28.02***
R-squared	0.24	0.50	0.40
N	86	86	86

Ϯ=p<.10; *=p < .05; **=p < .01; ***=p < .001

crime. However, it is important to be cautious about such claims. From the model results above, I do not have enough evidence to *conclude* that concentrated disadvantage has mediated the relationship between eviction and crime rate in Knoxville. To gain conclusive evidence of mediation, a causal inference model should be used. However, due to the small sample size (N=86) in these data, there is not enough power to run a good causal test (Ramos and Macau 2017). Thus, I cannot conclude that the relationship between eviction and crime rates is spurious, and that concentrated disadvantage causes both more crime and more eviction, while eviction is unassociated with crime rates in reality.

However, if there is an indirect causal relationship between eviction and crime rates, this relationship is worth examining. Thus, Table 4-5 examines crime rates regressed on eviction, including the controls, that is potentially mediated by concentrated disadvantage. Model 1 is identical to Model 1 in Table 4-4 which has already been discussed. In Model 2, for every one eviction count increase, the crime rate increased 0.11 per 100 people ($t=1.69$, $p=0.09$), controlling for other variables. Eviction is marginally significantly associated with the crime rate ($p<0.1$). In Model 3, when concentrated disadvantage is added, eviction appears to no longer be related to crime rates. Based on the Kenny and Baron test in Table 4-4, and the regression test in Table 4-5, I conclude that there is strong evidence that the relationship between the crime rate and eviction (controlled for other factors) is fully mediated by concentrated disadvantage. This suggests that more evictions occur in neighborhoods with concentrated disadvantage and more concentrated disadvantage is associated with more crime.

Table 4-5. Regression Test for Mediation of Concentrated Disadvantage on Eviction and Crime Rate Relationship

	Model 1 *coef/se*	Model 2 *coef/se*	Model 3 *coef/se*
Eviction	0.29***	0.11	0.00
	(0.06)	(0.06)	(0.07)
Percent of unoccupied	N/A	0.84***	0.59***
housing units		(0.19)	(0.19)
Median gross rent	N/A	-0.79	-0.74
		(0.45)	(0.42)
Median home value	N/A	-0.00	0.02
		(0.01)	(0.01)
Concentrated Disadvantage	N/A	N/A	4.85***
			(1.49)
Constant	3.62**	6.12	6.79
	(1.28)	(4.72)	(4.46)
F (1,84)/F (4,81)/F (5,80)	26.51***	15.85***	16.30***
R-squared	0.24	0.44	0.50
N	86	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

Research Question 3a

Research question Q3a tests whether there is spatial pattern between eviction and the crime rates across census tracts in Knoxville. In chapter 3, I explained the methodology and conducted a practical examination using concentrated disadvantage and crime. Following the strategy used, I use eviction as a predictor of crime in the following section.

First, it is necessary to conduct a univariate global and local Moran's I statistics for eviction in Knoxville. Figure 4-1 shows the global Moran's I statistic for eviction. The test statistic of Moran's I is 0.247, with z-score 4.110, which is to the far right of the reference distribution. This suggests a strong rejection of the null hypothesis that there is spatial randomness (no spatial autocorrelation) and I conclude that evictions across census tract in Knoxville are spatially autocorrelated. Figure 4-2 shows the results of Moran's scatter plot of eviction. The slope of the line is Moran's I value. The upper-right and lower-left quadrants are census tracts that have a positive spatial autocorrelation of eviction. These census tracts are similar to each other in terms of eviction patterns, while the lower right and upper left quadrant are tracts with a negative spatial correlation, these census tracts are different(dissimilar) from their neighboring tracts. Out of 86 census tracts, there are more tracts for eviction that are spatially clustered (i.e., they are positively autocorrelated) as well as less tracts for eviction that are spatial outliers (i.e., they are negatively autocorrelated).

Next, to show exactly which locations are spatially clustered and outliers, I conduct the Local Moran' I statistic test for eviction. Figures 4-3 and 4-4 show the result of local Moran's I test for both a significance map and a cluster map. From the cluster map, among 86 census tracts, there are 24 census tracts of eviction that are significantly autocorrelated. Table 4-6 displays

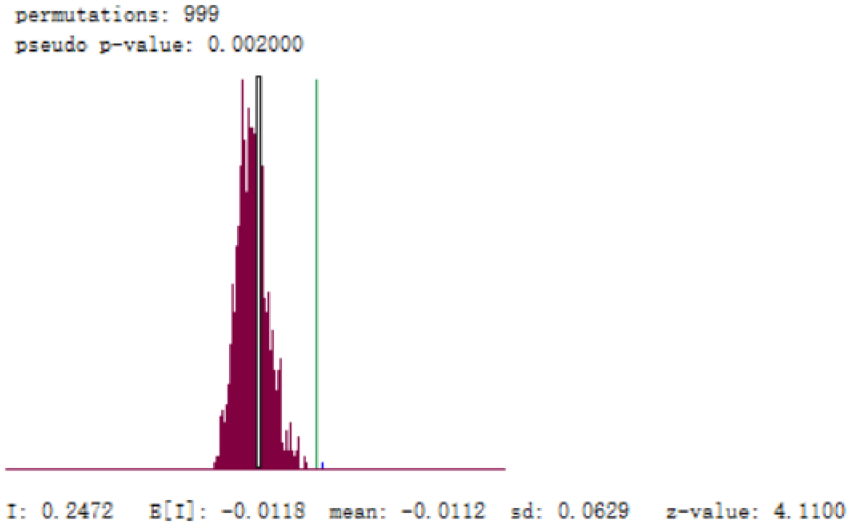

Figure 4-1. Test Statistics of Global Moran’s I of Eviction Four-Year (2016-2019) Average

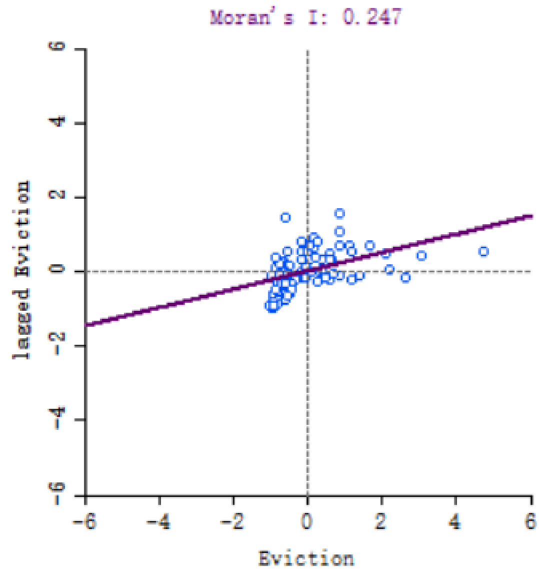

Figure 4-2. Global Moran's I Scatter Plot of Eviction Count Four-Year (2016-2019) Average

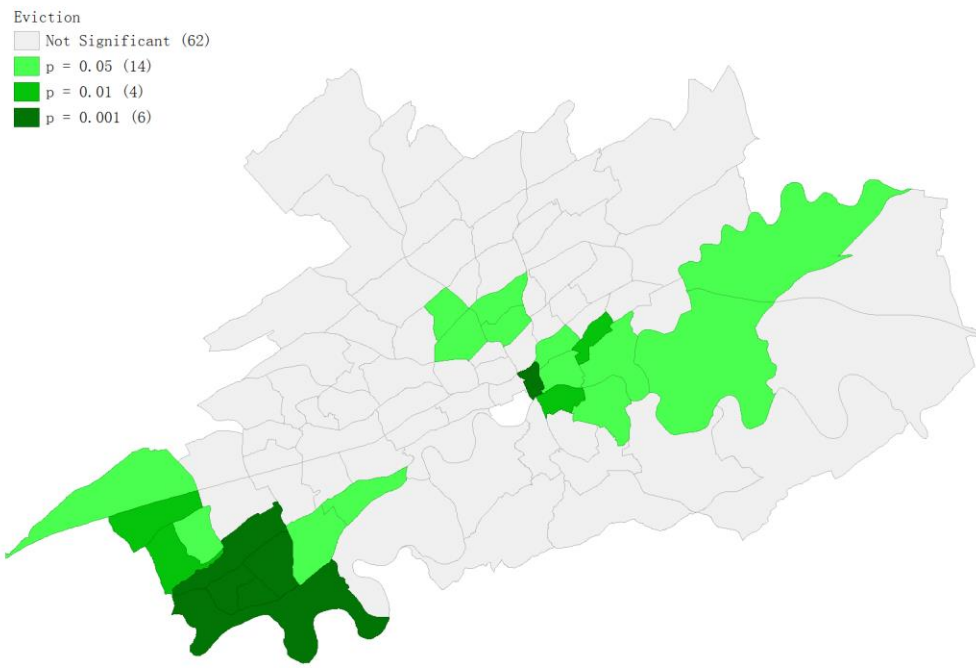

Figure 4-3. Local Moran's I Significance Map for Eviction

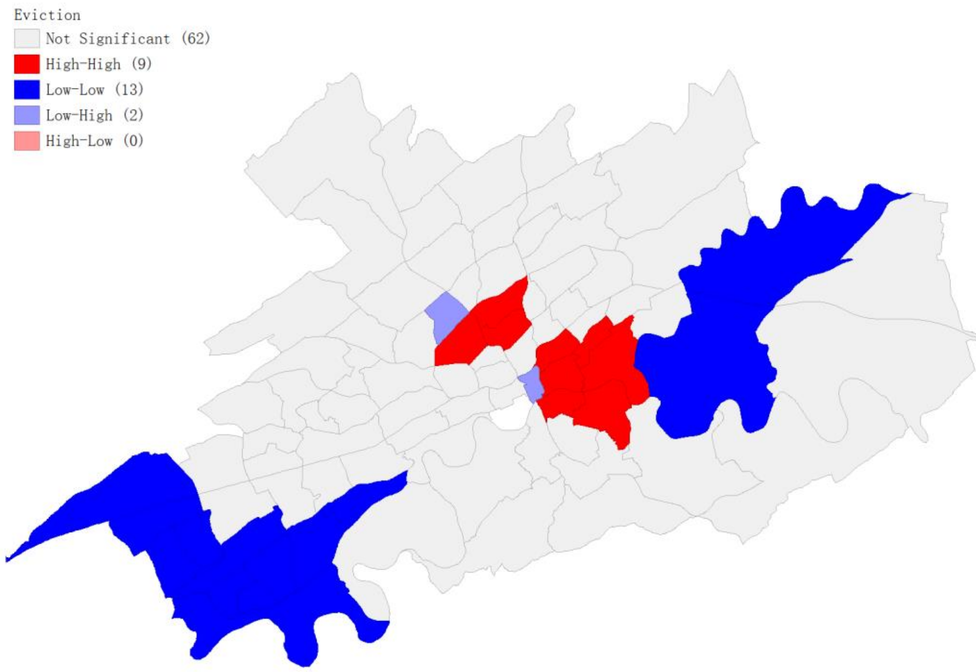

Figure 4-4. Local Moran's I Cluster Map for Eviction

Table 4-6. Geographic Information of Tracts and Corresponding Spatial Patterns for Eviction

Spatial Patterns	Census Tract	Places	Eviction Counts
High-high Spatial Pattern	8	Flagship Kerns; Suttree Landing Park; Lincoln Street	30.25
	15	Coster Yards; Oakwood-Lincoln Park	19
	20	Burlington	30
	21	Marble Hill; Holston Park	17.5
	22	Island Home	21
	28	Lonsdale	34.75
	29	Arlington	30
	67	Parkridge	43.25
	68	Mabry’s Hill	91
Low-low Spatial Pattern	44.01	Hickory Hills	4.75
	53.01	Eastwood	8
	54.01	Marbledale	8.75
	57.01	Riverbend; Westminister Ridge	2.75
	57.07	Lakewood; Ebenezer	2.25
	57.08	Garland	0.5
	57.09	Scenic Valley-Poplar Hill-Tierra Verde	0.75
	57.11	Pine Springs; Farmington	2.25
	57.12	Kensington; Farrington	2
	58.03	Boxwood Hills; Sweet Briar; Woodland Trace	4
	58.07	Lovell Heights; Tan Rara Oesta	1.75
	58.08	Farragut; Concord Woods	4
	59.04	Twin Springs; Amber Meadows	6.75
Low-high Spatial Pattern	1	Cumberland Ave; Summit Hill	6.75
	39.02	Norwood	15.25

geographic information of tracts and corresponding spatial patterns for eviction. The dark red and dark blue census tracts are spatially clustered. The dark red represents high eviction neighborhoods surrounded by other high eviction neighborhoods. These neighborhoods are clustered in the neighborhoods of Flagship Kens, Coster Yards, Burlington, Marble Hill, Island Home, Lonsdale, Mabry's Hill, Arlington, and Parkridge. The dark blue color represents low eviction neighborhoods surrounded by low eviction neighborhoods. The low-low eviction is clustered in two larger areas of Knoxville. One area includes neighborhoods of Eastwood and Marbledale which are located in east Knoxville. Another area includes neighborhoods of Hickory Hills, Riverbend, Lakewood, Garland, Scenic Valley-Poplar Hill-Tierra Verde, Farmington, Kensington, Woodland Trace, Lovell Heights, Twin Springs, Amber Meadow and Farragut, which is located in the west Knoxville on the cluster map. There are only two census tracts that are spatial outliers (light blue) because they are low eviction neighborhoods surrounded by high eviction neighborhoods. One is census tract 1, which is downtown Knoxville, the other is census tract 39.02, the neighborhood of Norwood.

Third, a bivariate Local Moran's I test between eviction and crime is shown in Figures 4-5, 4-6 and 4-7. As I have already discussed the Moran scatter plot and significance map, I will focus on the cluster map. Figure 4-7 displays a cluster map of spatial patterns of census tracts in terms of eviction and lagged crime. Table 4-7 displays geographic information of tracts and corresponding spatial patterns for eviction and lagged crime. The dark red and dark blue areas show the spatial cluster of the significant association. The dark red color represents the tracts of high eviction significantly associated with high crime in the neighboring tracts. Dark blue shading represents the tracts of low eviction significantly associated with low crime in the

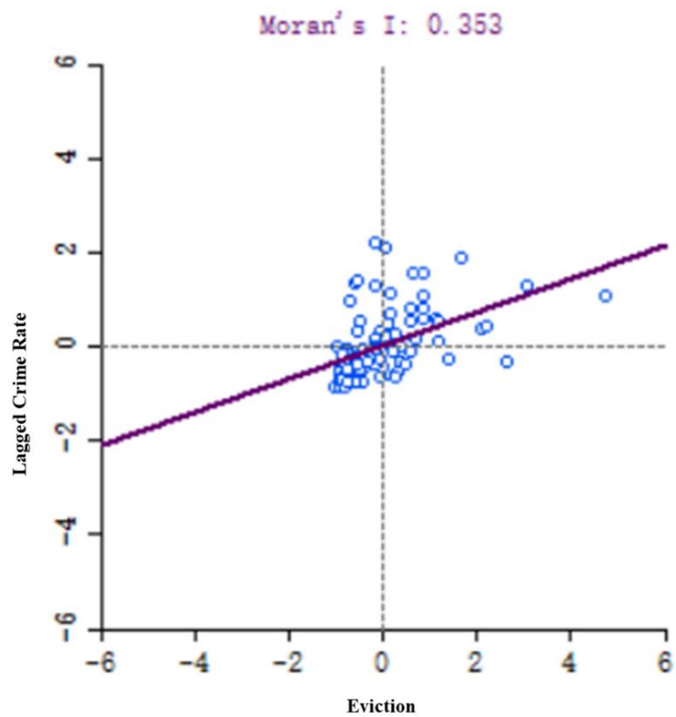

Figure 4-5. Bivariate Local Moran's I Scatter Plot for Eviction and Lagged Crime

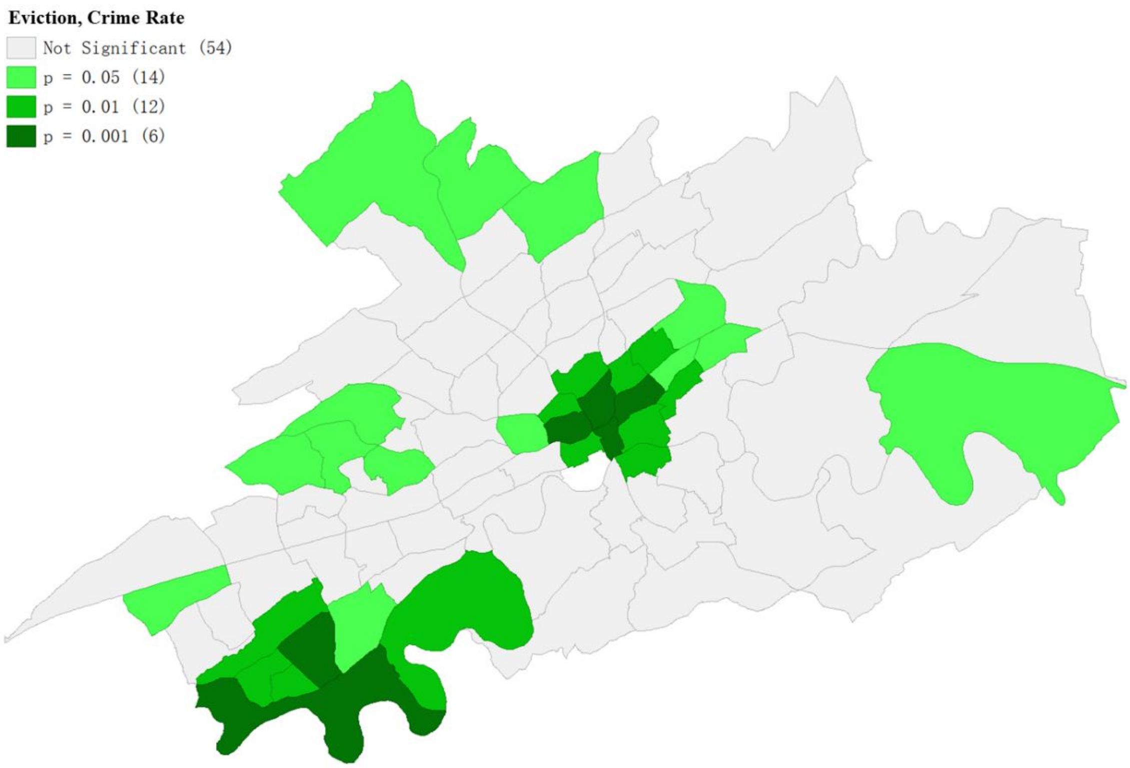

Figure 4-6. Bivariate Local Moran's I Significance Map for Eviction and Lagged Crime

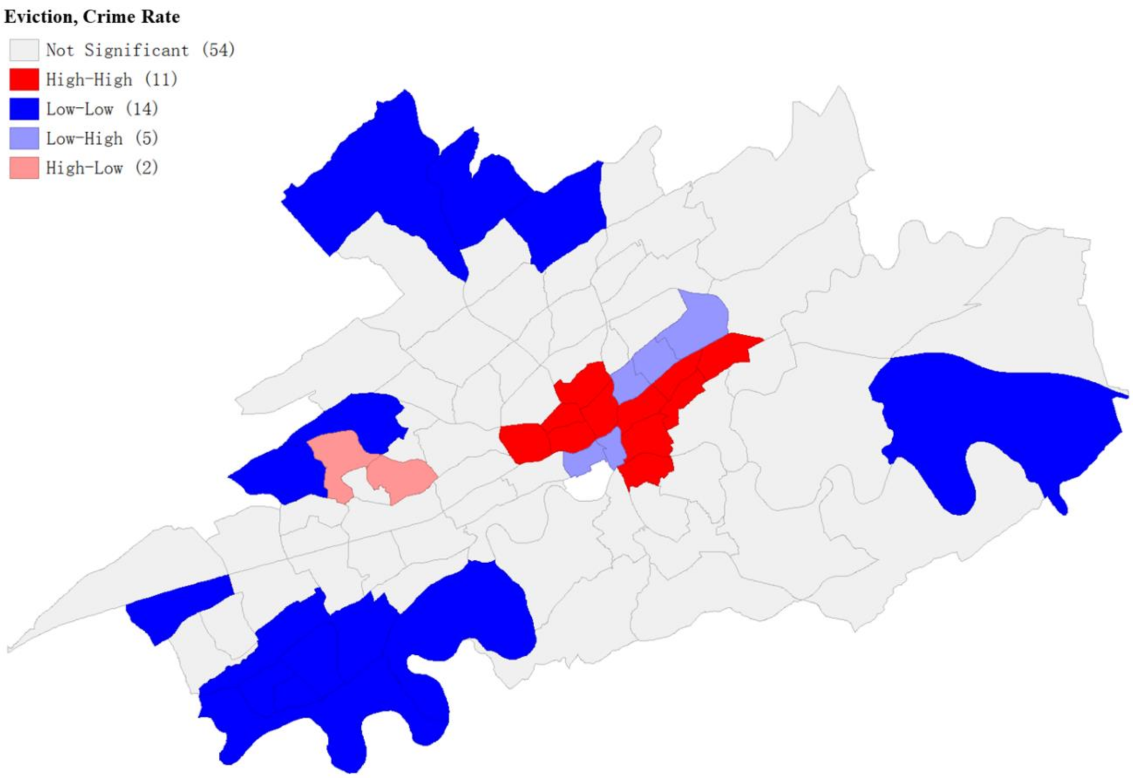

Figure 4-7. Bivariate Local Moran's I Cluster Map for Eviction and Lagged Crime

Table 4-7. Geographic Information of Tracts and Corresponding Spatial Patterns for Eviction and Lagged Crime Rate

Spatial Patterns	Census Tract	Places
High-high Spatial Pattern	8	Flagship Kerns; Suttree Landing Park; Lincoln Street
	14	College Hills
	15	Coster Yards; Oakwood-Lincoln Park
	19	Zoo Knoxville
	20	Burlington
	27	West View; Richmond Hill
	32	Chilhowee Hills
	66	Happy Holler; 4th And Gill
	67	Parkridge
	68	Mabry’s Hill
	70	Malcolm Martin Park
Low-low Spatial Pattern	46.06	Brentwood; Glen Arden; Berkshire Wood
	46.07	Hidden Hills, Fair Oaks
	54.02	Stony Point; Midway
	57.01	Riverbend; Westminister Ridge
	57.07	Lakewood; Ebenezer
	57.08	Garland
	57.09	Scenic Valley-Poplar Hill-Tierra Verde
	57.10	Blue Grass
	57.11	Pine Springs; Farmington
	57.12	Kensington; Farrington
	58.03	Boxwood Hills; Sweet Briar; Woodland Trace
	61.02	Heiskell
	62.06	Cedar Crest North
	62.08	Fieldview; Fountaincrest
Low-high Spatial Pattern	1	Cumberland Ave; Summit Hill
	17	Cecil Ave; 8th Ave
	18	Plantation Hills
	31	Loveland
	69	Fort Sanders
High-low Spatial Pattern	46.13	Hunting Hills West
	46.15	Amherst

neighboring tracts. The map also shows few tracts that are spatial outliers. The light blue represents low eviction significantly surrounded by high crime in neighboring tracts, and light red represents high eviction significantly surrounded by low crime neighborhoods.

In general, eviction and crime are spatially clustered in Knoxville. The high eviction and high lagged crime neighborhoods are clustered in a large area, and it is located right in the center of the city. This area includes neighborhoods of Flagship Kerns, College Hills, Coster Yards, Burlington, West View, Happy Holler, Parkridge, Zoo Knoxville, Chilhowee Hills, Mabry's Hill and Malcolm Martin Park. The low eviction and low lagged crime neighborhoods are clustered in four different areas of Knoxville. One area is Stony Point and Midway, this area is shown in east Knoxville on the cluster map. The second area includes one census tract in north Knoxville, which is the neighborhood of Fieldview, Fountaincrest, Heiskell, Cedar Crest North and Whispering Hills. The third area includes two census tracts, these are the neighborhoods of Berkshire Wood, Meadowbrook, Hidden Hills, and Fair Oaks. The last clustered low-low eviction area is in the west Knoxville, where are the neighborhoods of Riverbend, Northshore Woods, Westminister Ridge, Blue Grass, Farmington, Pine Springs, Garland, Boxwood Hills, Kensington, Farrington, Sweet Briar, and Woodland Trace. Five neighborhoods are identified as low eviction neighborhoods with high lagged crime. These are the neighborhoods of Loveland, Fort Sanders, Plantation Hills, Cecil Ave, and downtown Knoxville. There are only two high-low census tracts. One is tract 46.13, the neighborhood of Hunting Hills West, and the other tract is 46.15, including the neighborhood of Amherst.

Fourth, the spatial diagnostic test on model eviction and crime rate four-year average is displayed in Figures 4-8 and 4-9. As I have already discussed the regression results in the above

```
REGRESSION
----------
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Enriched_TIGER_Line_2018_Tracts
Dependent Variable  :    CrimeRate  Number of Observations:   86
Mean dependent var  :      8.37124  Number of Variables   :    6
S.D. dependent var  :      9.26712  Degrees of Freedom    :   80

R-squared           :     0.504617  F-statistic           :     16.2983
Adjusted R-squared  :     0.473656  Prob(F-statistic)     :  4.6457e-11
Sum squared residual:      3658.72  Log likelihood        :    -283.301
Sigma-square        :       45.734  Akaike info criterion :     578.602
S.E. of regression  :      6.76269  Schwarz criterion     :     593.328
Sigma-square ML     :      42.5433
S.E of regression ML:      6.52252
```

Variable	Coefficient	Std. Error	t-Statistic	Probability
CONSTANT	6.79185	4.46499	1.52114	0.13217
ConDis	4.84597	1.48866	3.25525	0.00166
Eviction	0.000988608	0.0678415	0.0145723	0.98835
Unoccupied	0.585993	0.193979	3.02091	0.00338
GrossRent	-0.741299	0.422338	-1.75523	0.08305
HomeValue	0.0153349	0.0116021	1.32174	0.19002

Figure 4-8. Spatial Model Diagnostics for Eviction and Crime

```
REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   15.999394
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE              PROB
Jarque-Bera            2           225.9059           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE              PROB
Breusch-Pagan test     5            38.4986           0.00000
Koenker-Bassett test   5             8.4153           0.13478

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Spatial Analysis 0425--Weights
   (row-standardized weights)
TEST                          MI/DF        VALUE          PROB
Moran's I (error)             0.1475        2.8945        0.00380
Lagrange Multiplier (lag)       1          17.4105        0.00003
Robust LM (lag)                 1          15.3772        0.00009
Lagrange Multiplier (error)     1           5.0203        0.02505
Robust LM (error)               1           2.9871        0.08393
Lagrange Multiplier (SARMA)     2          20.3976        0.00004
------------------------------ END OF REPORT -------------------------------
```

Figure 4-9. Spatial Model Diagnostics for Eviction and Crime paragraphs, I will only focus on regression diagnostics in Figure 4-9. The diagnostic for spatial dependence shows several tests and their significance levels. According to Anselin's (2005) spatial regression model selection decision rule, the diagnostic shows significance (a rejection of the null hypothesis) for all Moran's I, spatial lag and spatial error test. A general rule is that if all these tests (i.e., Moran's I, lag and error) demonstrate significance, then look at the robust lag and error test. In my results, the robust lag and error test are also significant.

In this situation, I chose the model with greatest significance in terms of orders of magnitude. The p-value for the spatial lag model test is 0.00003, while the p-value for the spatial error model test is 0.02505. As the spatial lag model is more significant than the spatial error model, I chose the spatial lag model. In the rare situations that both the statistical test and robust test are highly significant, it is suggested that researchers go with the model with the largest value for the test statistic (Anselin 2005: 200). From Figure 4-8, the model with the largest value for test statistic is the spatial lag test, with a test statistic of 17.41, while the spatial error test statistic is 5.02.

Table 4-8 displays the results of the spatial lag model for concentrated disadvantage, eviction, and crime rate in Knoxville. First, the spatial lag term has a positive coefficient (Rho=0.4732) and it is highly significant, which provides evidence of spatial interdependence. Substantively, this suggests that census tracts in Knoxville have more crime rates when their neighboring tracts also have more crime rates. Second, the likelihood ratio test is significant, which means that there is extra spatial correlation for the residuals in the lag model; the heteroskedasticity test is significant, showing evidence of heteroskedasticity in the residuals. Third, in spatial lag regression, concentrated disadvantage is statistically significant on crime rates, controlling for the spatial lag term. Variables of eviction, percent of unoccupied housing units, median gross rent, and median house value are not significantly associated with crime rates, controlling for the spatial dynamics.

Final Comments

To conclude and answer my research question on eviction, first, concentrated disadvantage does not better predict crime when eviction is added to the concentrated disadvantage index. Second, eviction does not mediate the relationship between concentrated disadvantage and the crime rate in the city of Knoxville, but concentrated disadvantage may mediate the relationship between eviction and crime. Third, eviction and crime are spatially clustered. The bivariate Local Moran's I test shows that there is a high eviction and high lag crime cluster in downtown Knoxville and its outer areas. The low eviction and low lag crime neighborhoods are clustered in four different areas of the city. The spatial lag model shows that the crime variable is spatially interdependent across 86 census tracts in the city of Knoxville.

Table 4-8. Spatial Lag Model for Concentrated Disadvantage and Eviction on Crime Rate

	Crime Rate *coef/se*
Spatial Lag Term	0.47***
	(0.11)
Concentrated Disadvantage	2.80*
	(1.32)
Eviction	0.02
	(0.06)
Percent of unoccupied housing units	0.44**
	(0.17)
Median gross rent	-0.47
	(0.37)
Median home value	0.01
	(0.01)
Constant	1.58
	(4.05)
R-Squared	0.61
Log-likelihood	-275.39
Likelihood-ratio test for spatial lag	15.83***
Breusch-Pagan Test (Heteroskedasticity)	51.72***

Ϯ=p<.10; *=p < .05; **=p < .01; ***=p < .001

CHAPTER FIVE

FORECLOSURE ANALYSIS

In this chapter, I focus on the analysis of foreclosure. According to the analytical strategy indicated in chapters 3 and 4, I investigate the roles foreclosure in the relationship between concentrated disadvantage and crime across tracts in the city of Knoxville. Specifically, I ask:

RQ1b. Does concentrated disadvantage better predict crime when foreclosure is added to the concentrated disadvantage index?

RQ2b. Do foreclosures mediate Sampson's model of concentrated disadvantage and crime?

RQ3b. If foreclosure in a neighborhood increase, in which neighborhood (if any) do crime rates change?

Research Question 1b

To answer my first research question (Q1b), factor analysis is examined with the six concentrated disadvantage variables in Sampson's index, and I also include foreclosure. Table 5-1 shows rotated factor loadings of these seven variables, which loaded on a single factor (meaning that the eigenvalues suggest only one underlying construct is measured by the seven variables). However, foreclosure did not load high on factor 1 with a loading of 0.23. This suggests that concentrated disadvantage is likely not improved by adding foreclosure to the index.

Thus, the answer to my first research question (Q1b) is likely "no" but since foreclosure doesn't load highly on any other factors, I looked more deeply by creating a new variable of

Table 5-1. Rotated Factor Loadings for Concentrated Disadvantage Variables and Foreclosure

Variables	Factor 1
Percent poverty	0.88
Prevent female-headed household	0.88
Precent government assistance	0.93
Percent unemployment	0.76
Percent people under 18 years	0.89
Percent Black	0.80
Foreclosure	0.24

concentrated disadvantage and foreclosure and z-score standardizing it. The Cronbach's alpha of concentrated disadvantage that includes the foreclosure variable is 0.87. Table 5-2 displays the regression results for the crime rate regressed on both the old and new concentrated disadvantage indices. Model 1 shows the OLS regression results of the crime rate regressed on the original Sampson's concentrated disadvantage index. Model 2 shows the OLS regression results of the crime rate regressed on the new concentrated disadvantage index. From the AIC, Model 1 had an AIC value of 576.60, which is smaller than the AIC of model 2 at 578.85. Model 1 exhibits the smaller AIC. Therefore, I conclude that Model 1 is the better model, and the new concentrated disadvantage index has not improved the prediction of crime in Knoxville compared to simply using Sampson's concentrated disadvantage index.

Model 1 has been interpreted in Table 4-2 of Chapter 4. From the results of Model 2, for a one standard deviation increase in the new concentrated disadvantage index, the crime rate significantly increases about 5 units per 100 people, controlling for percent of unoccupied housing units, median gross rent, and median home value ($t=3.40$, $p<0.01$). For each one percent increase in unoccupied housing units, the crime rate significantly increased 0.65 per 100 people across tracts in Knoxville, holding all other variables constant ($t=3.44$, $p<0.01$). Median gross rent is significantly marginally associated with crime rate in Model 2. For every $100 increase in the median gross rent, the crime rate dropped 0.76 per 100 people ($t=-1.84$, $p=0.07$), controlling for all other variables. Median home values are not significant ($t=1.41$, $p=0.16$), hold other variables constant. In Model 2, the new concentrated disadvantage index, the percent of unoccupied housing units, median gross rent, and median house value together explain 49 percent of the variance in crime rate across census tracts in Knoxville.

Table 5-2. Regression Results for Concentrated Disadvantage and Foreclosure Index on Crime Rate

	Model 1		Model 2	
	Coef/se	*Beta*	*Coef/se*	*Beta*
Sampson's concentrated disadvantage index	4.86*** (1.30)	0.46	N/A	N/A
Disadvantage index including Foreclosure	N/A	N/A	5.09** (1.50)	0.44
Percent of unoccupied housing units	0.59** (0.19)	0.30	0.65** (0.19)	0.33
Median gross rent	-0.74 (0.41)	-0.18	-0.76 (0.41)	-0.19
Median home value	0.02 (0.01)	0.15	0.02 (0.01)	0.17
Constant	6.82 (4.07)	N/A	6.02 (4.19)	N/A
F (4,81)	20.63***		19.57***	
R-squared	0.50		0.49	
AIC	576.60		578.85	
N	86		86	

†=p<.10; *=p < .05; **=p < .01; ***=p < .001

Again, to look deeper at the two indices and to compare relative strength of coefficients between Model 1 and Model 2, it is necessary to standardize the regression coefficient so that they are in the same metric. From Table 5-2, Sampson's concentrated disadvantage index has the beta coefficient of 0.46, while the new concentrated disadvantage index has the beta coefficient of 0.44, followed by percent of unoccupied housing unit at values of 0.30 in Model 1 and 0.33 in Model 2. Therefore, this information along with the AIC suggest that the contributions of Sampson's concentrated disadvantage index and the new concentrated disadvantage index have the most impact on models of crime rate, and it is quite clear from this, the factor analysis, but adding foreclosure is not improving Sampson's concentrated disadvantage index.

Research Question 2b

The strategy for answering the second research question (Q2b) is to add foreclosure to the crime rate regressed on the concentrated disadvantage model to look for possible mediation. As in Chapter 4, I use the method developed by Baron and Kenny (1986) to provide initial evidence for the possibility of mediation, as is outlined in Chapter 3.

Table 5-3 illustrates Baron and Kenny's steps for mediation. In Model 1 (first step), crime is regressed on concentrated disadvantage, as discussed in Chapter 4 but presented here for ease of interpretation. In Model 2 (second step), concentrated disadvantage is regressed on foreclosure, and the results show that concentrated disadvantage is significantly and positively associated with foreclosure. For every one standard deviation increase in Sampson's concentrated disadvantage index, foreclosure counts significantly increase by about 0.64 foreclosure ($t=2.16$, $p<0.05$). In Model 3 (third step), when concentrated disadvantage

Table 5-3. Baron and Kenny Steps for Mediation of Foreclosure

	Model 1 (step1) Crime Rate *Coef/se*	Model 2 (step2) Foreclosure *Coef/se*	Model 3 (step3) Crime Rate *Coef/se*
Concentrated disadvantage	6.68***	0.64*	7.02***
	(0.89)	(0.30)	(0.91)
Foreclosure	N/A	N/A	-0.54
			(0.32)
Constant	8.37***	3.72***	10.38***
	(0.78)	(0.26)	(1.43)
F (1,86)/F (1,84)/F (2,85)	55.87***	4.66*	29.92***
R-squared	0.40	0.05	0.42
N	86	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

and foreclosure are both included to predict the crime rate, concentrated disadvantage remains significant and positive, and the coefficient of concentrated disadvantage slightly increased from 6.68 in step 1 to 7.02 in step 3. However, foreclosure is not significant. For one standard deviation increase in Sampson's concentrated disadvantage index, the crime rate significantly increased 7.02 per 100 people ($t=7.73$, $p<0.001$), holding foreclosure constant. For one foreclosure count increase, the crime rate dropped 0.54 per 100 people ($t=-1.67$, $p=0.10$). Given that the strength of the coefficient of concentrated disadvantage is not reduced from step 1 to step 3, rather, it increased (maybe because foreclosure is a moderator or, more likely, due to chance), as the potential mediator of foreclosure is not significant in step 3. This suggests that foreclosure is not a mediator between the relationship of concentrated disadvantage and the crime rate.

But again, it may be that concentrated disadvantage mediates the significant relationship between foreclosure and the crime rate. Thus, Table 5-4 displays Baron and Kenny's steps for mediation of concentrated disadvantage on the potential relationship between foreclosure and crime rate. In Model 1 (first step), crime is regressed on foreclosure. For every one foreclosure count increase, the crime rate increased about 0.03 per 100 people ($t=0.08$, $p=0.93$). In Model 2 (second step), foreclosure is significantly associated with concentrated disadvantage. For one foreclosure count increase, concentrated disadvantage significantly increased approximately 0.04 standard deviations ($t=0.03$, $p<0.05$). In Model 3 (third step), when foreclosure and concentrated disadvantage are both included to predict crime rate, foreclosure is not significant, and the potential mediator of concentrated disadvantage remains significant. For one foreclosure count increase, the crime rate dropped 0.05 per 100 people ($t=-1.67$, $p=0.10$), controlling for concentrated disadvantage. For one standard deviation increase in Sampson's concentrated

Table 5-4. Baron and Kenny Steps for Mediation of the Relationship between Foreclosure and Crime

	Model 1 (step1) Crime Rate *Coef/se*	Model 2 (step2) Concentrated Disadvantage *Coef/se*	Model 3 (step3) Crime Rate *Coef/se*
Foreclosure	0.03	0.08*	-0.54
	(0.41)	(0.04)	(0.32)
Concentrated Disadvantage	N/A	N/A	7.02***
			(0.91)
Constant	8.24**	-0.30	10.38***
	(1.83)	(0.17)	(1.43)
F (1,84)/F (2,83)	0.01	4.66*	29.92***
R-squared	0.0001	0.05	0.41
N	86	86	86

Ɨ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

disadvantage index, crime rate significantly increased 7.02 per 100 people (t=7.73, p<0.001), holding foreclosure constant. From the model results above, I do not have enough evidence to conclude that concentrated disadvantage mediates the relationship between foreclosure and crime rate in Knoxville, but I have strong evidence of it. Again, greater certainty requires a causal inference model for which I do not have sufficient power (Ramos and Macau 2017).

Table 5-5 better displays the relationship between foreclosure and the crime rate. Model 1 has already been discussed. In Model 2, for every one foreclosure count increase, the crime rate *dropped* 0.29 per 100 people (t=-0.78, p=0.44), controlling for other variables. This change in sigh is remarkable and troubling and may indicate a suppression effect. In Model 3, when concentrated disadvantage is added, the coefficient of foreclosure is not significant (t=-0.75, p=0.45), holding all other variables constant. I conclude that there is no evidence that the relationship between the crime rate and foreclosure (controlled for other factors) is mediated by concentrated disadvantage, but it is clear that more investigation into the relationship between foreclosure and crime rate is warranted.

As the coefficient sign of foreclosure changed when control variables are added into the model, I investigate further the moderation and interaction of foreclosure. The diagnostic test suggests that foreclosure changed coefficient sign when concentrated disadvantage, median gross rent, and median home value are respectively added into the model of foreclosure on crime rate. Only the interaction term of foreclosure and median home value are significantly associated with crime rate, while the interaction term of foreclosure on both moderators concentrated disadvantage and median gross rent are not significantly associated with crime rate. Therefore, Table 5-6 displays the interaction effect of foreclosure and median home value on crime rate.

Table 5-5. Regression of Foreclosure on Crime Rate Mediated by Concentrated Disadvantage

	Model 1	Model 2	Model 3
	coef/se	*coef/se*	*coef/se*
Foreclosure	0.03	-0.29	-0.26
	(0.41)	(0.38)	(0.35)
Percent of unoccupied housing units	N/A	0.92***	0.56**
		(0.18)	(0.20)
Median gross rent	N/A	-1.01*	-0.75
		(0.43)	(0.41)
Median home value	N/A	-0.01	0.01
		(0.01)	(0.01)
Concentrated disadvantage	N/A	N/A	4.83***
			(1.30)
Constant	8.24**	11.71*	8.76
	(1.83)	(5.13)	(4.83)
F (1,84)/F (4,81)/F (5,80)	0.01	14.88***	16.52***
R-squared	0.0001	0.42	0.50
N	86	86	86

†=p<.10; *=p < .05; **=p < .01; ***=p < .001

Table 5-6. Interaction of Foreclosure and Median Home Value on Crime Rate

	Crime Rate *coef/se*
Foreclosure	1.72
	(0.98)
Median home value	0.01
	(0.02)
Foreclosure*median home value	-0.01*
	(0.01)
Percent of unoccupied housing units	0.80***
	(0.19)
Median gross rent	-0.89*
	(0.43)
Constant	7.34
	(5.39)
F (5,80)	13.45***
R-squared	0.46
N	86

Ϯ=p<.10; *=p < .05; **=p < .01; ***=p < .001

Figure 5-1 shows the margins plot of the relationship for crime rate regressed on foreclosure while holding the value of the moderator—median home value constant ranging from $100,000 to $500,000. Figures 5-2(1, 2 and 3) displays the marginal effect of crime rate regressed on foreclosure at different values of median home value. From the marginal result in Figure 5-2(1), the associations between foreclosure and crime rate are significantly negative when median home value is larger than $100,000. In Figure 5-2(2 and 3), with the increase of foreclosure, crime rate significantly decreased at median home values of $400,000 and $500,000. This suggests that foreclosures in neighborhoods with more expensive homes are associated with lower crime rates.

Research Question 3b

Research question Q3b tests whether a spatial pattern exists on the relationship between foreclosure and the crime rate across census tracts in Knoxville. Utilizing the strategy on concentrated disadvantage and crime outlined in Chapter 3, I use foreclosure as a predictor of crime in the following section.

First, a univariate of global and local Moran's I statistics is conducted to examine the spatial patterns of foreclosure in Knoxville. Figure 5-3 shows the global Moran's I statistic for foreclosure. The test statistic of Moran's I is 0.348, with a z-score 5.741, which is to the far right of the reference distribution. This suggests a strong rejection of the null hypothesis that there is spatial randomness (no spatial autocorrelation) and concludes that foreclosures in Knoxville are spatially autocorrelated. Figure 5-4 shows the results of Moran's scatter plot of foreclosure. The slope line is Moran's I value. The upper-right and lower-left quadrants are census tracts that have

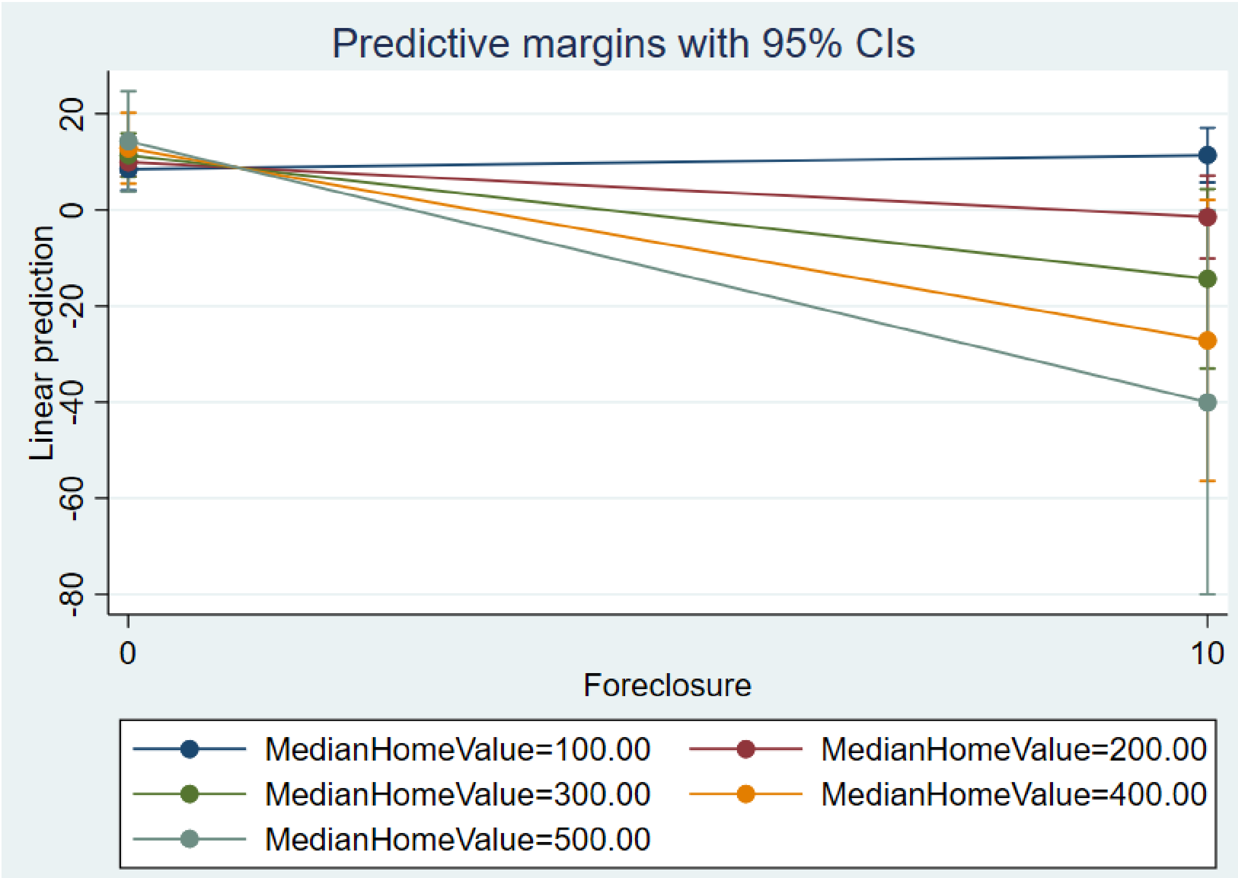

Figure 5-1. Margins Plot of Foreclosure on Crime Rate at Levels of Median Home Value

```
Average marginal effects                              Number of obs = 86
Model VCE: OLS

Expression: Linear prediction, predict()
dy/dx wrt:  Foreclosure
1._at: MedianHomeValue = 100
2._at: MedianHomeValue = 200
3._at: MedianHomeValue = 300
4._at: MedianHomeValue = 400
5._at: MedianHomeValue = 500
```

	dy/dx	Delta-method std. err.	t	P>|t|	[95% conf.	interval]
Foreclosure						
_at						
1	.2910495	.4522139	0.64	0.522	-.6088848	1.190984
2	-1.139746	.5296657	-2.15	0.034	-2.193815	-.0856782
3	-2.570542	1.092997	-2.35	0.021	-4.745675	-.3954099
4	-4.001338	1.71662	-2.33	0.022	-7.417521	-.5851554
5	-5.432134	2.353078	-2.31	0.024	-10.11491	-.7493601

Figure 5-2. Marginal Effects of Foreclosure on Crime Rate at Levels of Median Home Value (1)

```
. margins, at(Foreclosure=(0 10) MedianHomeValue=(100(100)500))

Predictive margins                                      Number of obs = 86
Model VCE: OLS

Expression: Linear prediction, predict()
1._at:  Foreclosure     =   0
        MedianHomeValue = 100
2._at:  Foreclosure     =   0
        MedianHomeValue = 200
3._at:  Foreclosure     =   0
        MedianHomeValue = 300
4._at:  Foreclosure     =   0
        MedianHomeValue = 400
5._at:  Foreclosure     =   0
        MedianHomeValue = 500
6._at:  Foreclosure     =  10
        MedianHomeValue = 100
7._at:  Foreclosure     =  10
        MedianHomeValue = 200
8._at:  Foreclosure     =  10
        MedianHomeValue = 300
9._at:  Foreclosure     =  10
        MedianHomeValue = 400
10._at: Foreclosure     =  10
        MedianHomeValue = 500
```

Figure 5-2. Marginal Effects of Foreclosure on Crime Rate at Levels of Median Home Value (2)

_at	Margin	Delta-method std. err.	t	P>|t|	[95% conf.	interval]
1	**8.472774**	**2.196271**	**3.86**	**0.000**	**4.102056**	**12.84349**
2	**9.925974**	**1.50176**	**6.61**	**0.000**	**6.937377**	**12.91457**
3	**11.37917**	**2.277884**	**5.00**	**0.000**	**6.84604**	**15.91231**
4	**12.83237**	**3.691074**	**3.48**	**0.001**	**5.486902**	**20.17784**
5	**14.28557**	**5.249866**	**2.72**	**0.008**	**3.838006**	**24.73314**
6	**11.38327**	**2.857813**	**3.98**	**0.000**	**5.696039**	**17.0705**
7	**-1.471491**	**4.326809**	**-0.34**	**0.735**	**-10.08211**	**7.139133**
8	**-14.32625**	**9.382763**	**-1.53**	**0.131**	**-32.99854**	**4.346044**
9	**-27.18101**	**14.70075**	**-1.85**	**0.068**	**-56.43643**	**2.074413**
10	**-40.03577**	**20.07358**	**-1.99**	**0.050**	**-79.98347**	**-.0880732**

Figure 5-2. Marginal Effects of Foreclosure on Crime Rate at Levels of Median Home Value (3)

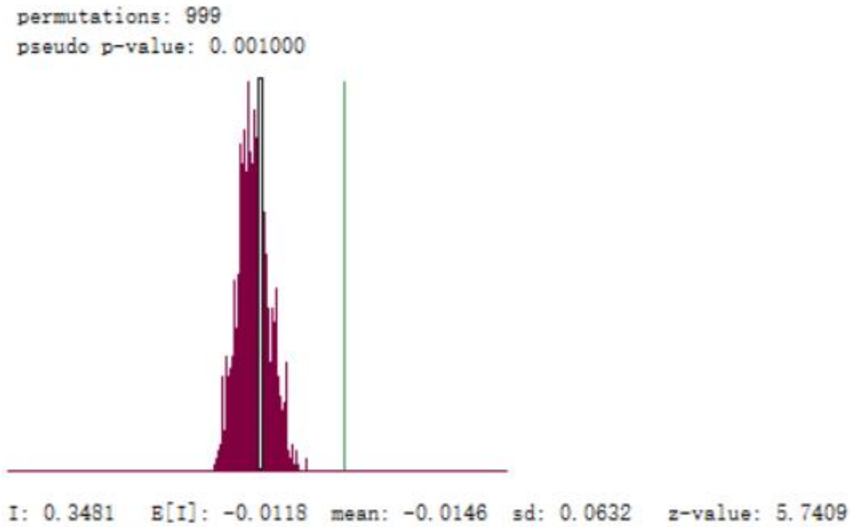

Figure 5-3. Test Statistics of Global Moran's I of Foreclosure Four-Year Average

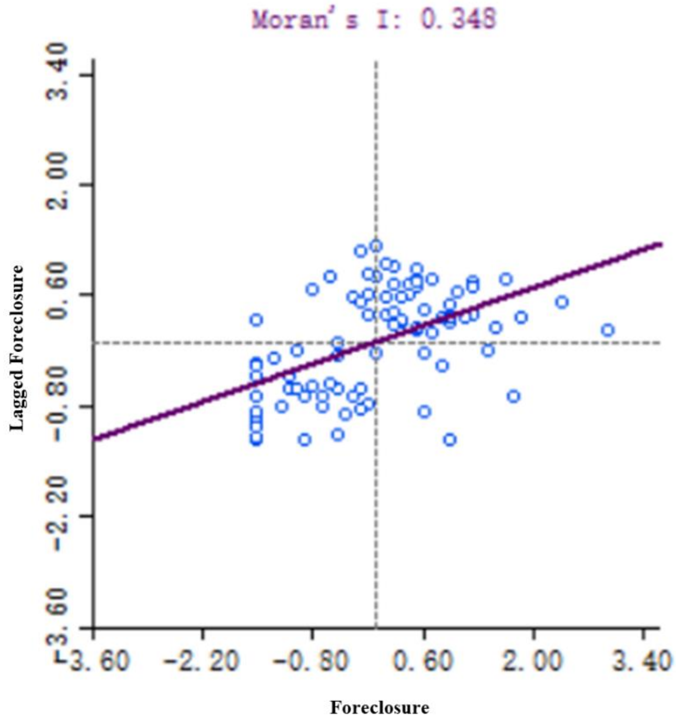

Figure 5-4. Global Moran Scatter Plot of Foreclosure Count Four-Year Average

a positive spatial autocorrelation of foreclosure. These census tracts are similar to each other in terms of foreclosure patterns, although the lower right and upper left quadrant are tracts with a negative spatial correlation, these census tracts are different(dissimilar) from their neighboring tracts. Out of 86 census tracts, the tracts where there are higher incidences of foreclosure are spatially clustered (i.e., they are positively autocorrelated) as well as less tracts with lower levels of foreclosure, which are spatial outliers (i.e., they are negatively autocorrelated).

Next, to show exactly which locations are spatially clustered and outliers. I conduct Local Moran' I statistic test for foreclosure. Figures 5-5 and 5-6 show the result of local Moran's I test for both a significance map and a cluster map. Table 5-7 displays geographic information of tracts and corresponding spatial patterns for foreclosure. From the cluster map, among 86 census tracts, there are 29 census tracts of foreclosure that are significantly autocorrelated. The high spatial clustering (dark red) neighborhoods of foreclosure include Marble Hill, Holston Hills, Deep Creek, Norwood, Inskip, Pleasant Ridge, Crossfield, Powell, Northbrook, and Baker Creek Preserve. The neighborhoods of low foreclosure clustering are Forest Hills, Middlebrook Heights, Hickory Hills, Montvue, Deane Hill, West Hills, Hidden Valley, Crestwood Hills, Meadowbrook, Riverbend, Sevenoaks, Garland, Blue Grass, Pine Springs, Kensington, Farragut, and Sequoyah Hills. The areas with low levels of foreclosure are clustered in a large area of southwest Knoxville. Also, there are seven census tracts that are spatial outliers (light blue and light red). Three light blue tracts are the neighborhoods of Black Oak, Oakland, and Lazy Acres, which have low foreclosure rates and are surrounded by high foreclosure in neighboring tracts. The neighborhoods of Vestal and Echo Valley are low foreclosure neighborhoods surrounded by high foreclosure neighborhoods.

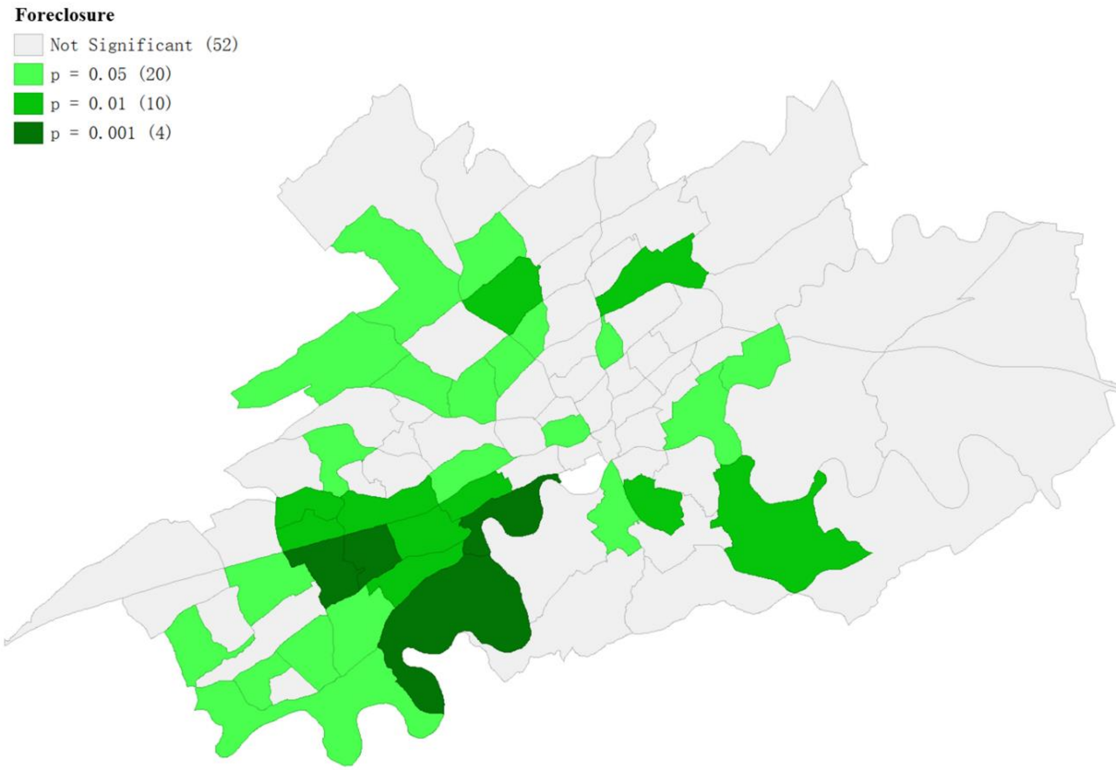

Figure 5-5. Local Moran's I Significance Map for Foreclosure

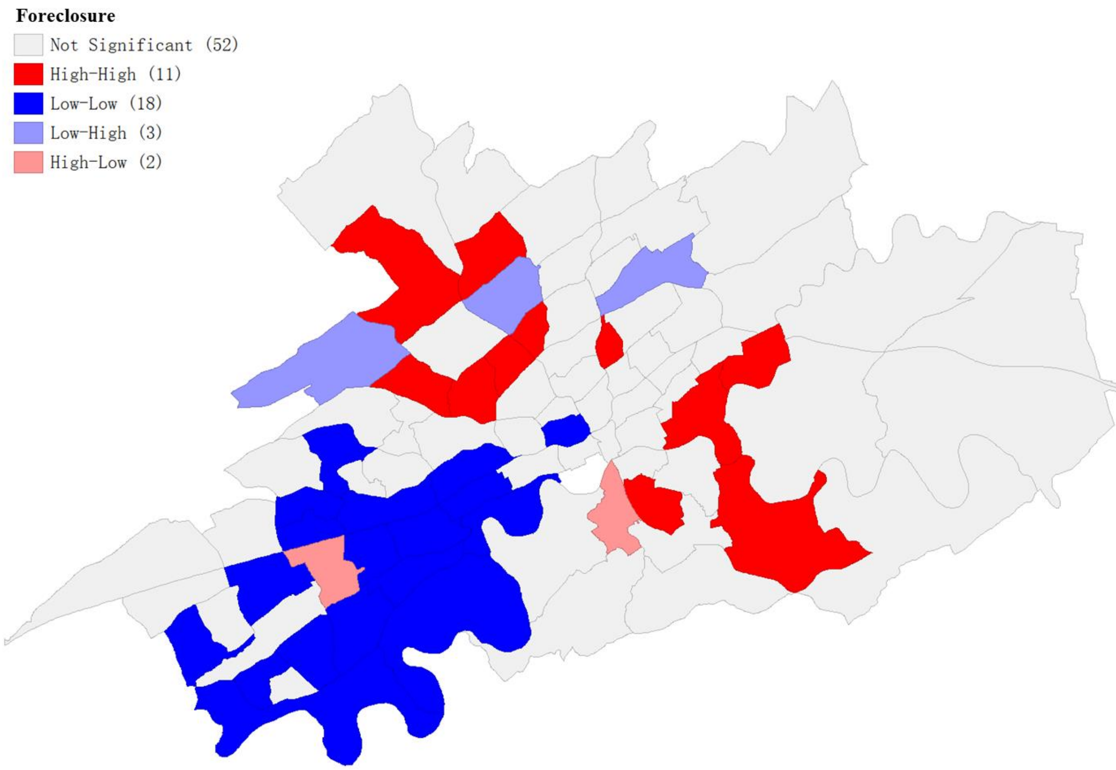

Figure 5-6. Local Moran’s I Cluster Map for Foreclosure

Table 5-7. Geographic Information of Tracts and Corresponding Spatial Patterns for Foreclosure

Spatial Patterns	Census Tract	Places	Foreclosure Counts
High-high Spatial Pattern	16	Fairmount Blvd NE	4.8
	21	Marble Hill	4.2
	23	Baker Creek Preserve	
	33	Holston Hills	3.8
	39.01	Deep Creek	6.8
	39.02	Norwood	4.4
	40	Inskip	3.8
	47	Pleasant Ridge	3.6
	55.01	Crossfield	3.4
	61.04	Powell	5.6
	62.07	Northbrook	4.4
Low-low Spatial Pattern	37	Forest Hills	0
	38.01	Middlebrook Heights	
	44.01	Hickory Hills	0
	44.03	Montvue	0
	44.04	Deane Hill;	0
	45	West Hills	0
	46.09	Hidden Valley	0
	46.10	Crestwood Hills	0
	46.13	Meadowbrook	3
	57.01	Riverbend; Westminister Ridge	2
	57.06	Sevenoaks	2
	57.08	Garland	
	57.10	Blue Grass	1.6
	57.11	Pine Springs; Farmington	2.4
	57.12	Kensington; Farrington	1.4
	58.08	Farragut; Concord Woods	2.8
	70	College St.	
	71	Sequoyah Hills	1.2
Low-high Spatial Pattern	43	Oakland	2
	49	Black Oak	
	60.02	Lazy Acres	5.8
High-low Spatial Pattern	24	Vestal	2.6
	57.04	Suburban Hills; Echo Valley	4.8

Third, a bivariate Local Moran's I test between foreclosure and lagged crime is shown in Figures 5-7, 5-8 and 5-9. As I have discussed the Moran' I scatter plot and significance map above, I will focus on the cluster map. Figure 5-7 displays the significance (colored tracts) and non-significance tracts (gray tracts) in terms of foreclosure and lagged crime. Table 5-8 shows geographic information of tracts and corresponding spatial patterns for foreclosure and lagged crime. The dark red and dark blue areas show the spatial cluster of the significant association. The dark red area represents the tracts of high foreclosure significantly associated with high crime in the neighboring tracts. According to the cluster map, these high foreclosure neighborhoods that are surrounded by high crime are the neighborhoods of Coster Yards, Burlington, West View, Loveland, Chilhowee Hill, Parkridge and Mabry's Hill. The dark blue color represents the tract of low foreclosure significantly associated with low crime in the neighboring tracts. These neighborhoods are Berkshire Wood, Meadowbrook, Amherst, Riverbend, Lakewood, Garland, Scenic Valley-Poplar Hill-Tierra Verde, Blue Grass, Pine Springs, Kensington, Farrington, and Sweet Briar. The cluster map also shows few tracts that are spatial outliers. The light blue represents low foreclosure tracts surrounded by high lagged crime in neighboring tracts: these neighborhoods are downtown Knoxville, Flagship Kerns, College Hills, Plantation Hills, Zoo Knoxville, Happy Holler, Fort Sanders, and Malcolm Martin Park. The light red represents high foreclosure tracts surrounded by low crime in neighboring tracts. These tracts represent neighborhoods of Hidden Hills, Stony Point, Heiskell, Cedar Crest North, Fieldview, and Fountaincrest . In general, foreclosure and crime are spatially clustered in Knoxville.

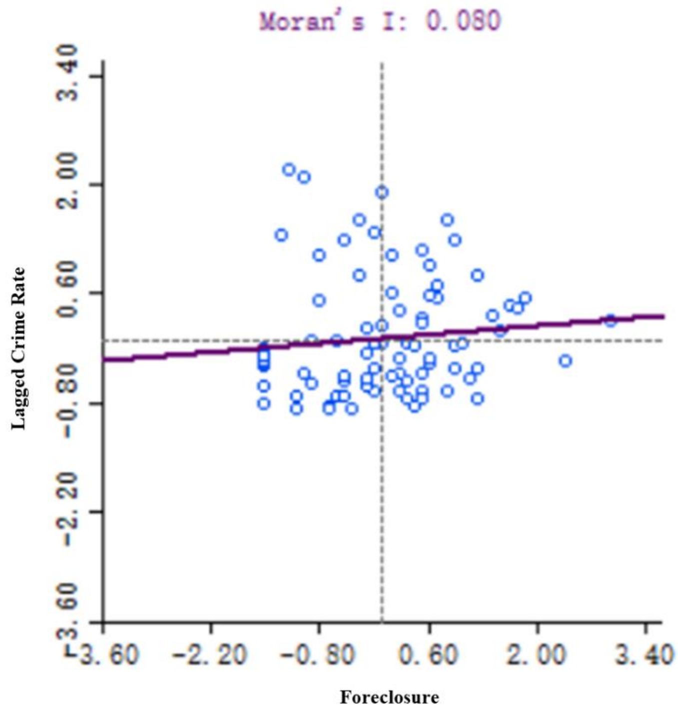

Figure 5-7. Bivariate Local Moran's I Scatter Plot for Foreclosure and Lagged Crime

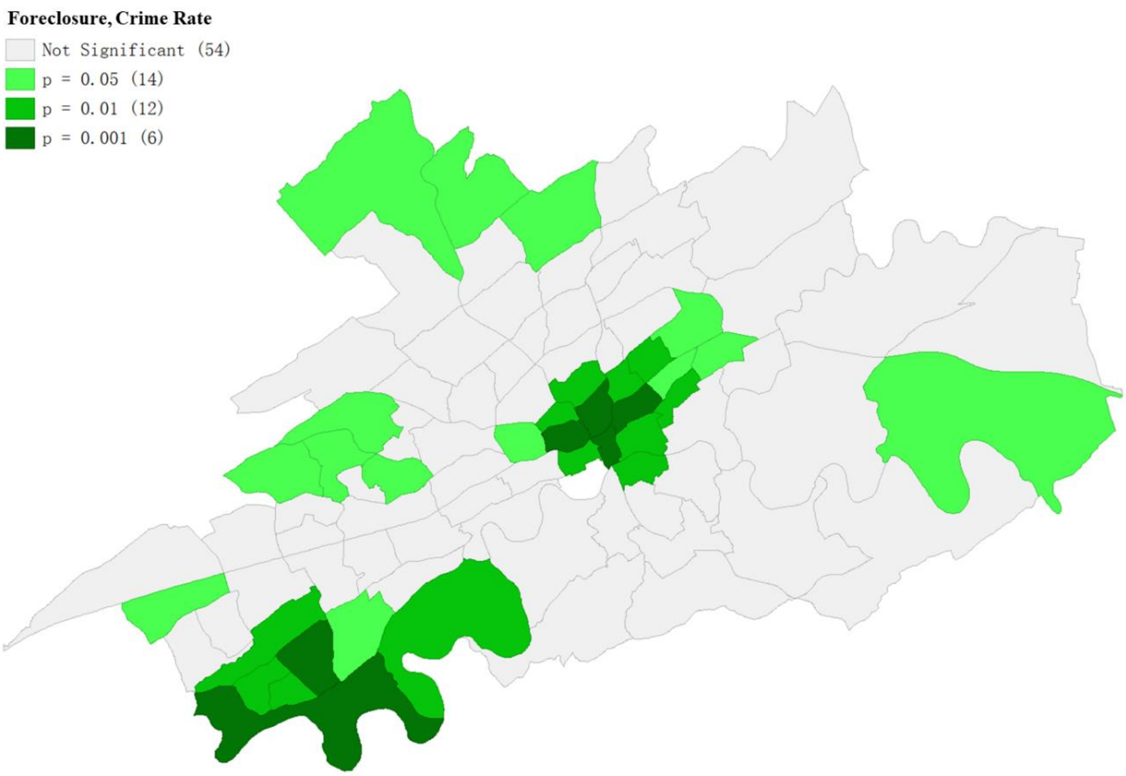

Figure 5-8. Bivariate Local Moran's I Significance Map for Foreclosure and Lagged Crime

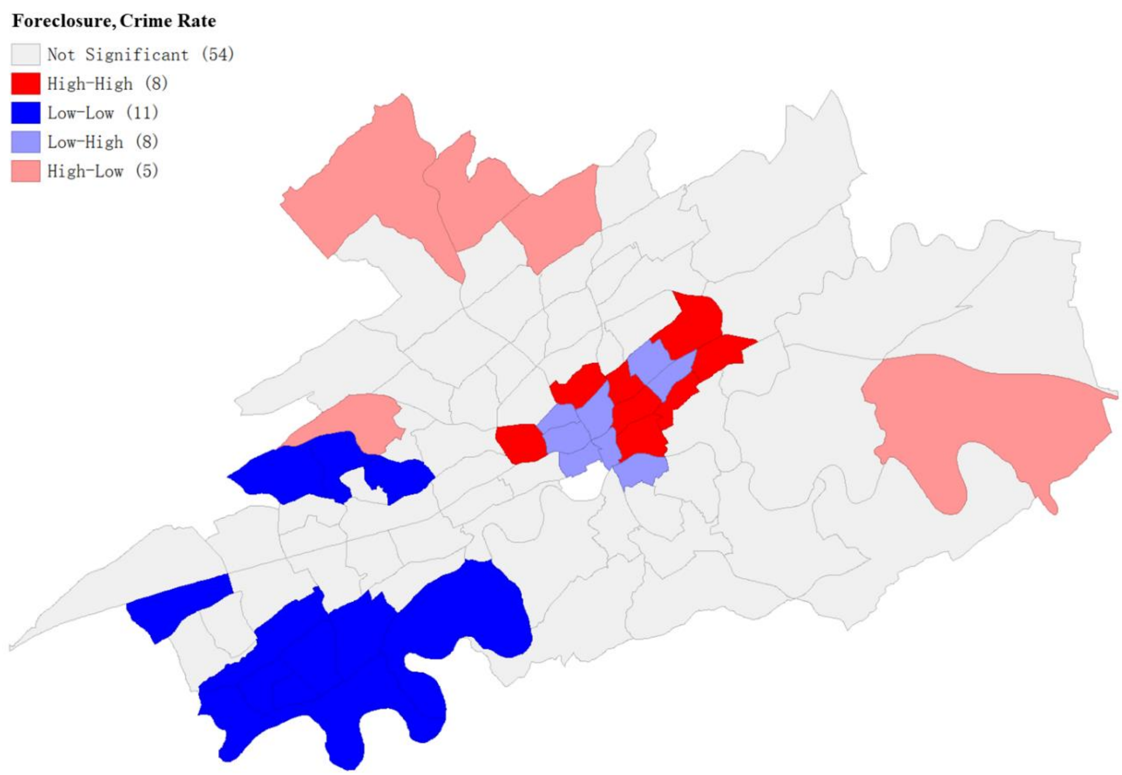

Figure 5-9. Bivariate Local Moran’s I Cluster Map for Foreclosure and Lagged Crime

Table 5-8. Geographic Information of Tracts and Corresponding Spatial Patterns for Foreclosure and Lagged Crime

Spatial Patterns	Census Tract	Places
High-high Spatial Pattern	15	Coster Yards; Oakwood-Lincoln Park
	17	Cecil Ave
	20	Burlington
	27	West View; Richmond Hill
	31	Loveland
	32	Chilhowee Hills
	67	Parkridge
	68	Mabry's Hill
Low-low Spatial Pattern	46.06	Berkshire Wood
	46.13	Meadowbrook
	46.15	Amherst
	57.01	Riverbend; Westminister Ridge
	57.07	Lakewood; Ebenezer
	57.08	Garland
	57.09	Scenic Valley-Poplar Hill-Tierra Verde
	57.10	Blue Grass
	57.11	Pine Springs; Farmington
	57.12	Kensington; Farrington
	58.03	Boxwood Hills; Sweet Briar; Woodland Trace
Low-high Spatial Pattern	1	Cumberland Ave; Summit Hill
	8	Flagship Kerns; Suttree Landing Park; Lincoln Street
	14	College Hills
	18	Plantation Hills
	19	Zoo Knoxville
	66	Happy Holler; 4th And Gill
	69	Fort Sanders
	70	Malcolm Martin Park
High-low Spatial Pattern	46.07	Hidden Hills, Fair Oaks
	54.02	Stony Point; Midway
	61.02	Heiskell
	62.06	Cedar Crest North
	62.08	Fieldview, Fountaincrest

Fourth, the spatial diagnostic test results on model foreclosure and crime rate are displayed in Figures 5-10 and 5-11. As I have already discussed the regression results in the above paragraphs, I will only focus on regression diagnostics in Figure 5-11. The diagnostic for spatial dependence shows several tests and their significance levels. According to Anselin's (2005) spatial regression model selection decision rule, the diagnostic results show significance (a rejection of the null hypothesis) for all Moran's I, spatial lag and spatial error test. A general rule is that if all these tests (i.e, Moran's I, lag and error) demonstrate significance, then look at the robust lag and error test. In my results, the robust lag and error test are also significant.

In this situation, I chose the model with greatest significance in terms of orders of magnitude. The p-value for the spatial lag model test is 0.00003, while the p-value for the spatial error model test is 0.02787. As the spatial lag model is more significant than the spatial error model. I chose the spatial lag model. Also, In the rare situations that both the statistic test and robust test are highly significant, it is suggested that researchers go with the model with the largest value for test statistic (Anselin 2005). As displayed in Figure 5-11, the model with the largest value for the test statistic is the spatial lag test, with test statistics of 17.23, while spatial error test is 4.84.

Table 5-9 displays the results of the spatial lag model for concentrated disadvantage, foreclosure, and crime rate in Knoxville. First, spatial lag term has a positive coefficient (Rho=0.4694) and it is highly significant. It provides evidence of spatial interdependence. Substantively, this suggests that census tracts in Knoxville have more crime rates when their neighboring tracts also have more crime rates. Second, the likelihood ratio test is significant, which suggests that there is extra spatial correlation for the residuals in the lag

```
REGRESSION
----------
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Enriched_TIGER_Line_2018_Tracts
Dependent Variable  :   CrimeRate  Number of Observations:   86
Mean dependent var  :     8.37124  Number of Variables   :    6
S.D. dependent var  :     9.26712  Degrees of Freedom    :   80

R-squared           :    0.508058  F-statistic           :     16.5242
Adjusted R-squared  :    0.477312  Prob(F-statistic)     : 3.54973e-11
Sum squared residual:     3633.31  Log likelihood        :    -283.001
Sigma-square        :     45.4164  Akaike info criterion :     578.003
S.E. of regression  :     6.73917  Schwarz criterion     :     592.729
Sigma-square ML     :     42.2478
S.E of regression ML:     6.49983

-----------------------------------------------------------------------------
       Variable      Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------------
          CONSTANT        8.7556        4.83401         1.81125       0.07386
            ConDis       4.83109        1.30289         3.70797       0.00038
        Foreclosur     -0.260992       0.348853       -0.748145       0.45657
        Unoccupied      0.562718       0.195375         2.88019       0.00510
         GrossRent     -0.750839       0.409778        -1.83231       0.07063
         HomeValue     0.0113931      0.0127017        0.896971       0.37243
-----------------------------------------------------------------------------
```
Figure 5-10. Spatial Model Diagnostics for Foreclosure and Crime

```
REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   16.498829
TEST ON NORMALITY OF ERRORS
TEST                  DF          VALUE             PROB
Jarque-Bera            2          221.9950          0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF          VALUE             PROB
Breusch-Pagan test     5           33.2401          0.00000
Koenker-Bassett test   5            7.3236          0.19766

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Spatial Analysis 0425--Weights
   (row-standardized weights)
TEST                         MI/DF        VALUE          PROB
Moran's I (error)            0.1448        2.8660        0.00416
Lagrange Multiplier (lag)      1          17.2327        0.00003
Robust LM (lag)                1          15.3331        0.00009
Lagrange Multiplier (error)    1           4.8359        0.02787
Robust LM (error)              1           2.9363        0.08661
Lagrange Multiplier (SARMA)    2          20.1690        0.00004
============================== END OF REPORT ================================
```

Figure 5-11. Spatial Model Diagnostics for Foreclosure and Crime

Table 5-9. Spatial Lag Model for Concentrated Disadvantage and Foreclosure on Crime Rate

	Crime Rate *coef/se*
Spatial Lag Term	0.47***
	(0.11)
Concentrated Disadvantage	3.00**
	(1.16)
Foreclosure	-0.23
	(0.30)
Percent of unoccupied housing units	0.42*
	(0.17)
Median gross rent	-0.51
	(0.36)
Median home value	0.01
	(0.01)
Constant	3.83
	(4.30)
R-Squared	0.61
Log-likelihood	-275.15
Likelihood-ratio test for spatial lag	15.71***
Breusch-Pagan Test (Heteroskedasticity)	43.08***

Ϯ=p<.10; *=p < .05; **=p < .01; ***=p < .001

model; the heteroskedasticity test is significant, showing evidence of heteroskedasticity in the residuals. Third, in the spatial lag regression, concentrated disadvantage is statistically significant on crime rates, controlling for the spatial lag term. Variables of foreclosure, percent of unoccupied housing units, median gross rent, and median house value are not significantly associated with crime rates, controlling for the spatial dynamics.

Final Comments

To conclude and answer research question on foreclosure, first, concentrated disadvantage does not predict crime better when foreclosure is added into the concentrated disadvantage index. Second, foreclosure does not mediate the relationship between concentrated disadvantage and the crime rate in the city of Knoxville. Foreclosure and median home value are significantly interacting to predict crime. The result shows that foreclosures in neighborhoods with more expensive homes are associated with lower crime rates. Third, foreclosure and crime are spatially clustered. The bivariate Local Moran's I test shows that there is a high foreclosure and high lag crime cluster in downtown Knoxville and its outer areas, as well as surrounded by several low foreclosure tracts in this area. The low foreclosure and low lag crime are clustered in the west of Knoxville. The spatial lag model shows that the rime variable is spatially interdependent across 86 census tracts in the city of Knoxville.

CHAPTER SIX

SUBPRIME LOAN ANALYSIS

In this chapter, I focus on the analysis of subprime loans. According to the analytical strategy indicated in the previous chapters, I investigate the roles of subprime loans in the relationship between concentrated disadvantage and crime across tracts in the city of Knoxville. Specifically, I ask:

RQ1c. Does concentrated disadvantage better predict crime when the subprime loans variable is added to the concentrated disadvantage index?

RQ2c. Do subprime loans mediate Sampson's model of concentrated disadvantage and crime?

RQ3c. If subprime loans in a neighborhood increase, in which neighborhood (if any) do crime rates change?

Research Question 1c

To answer my first research question (Q1c), factor analysis is examined with the six concentrated disadvantage variables in Sampson's index and the variable measuring the average number of subprime loans in each neighborhood. Table 6-1 shows rotated factor loadings of these seven variables, which loaded on a single factor with an eigenvalue greater than 1, according to the Kaiser-Guttman rule. Despite loading on a single factor, subprime lending did not load high on factor 1 with a loading of -0.30. This suggests that concentrated disadvantage is not improved by adding subprime lending to the index. Additionally, the loading is negative, meaning that to the degree that the seven variables are all measuring a single "concentrated

Table 6-1. Rotated Factor Loadings for Concentrated Disadvantage Variables and Subprime Lending

Variables	Factor 1
Percent poverty	0.89
Prevent female-headed household	0.88
Precent government assistance	0.91
Percent unemployment	0.77
Percent people under 18 years	0.88
Percent Black	0.81
Subprime lending	-0.30

disadvantage factor, subprime lending is loading on that factor in the “wrong” direction.

Research Question 2c

The strategy for answering the second research question (Q2c) is to see if the subprime loan variable is a mediator in the model with the crime rate regressed on concentrated disadvantage model. As in the previous two chapters, I use the method developed by Baron and Kenny (1986) to provide greater evidence for the possibility of mediation, as is outlined in Chapter 3.

Table 6-2 illustrates Baron and Kenny’s steps for mediation. In Model 1 (first step), crime is regressed on concentrated disadvantage. For one standard deviation increase in Sampson’s concentrated disadvantage index, crime rate significantly increases about 6.68 per 100 people ($t=7.47$, $p<0.001$). In Model 2 (second step), concentrated disadvantage is significantly and negatively associated with subprime lending. For every one standard deviation increase in Sampson’s concentrated disadvantage index, subprime lending significantly dropped by about 0.85 loans ($t=-2.81$, $p<0.05$). The negative relationship is interesting. It indicates that even “predatory” lenders may be less willing to provide financing for homes in “bad” neighborhoods. In Model 3 (third step), when concentrated disadvantage and subprime loan are both included to predict crime rate, concentrated disadvantage remains significant and positive, the coefficient of concentrated disadvantage dropped from 6.68 in step 1 to 6.25 in step 3. However, subprime lending is not significant using a conventional p-value cut-off at $p<.05$. Indeed, for one subprime loan count increase, crime rate dropped 0.50 per 100 people ($t=-1.56$, $p=0.12$). This suggests that the subprime loan variable is not a mediator in the relationship between concentrated disadvantage and crime rate. The reason is that the strength of the

Table 6-2. Baron and Kenny Steps for Mediation of Subprime Loan

	Model 1 (step1) Crime Rate *Coef/se*	Model 2 (step2) Subprime Loan *Coef/se*	Model 3 (step3) Crime Rate *Coef/se*
Concentrated disadvantage	6.68***	-0.85**	6.25***
	(0.89)	(0.30)	(0.93)
Subprime Loan	N/A	N/A	-0.50
			(0.32)
Constant	8.37***	3.89***	10.32***
	(0.78)	(0.26)	(1.47)
F (1,86)/F (1,84)/F (2,85)	55.87***	7.92**	29.63***
R-squared	0.40	0.08	0.42
N	86	86	86

Ϯ=p<.10; *=p < .05; **=p < .01; ***=p < .001

coefficient of concentrated disadvantage is only slightly decreased from step 1 to step 3, and the potential mediator subprime is not significant in step 3.

As in the previous chapters, I consider the possibility that concentrated disadvantage mediates the relationship between subprime lending and crime. Table 6-3 displays Baron and Kenny's steps for mediation of concentrated disadvantage on the relationship between subprime loans and the crime rate. In Model 1 (first step), crime is regressed on subprime loans. For one subprime loan count increase, crime rate significantly decreased about 1.14 per 100 people ($t=-2.99$, $p<0.01$). Again, this is a surprising finding that there are fewer crimes where there is more subprime lending. In Model 2 (second step), subprime lending is significantly associated with concentrated disadvantage. For every additional subprime loan, concentrated disadvantage significantly decreased approximately 0.1 standard deviation ($t=-2.81$, $p<0.01$). In Model 3 (third step), when subprime loans and concentrated disadvantage are both included to predict crime rate, the subprime loans variable is not significant, and the potential mediator, concentrated disadvantage, remains significant. For one subprime loan count increase, crime rate dropped 0.5 per 100 people ($t=-1.56$, $p=0.12$), controlling for concentrated disadvantage. For one standard deviation increase in Sampson's concentrated disadvantage index, crime rate significantly increased 6.25 per 100 people ($t=6.75$, $p<0.001$), holding subprime loans constant. From the model results above, I do not have enough evidence to *conclude* that concentrated disadvantage mediates the relationship between the subprime loans counts and crime rate in Knoxville, but I have strong evidence. However, I cannot ignore the fact that the direction of the relationship between subprime lending, concentrated disadvantage, and crime is not as expected. Given that the types of people who are typically the customers of subprime lenders (i.e., poorer and non-

Table 6-3. Baron and Kenny Steps for Mediation of Concentrated Disadvantage

	Model 1 (step1) Crime Rate *Coef/se*	Model 2 (step2) Concentrated Disadvantage *Coef/se*	Model 3 (step3) Crime Rate *Coef/se*
Subprime Loan	-1.14**	-0.10**	-0.50
	(0.38)	(0.04)	(0.32)
Concentrated Disadvantage	N/A	N/A	6.25***
			(0.93)
Constant	12.79***	0.40*	10.32***
	(1.76)	(0.17)	(1.47)
F (1,84)/F (2,83)	8.96**	7.92**	29.63***
R-squared	0.10	0.09	0.42
N	86	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

white) are, by definition, concentrated in disadvantaged neighborhoods (Geraldi and Willen 2008; George, Newberger and O'Dell 2019), I would expect a positive association between subprime lending and concentrated disadvantage and subprime lending and crime. However, perhaps because the subprime loan is associated with the purchased house and not the location of the borrower at the time of the loan purchase, this is distorting the finding. In other words, it is possible that residents of neighborhoods with concentrated disadvantage are more likely to take out subprime loans, but the loan may be for a home in a better neighborhood.

Table 6-4 examines the relationship between subprime loans and the crime rate, including the controls. Model 1 is the same as in Table 6-4 and has already been discussed. In Model 2, for every additional subprime loan, the crime rate dropped 0.50 per 100 people (t=-1.57, p=0.12), controlling for other variables. In Model 3, when concentrated disadvantage is added, the coefficient of subprime loan is -0.30 but is not significant (t=-0.99, p=0.32), holding all other variables constant.

Research Question 3c

Research question Q3c tests whether a spatial pattern exists in the relationship of subprime loans and the crime rate. Utilizing the strategy in chapter 3 on concentrated disadvantage and crime, I use subprime loan as a predictor of crime in the following section. First, a univariate of global and local Moran's I statistics is conducted to examine the spatial patterns of subprime loan in Knoxville. Figure 6-1 shows the global Moran's I statistic for subprime loan. The test statistic of Moran's I is 0.0265, with a z-score 0.6140 and a pseudo p-value of 0.255. This suggests a fail to reject the null hypothesis that there is spatial randomness

Table 6-4. Regression Test for Mediation of Concentrated Disadvantage on Subprime Loan and Crime Rate Relationship

	Model 1 *coef/se*	Model 2 *coef/se*	Model 3 *coef/se*
Subprime Loan	-1.14**	-0.50	-0.30
	(0.38)	(0.32)	(0.30)
Percent of unoccupied	N/A	0.89***	0.57**
housing units		(0.18)	(0.19)
Median gross rent	N/A	-0.91*	-0.70
		(0.43)	(0.41)
Median home value	N/A	-0.01	0.01
		(0.01)	(0.01)
Concentrated Disadvantage	N/A	N/A	4.61**
			(1.32)
Constant	12.79***	11.31*	8.02
	(1.76)	(4.42)	(4.25)
F (1,84)/F (4,81)/F (5,80)	8.96**	15.67***	16.70***
R-squared	0.10	0.44	0.51
N	86	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

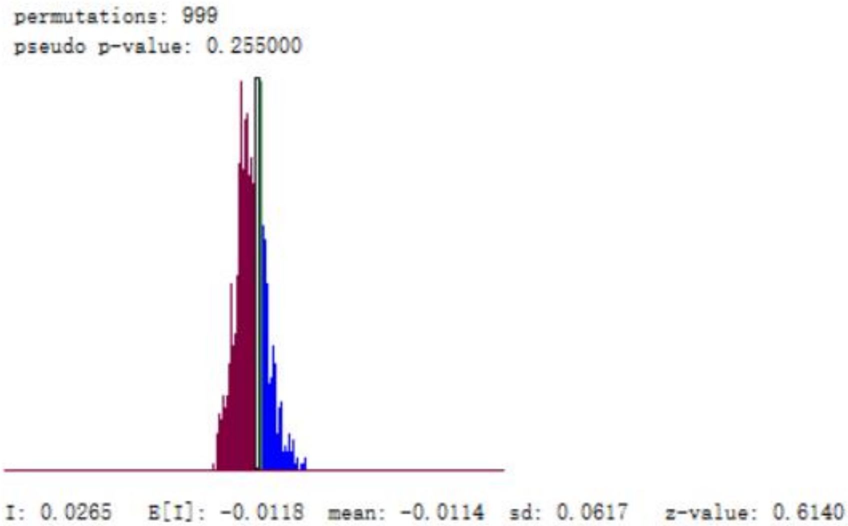

Figure 6-1. Test Statistics of Global Moran’s I of Subprime Loan Two-Year Average

Figure 6-2 shows the result of a Moran scatter plot of subprime loan. The slope of the line is Moran's I value. The upper-right and lower-left quadrants are census tracts that are positive spatial autocorrelations of subprime loan counts. These census tracts are similar to each other in terms of subprime loan patterns, while the lower right and upper left quadrant are tracts that have negative spatial correlation, these census tracts are different(dissimilar) from their neighboring tracts. Out of 88 census tracts, there are more census tracts that are positively autocorrelated than negatively autocorrelated.

Second, to show exactly which tracts are spatially clustered and outliers, I conduct Local Moran' I statistic test for the subprime loans count. Figure 6-3 and 6-4 shows the result of local Moran's I test for both significance map and cluster map. Table 6-5 displays geographic information of tracts and corresponding spatial patterns for the subprime loans. From the cluster map, among 88 census tracts, there are only 12 census tracts with subprime loans that are significantly spatially autocorrelated. The dark red and dark blue areas represent the census tracts that are spatially clustered in terms of subprime loans. The dark red represents tracts with a high level of subprime loans that are surrounded by other tracts with high levels of subprime loans. This dark red area is made up of census tracts 46.06 and 60.02, and it includes the neighborhoods of Brentwood, Berkshire Wood, Glen Arden, and Lazy Acres. The dark blue section represents tracts with low subprime loan counts surrounded by areas with low subprime loan counts. This dark blue area is made up of census tracts 27 and 42, and it includes neighborhoods of West View and Harrill Hills. There are eight census tracts that are spatial outliers (light blue and light red). Two light blue tracts (i.e., 56.04 and 58.03) have low levels of subprime loans surrounded by tracts with a high amount of subprime loans. These are the neighborhoods of Arrowhead,

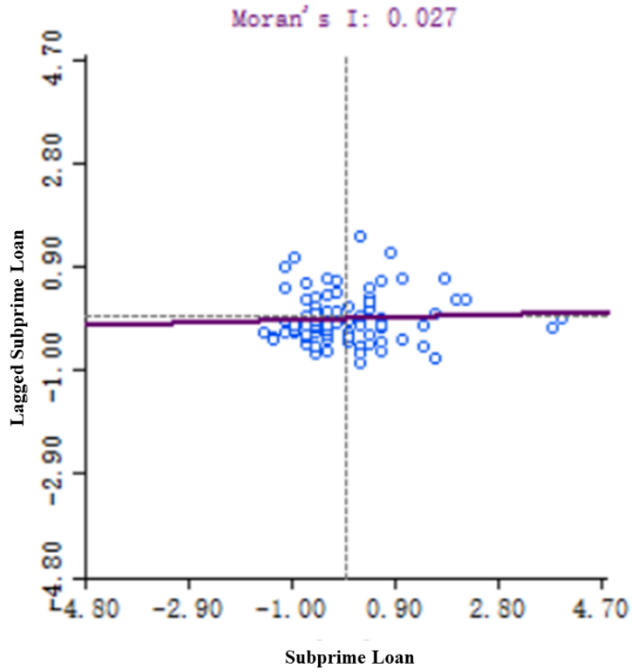

Figure 6-2. Global Moran Scatter Plot of Subprime Loan Count Two-Year Average

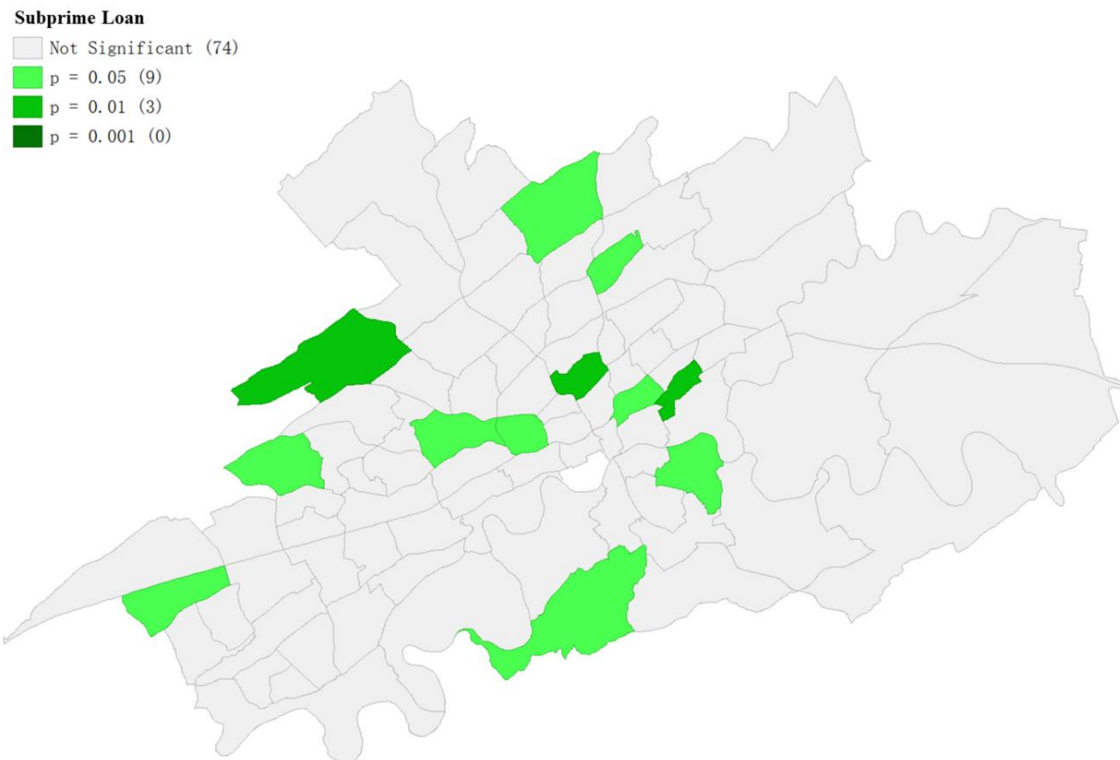

Figure 6-3. Local Moran's I Significance Map for Subprime Loan

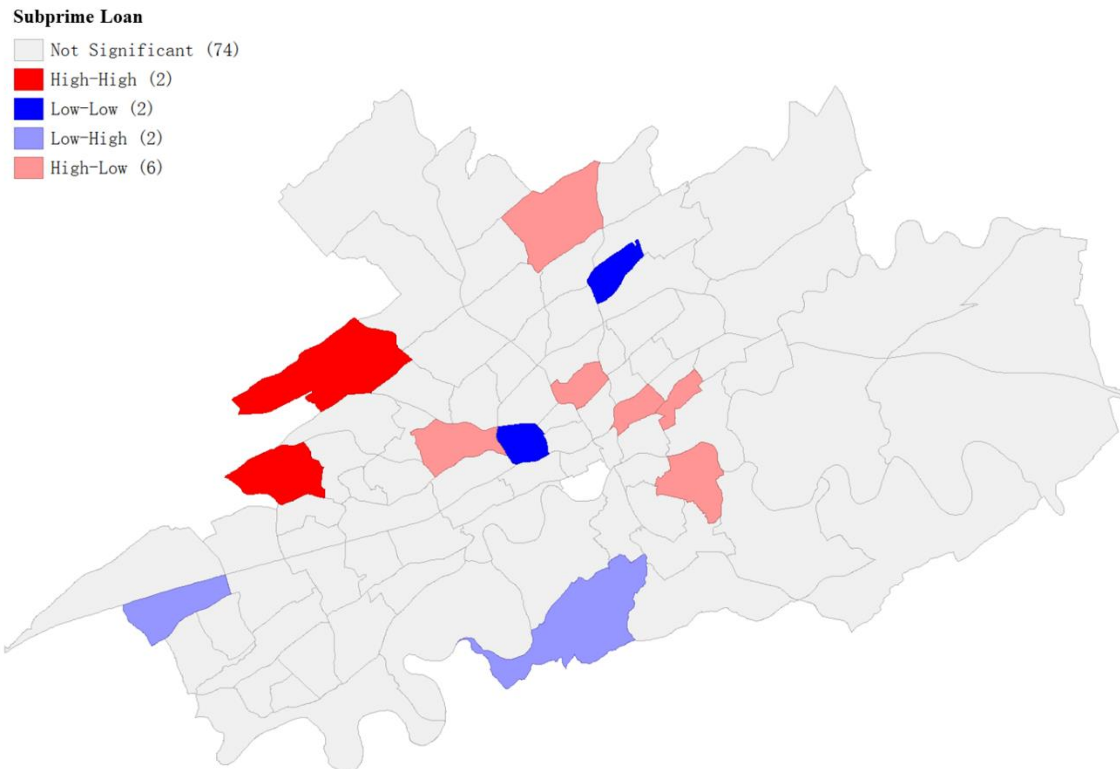

Figure 6-4. Local Moran's I Cluster Map for Subprime Loan

Table 6-5. Geographic Information of Tracts and Corresponding Spatial Patterns for Subprime Loan

Spatial Patterns	Census Tract	Places	Subprime Lending Counts
High-high Spatial Pattern	46.06	Brentwood; Berkshire Wood; Glen Arden	6
	60.02	Lazy Acres	4.5
Low-low Spatial Pattern	27	West View	2
	42	Harrill Hills	2.5
Low-high Spatial Pattern	56.04	Arrowhead	1
	58.03	Sweet Briar; Boxwood Hills	1.5
High-low Spatial Pattern	15	Coster Yards	8
	20	Burlington	4.5
	22	Island Home	4.5
	38.02	Holiday Hills	5
	62.08	Fieldview	5.5
	67	Parkridge	4.5

Sweet Briar, and Boxwood Hills. surrounded. The six light red tracts have high levels of subprime loans and are surrounded by areas with low levels of subprime loans. These areas are made up of the neighborhoods of Coster Yards, Burlington, Island Home, Fieldview, and Parkridge.

Third, Bivariate Local Moran's I test between subprime loan counts and lagged crime is shown in figures 6-5, 6-6 and 6-7. As I have discussed the Moran scatter plot and significance map, I will focus on the cluster map. Figure 6-7 displays the significance (colored tracts) and non-significance tracts (gray tracts) in terms of subprime loan and lagged crime in neighboring tracts. Table 6-6 displays geographic information of tracts and corresponding spatial patterns for subprime loan and lagged crime. The dark red and dark blue shading show the spatial cluster of the significant association. The dark red area represents the tracts with high levels of subprime lending that are significantly associated with high lagged crime in the neighboring tracts. These high subprime lending neighborhoods are Coster Yards, Burlington, Fort Sanders, and Parkridge, largely clustered in and around downtown. The dark blue color represents the tract with low levels of subprime lending that is significantly associated with low crime in the neighboring tracts. These neighborhoods are Meadowbrook, Amherst, Lakewood, Garland, Scenic Valley-Poplar Hill-Tierra Verde, Blue Grass, Boxwood Hills, Kensington, and Cedar Crest North. As is shown in the cluster map, these neighborhoods are mainly located in the west side of Knoxville. The map also shows tracts that are spatial outliers. The light blue color represents low subprime lending neighborhoods with high crime levels in neighboring tracts, these 12 light blue tracts include neighborhoods of downtown, Flagship Kerns, College Hills, Burlington, Plantation Hills, West View, Zoo Knoxville, Arlington, Loveland, Chilhowee Hills, Happy Holler, Mabry's Hill,

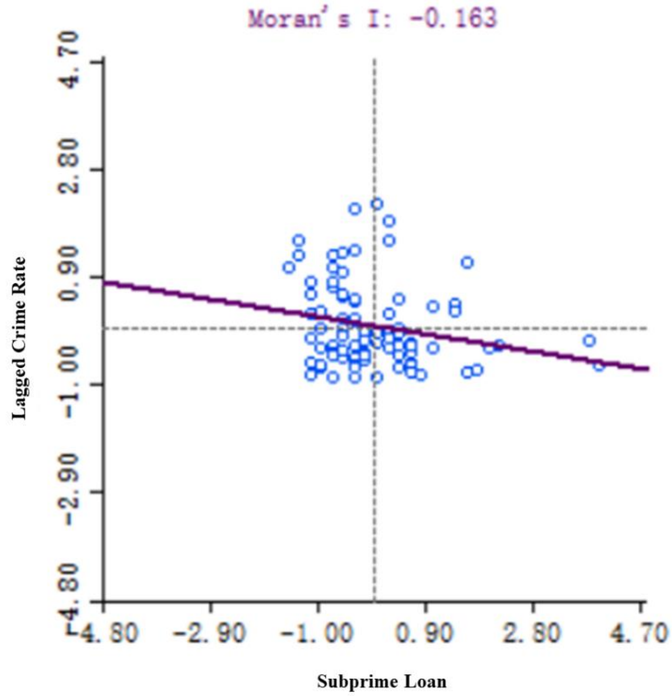

Figure 6-5. Bivariate Local Moran's I Scatter Plot for Subprime Loan and Lagged Crime

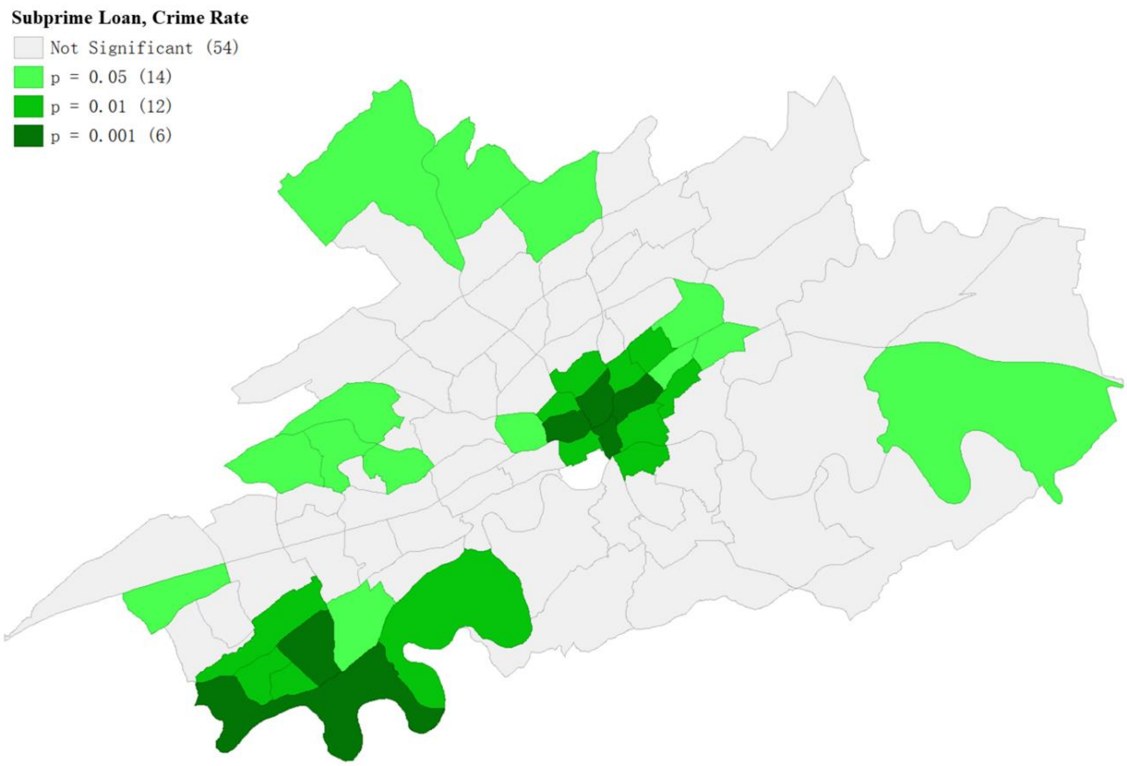

Figure 6-6. Bivariate Local Moran's I Significance Map for Subprime Loan and Lagged Crime

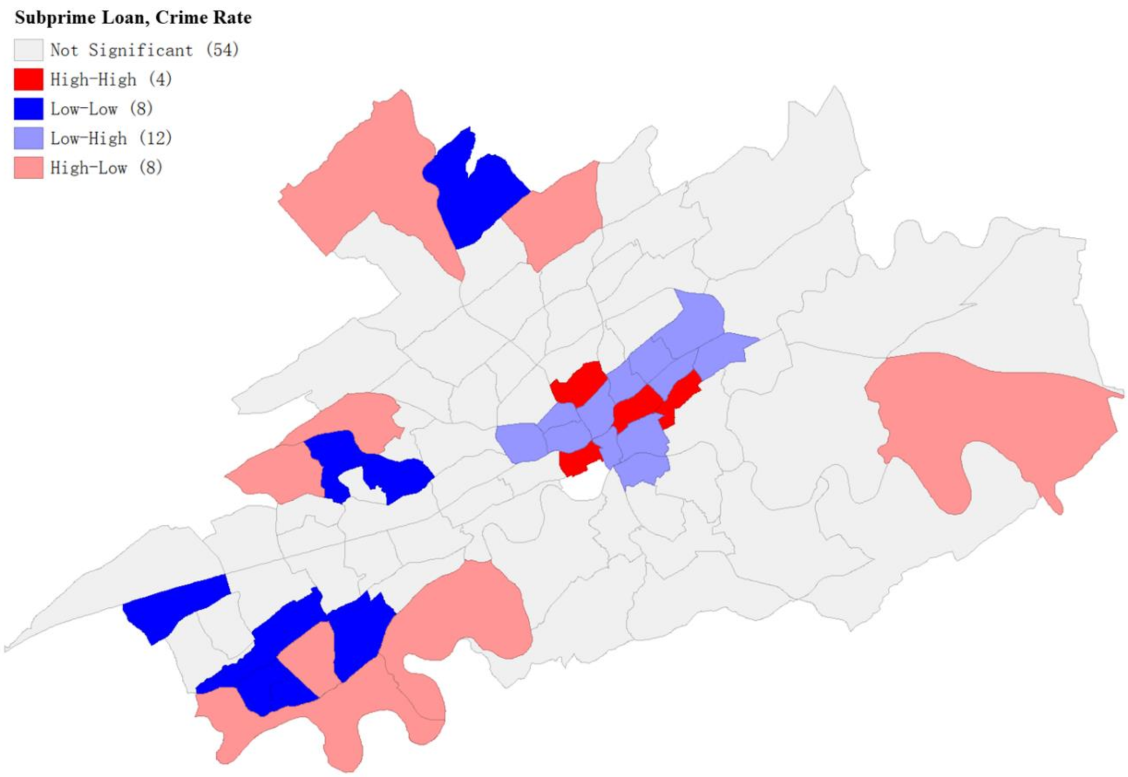

Figure 6-7. Bivariate Local Moran's I Cluster Map for Subprime Loan and Lagged Crime

Table 6-6. Geographic Information of Tracts and Corresponding Spatial Patterns for Subprime Loan and Lagged Crime

Spatial Patterns	Census Tract	Places
High-high Spatial Pattern	15	Coster Yards; Oakwood-Lincoln Park
	20	Burlington
	67	Parkridge
	69	Fort Sanders
Low-low Spatial Pattern	46.13	Meadowbrook
	46.15	Amherst
	57.07	Lakewood; Ebenezer
	57.08	Garland
	57.09	Scenic Valley-Poplar Hill-Tierra Verde
	57.12	Kensington; Farrington
	58.03	Boxwood Hills; Sweet Briar; Woodland Trace
	62.06	Cedar Crest North
Low-high Spatial Pattern	1	Cumberland Ave; Summit Hill
	8	Flagship Kerns; Suttree Landing Park; Lincoln Street
	14	College Hills
	17	Cecil Ave
	18	Plantation Hills
	19	Zoo Knoxville
	27	West View
	31	Loveland
	32	Chilhowee Hills
	66	Happy Holler; 4^{th} And Gill
	68	Mabry's Hill
	70	Malcolm Martin Park
High-low Spatial Pattern	46.06	Brentwood; Berkshire Wood; Glen Arden
	46.07	Hidden Hills, Fair Oaks
	54.02	Stony Point; Midway
	57.01	Riverbend; Westminister Ridge
	57.10	Blue Grass
	57.11	Pine Springs; Farmington;
	61.02	Heiskell
	62.08	Fieldview, Fountaincrest

and Malcolm Martin Park. The light red sections represent high subprime lending neighborhoods surrounded by tracts with low crime rates. These neighborhoods are scattered around the city, such as Brentwood, Hidden Hills, Stony Point, Riverbend, Pine Springs, Heiskell, Blue Grass, and Fieldview. In general, subprime loan and crime rates are spatially heterogeneous in Knoxville as there are 20 census tracts that are significantly spatial outliers and only 12 census tracts are spatially clustered.

Fourth, the spatial diagnostic test on the model combining subprime loan and crime rates is displayed in Figures 6-8 and 6-9. As I have already discussed the regression results in the above paragraphs, I will only focus on regression diagnostics in Figure 6-9. The diagnostic for spatial dependence shows several tests and their significance levels. According to the spatial regression model selection decision rule outlined by Anselin (2005), the diagnostic shows significance (a rejection of the null hypothesis) for all Moran's I, spatial lag, and spatial error tests. A general role is that if all these tests (Moran's I, lag, and error) show significance, then look at the robust lag and error test. In my results, the robust lag and error tests are also significant. In this situation, I chose the model in which orders of magnitude most significant. The p-value for the spatial lag model test is 0.00003, while the p-value for spatial error model test is 0.02192. Therefore, I chose the spatial lag model. Also, in the rare situations that both test and robust test are highly significant, it is suggested that researchers go with the model with the largest value for the test statistic (Anselin 2005). From Figure 6-9, the model with the largest value for test statistic is the spatial lag test, with a value of 17.61, while spatial error test is 5.25.

Table 6-7 displays the results of the spatial lag model for concentrated disadvantage, subprime loan, and crime rate in Knoxville. First, the spatial lag term has a positive coefficient

```
REGRESSION
----------
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Enriched_TIGER_Line_2018_Tracts
Dependent Variable  :   CrimeRate  Number of Observations:   86
Mean dependent var  :     8.37124  Number of Variables    :    6
S.D. dependent var  :     9.26712  Degrees of Freedom     :   80

R-squared           :    0.510658  F-statistic            :      16.697
Adjusted R-squared  :    0.480074  Prob(F-statistic)      : 2.89268e-11
Sum squared residual:     3614.11  Log likelihood         :    -282.774
Sigma-square        :     45.1763  Akaike info criterion  :     577.547
S.E. of regression  :     6.72133  Schwarz criterion      :     592.273
Sigma-square ML     :     42.0245
S.E of regression ML:     6.48263
```

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	8.02193	4.24717	1.88877	0.06255
Subprime	-0.302946	0.304813	-0.993873	0.32328
ConDis	4.61174	1.32212	3.48814	0.00079
Unoccupied	0.570719	0.192959	2.95773	0.00407
GrossRent	-0.701298	0.410669	-1.7077	0.09157
HomeValue	0.0138889	0.0116152	1.19576	0.23532

Figure 6-8. Spatial Model Diagnostics for Subprime Loan and Crime

```
REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   15.511378
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE            PROB
Jarque-Bera            2           225.0534         0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE            PROB
Breusch-Pagan test     5            34.7569         0.00000
Koenker-Bassett test   5             7.6052         0.17938

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Spatial Analysis 0425--Weights
   (row-standardized weights)
TEST                          MI/DF        VALUE          PROB
Moran's I (error)             0.1509        2.9171        0.00353
Lagrange Multiplier (lag)       1          17.6070        0.00003
Robust LM (lag)                 1          14.8710        0.00012
Lagrange Multiplier (error)     1           5.2524        0.02192
Robust LM (error)               1           2.5164        0.11267
Lagrange Multiplier (SARMA)     2          20.1234        0.00004
------------------------------ END OF REPORT --------------------------------
```

Figure 6-9. Spatial Model Diagnostics for Subprime Loan and Crime

Table 6-7. Spatial Lag Model for Concentrated Disadvantage and Subprime Loan on Crime Rate

	Crime Rate
	coef/se
Spatial Lag Term	0.47***
	(0.11)
Concentrated Disadvantage	4.39***
	(1.18)
Subprime Loan	-0.32
	(0.26)
Percent of unoccupied housing units	0.43
	(0.17)
Median gross rent	-0.45
	(0.36)
Median home value	0.01
	(0.01)
Constant	3.35
	(3.80)
R-Squared	0.61
Log-likelihood	-274.69
Likelihood-ratio test for spatial lag	16.17***
Breusch-Pagan Test (Heteroskedasticity)	45.74***

†=p<.10; *=p < .05; **=p < .01; ***=p < .001

(Rho=0.4747) and it is highly significant, which provides evidence of spatial interdependence. Substantively, this suggests that census tracts in Knoxville have more crime rates when their neighboring tracts also have more crime rates. Second, the likelihood ratio test is significant, which means that there is extra spatial correlation for the residuals in the lag model; the heteroskedasticity test is significant, showing evidence of heteroskedasticity in the residuals. Third, in spatial lag regression, concentrated disadvantage and percent of unoccupied housing units are statistically significant associated with crime rates, controlling for spatial lag term. Subprime lending, median gross rent, and median home value variables are not significantly associated with crime rates, controlling for spatial dynamics.

Final Comments

To conclude and answer my research question on subprime loan, first, concentrated disadvantage is not improved as a prediction of crime when subprime lending is added to the concentrated disadvantage index. Second, subprime loan variable is not a mediator in the relationship between concentrated disadvantage and crime rate in the city of Knoxville. Third, generally speaking, subprime loan in Knoxville is spatially dissimilar across the city, and there is not enough evidence for to conclude subprime loan is spatially clustered. The bivariate Local Moran’s I test shows that there is a low subprime loan census tracts surrounded by high lag crime census in downtown Knoxville and its outer areas. The spatial lag model shows that the crime variable is spatially interdependent across 86 census tracts in the city of Knoxville.

CHAPTER SEVEN

CONCLUSION

Summary

Two perspectives emphasize the development of concentrated disadvantage. The first and foremost perspective comes from William Julius Wilson's theory of the creation of the urban underclass (1987, 1996). Wilson argues that deindustrialization is the driving factor that concentrate the urban poor in the inner city. The social transformation represents a change in the class structure in the inner-city neighborhoods as the nonpoor Black middle and working classes tend to no longer to reside in these neighborhoods, thus leaving the proportion of truly disadvantaged individuals and families behind (Wilson 1987). Therefore, this social transformation (e.g., joblessness, out-of-wedlock births, female-headed families, and welfare dependency) has *concentration effects* because it results in a disproportionate concentration of the most disadvantaged segments of the urban Black population in the inner city (Wilson 1987). In other words, it is worse to be poor in a disadvantaged neighborhood than in a neighborhood without concentrated disadvantage. The second perspective is Massey and Denton's theory on residential and racial segregation. They argue that racial segregation is the driving factor that is responsible for the creation of urban underclass (Massey and Denton 1993). Due to racial segregation, a large number of Black Americans "experience social environments where poverty and jobless are the norm, where the majority of children are born out of wedlock, where most families are on welfare, where education failure prevails, and where social and physical deterioration abound" (Massey and Denton, 1993:2).

Both theoretical perspectives mark the creation of the urban disadvantaged population. To be disadvantaged is to live in poverty, be unemployment, live in single-parent households (especially female headed), be Black, live on government welfare etc. In the context of neighborhood, these disadvantaged social factors cluster together as residents experience consistent and endurable inequality. To make matters worse, the disadvantaged social factors have the concentration effect. Disadvantaged neighborhoods are natural contexts that create social and economic barriers which prevent residents from getting out.

The purpose of this dissertation is to assess the relationship between neighborhood concentrated disadvantage and crime, and to test whether housing market conditions (i.e., numbers of eviction, foreclosure, and subprime loans) are a neglected part of concentrated disadvantage on the effects of crime and victimization in the city of Knoxville, Tennessee or mediate that relationship. In doing so, my goal is to provide a better understanding of neighborhood concentrated disadvantage and extend the discussion to neighborhood housing market conditions as they are related to crime and victimization. As I briefly stated in Chapter 1 and more thoroughly discussed in Chapter 2, I argue that although neighborhood concentrated disadvantage is important to predicting criminal behavior (Sampson 2012) or reported crimes as a condition of overpolicing, eviction, foreclosure, and subprime loans maybe an important part of the concentrated disadvantage index as it predicts crime and victimization; or may have an important mediating effect on the relationship between concentrated disadvantage and crime (Chan et al. 2013; Faber 2013; Desmond 2016). Studies (e.g., Sampson 1997; Wodtke et al. 2011) have shown that concentrated disadvantage includes six variables that measure a single underlying factor that is typically produced as an index representing neighborhood—level disadvantage. This concentrated disadvantage index is limited because housing market factors may also be a process of disadvantage at the neighborhood level. Focusing on socioeconomic variables only may not capture the entire range of a neighborhood's disadvantage.

My first general research question posed in this dissertation is "Are housing market characteristics a neglected part of concentrated disadvantage with regard to crime?" Overall, my research shows that the three housing market conditions I examined (eviction, foreclosure, and subprime lending) are related to neighborhood crime rates, but the relationship between these variables and crime is complex. Overall, I find that none of the three housing market conditions improves models of concentrated disadvantage predicting crime when added to the index. Results of factor analysis show that it is not unreasonable to add eviction to the concentrated disadvantage index, but it does not improve the index's ability to predict crime when foreclosure and subprime loan is added. (i.e., model fit is not improved by using a new index that includes foreclosure).

Additionally, some previous studies have focused on neighborhood crime rate due to eviction and foreclosure (Boessen and Chamberlain 2017; Desmond 2016; Faber 2013; Haupert 2019; Jones and Pridemore 2012). These studies suggest that criminal activity becomes a survival strategy after eviction because the socially acceptable ways of leading life and earning income is restricted (Alm and Bäckman 2020). The presence of unoccupied foreclosed houses is significantly associated with the increase of local neighborhood crime (Boessen and Chamberlain 2017; Cui and Walsh 2015; Ellen et al. 2013) because the foreclosured houses create an opportunity for criminal activity in the surrounding environment. Given this, as I have argued above, housing market factors may represent a neighborhood—level disadvantage, therefore, the relationship between neighborhood disadvantage and crime rates are also potentially mediated by certain housing market variables. My second research question is “Do housing market characteristics mediate Sampson’s model of concentrated disadvantage and crime?”

I find that none of the three housing market factors mediates the relationship between concentrated disadvantage and crime. It seems quite likely that concentrated disadvantage, however, mediates the relationship between eviction and crime, as seen in other studies (Boessen and Chamberlain 2017; Desmond 2016; Faber 2013; Haupert 2019; Jones and Pridemore 2012) and I document in Knoxville. Foreclosure does not mediate the relationship between concentrated disadvantage and crime, nor does conentrated disadvantage mediate the relationship between foreclosure and crime. However, there is moderating effects of median home value on the relationship between foreclosure and crime, and the relationship between foreclosures and crime is different at different median home values in a neighborhood. Specifically, and oddly, foreclosures in neighborhoods with more expensive homes are associated with lower crime rates. Finally, the number of subprime loans does not mediate the relationship between concentrated disadvantage and crime rates; indeed, the relationship between the number of subprime loans and crime is negative, This is a surprising finding that I cannot easily explain.

Finally, my dissertation examined the spatial effect of neighborhood disadvantage and housing market factors on crime in Knoxville. In Chapter 2, I argue that when eviction and foreclosure occur in a neighborhood they not only increase the risk of actual crime, but also increase the actual crime in the surrounding neighborhoods considering the hypremobility of residents after eviction and foreclosure (Semenza et al. 2022). As predatory financial institutions are purposefully set up and target the disadvantaged population in certain neighborhoods (Brooks and Simon 2007; Mayer, Pence, and Sherlund 2009), it is highly likely that disadvantaged neighborhoods are held together by these questionable financial institutions.

The spatial analysis shows that eviction is spatially clustered in the census tracts that are in the east of downtown Knoxville. Also, bivariate local Moran's I analysis results shows that the census tracts that are in the downtown Knoxville area have a high eviction count surrounded by high crime rates in their neighboring census tracts. The spatial lag model indicates that crime rates are positively spatially interdependent across 86 census tracts in Knoxville.

The spatial analysis shows that foreclosure is also spatially clustered in certain census tracts in Knoxville, mainly in areas of north and south Knoxville. Also, bivariate local Moran's I analysis results show that the census tracts that are in the downtown Knoxville and surrounding areas are high foreclosure census tracts adjacent to high crime rate census tracts. A large area of southwest Knoxville consists of low foreclosure census tracts with low crime rates in their neighboring census tracts.

However, contrary to eviction and foreclosure, subprime lending in Knoxville is, generally speaking, structured in a spatial heterogeneously way. There is not enough evidence to claim that there is spatial clustering of subprime lending in Knoxville. Furthermore, bivariate local Moran's I analysis results shows that there is a large area of low subprime loan census tracts surrounded by high crime rate census tracts, which is the east side of downtown Knoxville. Since the method for measuring subprime loans in my study attaches these loans to houses, it may be that people who live in high crime census tracts are the targets of predatory (or, at least, subprime) lenders who provide the funds for people to move to nearby neighborhoods with less crime. This may also explain why the relationship between the number of subprime loans and crime is negative.

In sum, this dissertation seeks to address the neighborhood disadvantage and crime relationship in consideration with three housing market variables in a mid-sized city—Knoxville, Tennessee—in hopes of providing a better understanding of the causes of neighborhood crime and victimization as a result of housing market factors. Overall, I find relationships between housing market conditions, concentrated disadvantage, and crime, but these relationships are quite complex.

Contributions

This dissertation makes several contributions to the field of neighborhood concentrated disadvantage on crime. From factor analysis, I find that housing market factors are all measuring the same underlying construct with Sampson's concentrated disadvantage index in the city of Knoxville as they are all loaded on a single factor. This substantively shows that in Knoxville, citizens living in disadvantaged neighborhoods might also suffer eviction, housing foreclosure and high-interest lending mortgage, along with other social issues, such as poverty and unemployment. But this interpretation needs to be illustrated with caution. Only eviction factor loadings are high, while foreclosure and subprime loans are not. Therefore, eviction can be included into Sampson's concentrated disadvantage (although it does not appear to improve it), while foreclosure and subprime loans cannot. Furthermore, all new concentrated disadvantage with three housing market variables included are not improved in models of crime in the city of Knoxville.

Second, contrary to my hypotheses (1b, 2b, and 3b). None of the housing market factors are mediating the relationship between concentrated disadvantage and crime. However, as I investigate deeply in Chapter 4, 5, and 6 that concentrated disadvantage as a potential mediator on the relationship between eviction, foreclosure, and subprime lending respectively and crime rate, concentrated disadvantage strongly mediated the relationship between eviction and crime. However, there is no evidence that subprime and foreclosure on crime are mediated by concentrated disadvantage. Substantively, neighborhoods with high rental apartment evictions would make the neighborhood more disadvantaged, thus leading to crime and criminal behavior.

Third, the spatial analysis shows that eviction and foreclosure are spatially clustered in Knoxville, while the subprime lending variable shows a spatially dissimilar pattern across the city. The cluster area of high eviction is mainly concentrated in the east and north side of downtown, and the cluster regions for high foreclosure are in the south and north of the city. The low levels of eviction and foreclosure are clustered in the southwest of the city. The bivariate Moran's I between eviction and the crime rates suggests that the high eviction census tracts are in the east side of downtown that are significantly surrounded by high crime census tracts in the east side of downtown. The same situation applies to the bivariate Moran's I between foreclosure and crime rates. However subprime lending is spatially heterogeneously patterned in Knoxville, and there is no evidence that subprime lending is spatially clustered. It appears that the spatial patterns of low subprime loan and high crime rate in neighboring tracts are the most prevalent across the city. This spatially dissimilar pattern on crime is mainly located in downtown Knoxville and its outer areas.

Limitations

One limitation of this dissertation is the use of official crime data. As the crime data are directly collected from Knoxville Police Department, I cannot separate real crime from crime that is reported due to over-policing. Police are dispatched disproportionally to disadvantaged neighborhoods. This enforcement will bias the official crime data from the police department because more police activities drive up more official crimes. For neighborhoods with low crime reports, that might reflect the fact that there is low crime occurring in those neighborhoods, but they are less policed. Therefore, the crime data suffer this bias due to police engagement.

It is also worth considering how generalizable my findings may be to another mid-sized city. One factor that sets Knoxville apart from other cites of its size is that it is home to a large university. As such, crime rates (especially for property crimes) would likely be higher. Moreover, college towns experience considerable population churning. There is a large and constantly changing base of renters, and this may impact the rental market differently than elsewhere. It is unclear what the impact of this is. Landlords may be more willing to evict tenants because they know that they can find others. Alternatively, landlords may be less willing to bear the cost of eviction because they know that tenants who do not pay the rent may stay for only a short time. Another factor that may differentiate Knoxville from other mid-sized cities is that it has a robust economy and—during the time studied—a relatively stable housing market. This is not true elsewhere, so one may find a stronger relationship between housing market characteristics and crime in places where the housing market is less stable.

Political Implications

This dissertation has several implications for government agencies implementing political and public policy in the city of Knoxville. First and foremost, according to my data, around 31 out of 86 census tracts lie in the somewhat disadvantaged or high disadvantaged category. As the concentrated disadvantage index does not represent a single factor, but a composite of socio-economic factors, government agencies should consider improving the disadvantaged neighborhoods by improving residents' living condition across various social aspects. For example, a poor neighborhood not only a home to poor people but simultaneously, people with low educational levels coupled with high levels of unemployment, disability, illness, etc. Also, my results show that housing market conditions also represent a degree of disadvantage. For the residents suffering disadvantage, they might also suffer from high levels of eviction, foreclosure, and predatory mortgage and financial issues. What happens within neighborhoods is partially shaped by these socioeconomic and housing market factors, which are linked to the wider political economy (Sampson et al. 1997). Besides developing social welfare programs distributing monthly stipend to those who have needs, perhaps establishing neighborhood-based development programs where all residents participate and contribute may also apply. Besides pouring financial assistance into citizens' hands, government agencies also need to direct financial support into those disadvantaged neighborhoods for infrastructure investment. This way, local residents can fully participate and work collectively to develop their own neighborhood. Places like Detroit have city land banks where people can buy abandoned houses cheaply if they rehabilitate the house within a year. This way, the stock of affordable housing is improved, simultaneously, it could reduce crime either directly or indirectly.

Second, the spatial analysis shows that in Knoxville, there are 9 census tracts clustered with high evictions; 13 census tracts clustered with high foreclosures; and 8 census tracts have high subprime loans. As Desmond (2019) suggested that homeownership in distressed communities could go a long way toward decreasing families' house cost burden, because in some communities, rents are considerably higher than mortgage payments. This is not to say that in neighborhoods with high eviction, evictees should be directed to instead buy house with mortgages, but government agencies must deeply investigate those neighborhoods with high eviction to make corresponding plans. One possibility is to regulate the amount that landlords charge for rent. Another possibility is to expand options for low-cost mortgages for the working poor. Moreover, renting at higher rates makes rental prohibitively expensive to start with, which keeps the poor out of rental housing. This, in turn, increases homelessness, which may also increase crime. Government officials and law makers should consider the consequences that price increases bring into the rental market.

Perhaps strategies also need to be developed to address how to prevent eviction itself. For example, as Desmond (2019) proposed, renters could buy subsidized insurance pools to cover landlord losses so that risk among poor renters is shared. Last but not least, policy makers need to create laws to regulate the mortgage market as a large share of foreclosures occur in situations of owners purchasing predatory subprime mortgages (Faber 2019; Reid et al. 2017). Policy makers could investigate those financial institutions whose services provide high mortgage interest rates, especially those financial institutions located in the disadvantaged and low socio-economic neighborhoods, as is displayed in this dissertation.

Neighborhoods provide a social context to the residents who live in them, and disadvantaged neighborhoods will by no means provide an advantage to the residents. For residents living in a disadvantaged neighborhood, they spend much of their money on basic living costs, such as food and rental or mortgage. However, residents do not have extra money for education and health that make the neighborhood better. Disadvantaged Neighborhoods function as a context by creating social, economic, political, and cultural barriers, that are difficult for residents in these neighborhoods to escape. This neighborhood context has the "*concentration effect*" (Wilson 1978:58). The neighborhood concentrated poverty also has durable effect that persist through time (Sampson 2012). To fix this, policy needs more in-depth interventions so that the lives of people living in disadvantaged neighborhoods can be improved.

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APPENDIX

APPENDIX A

CHOOSING BETWEEN POISSON MODEL AND NEGATIVE BINOMIAL MODEL TO MODEL CRIME COUNT

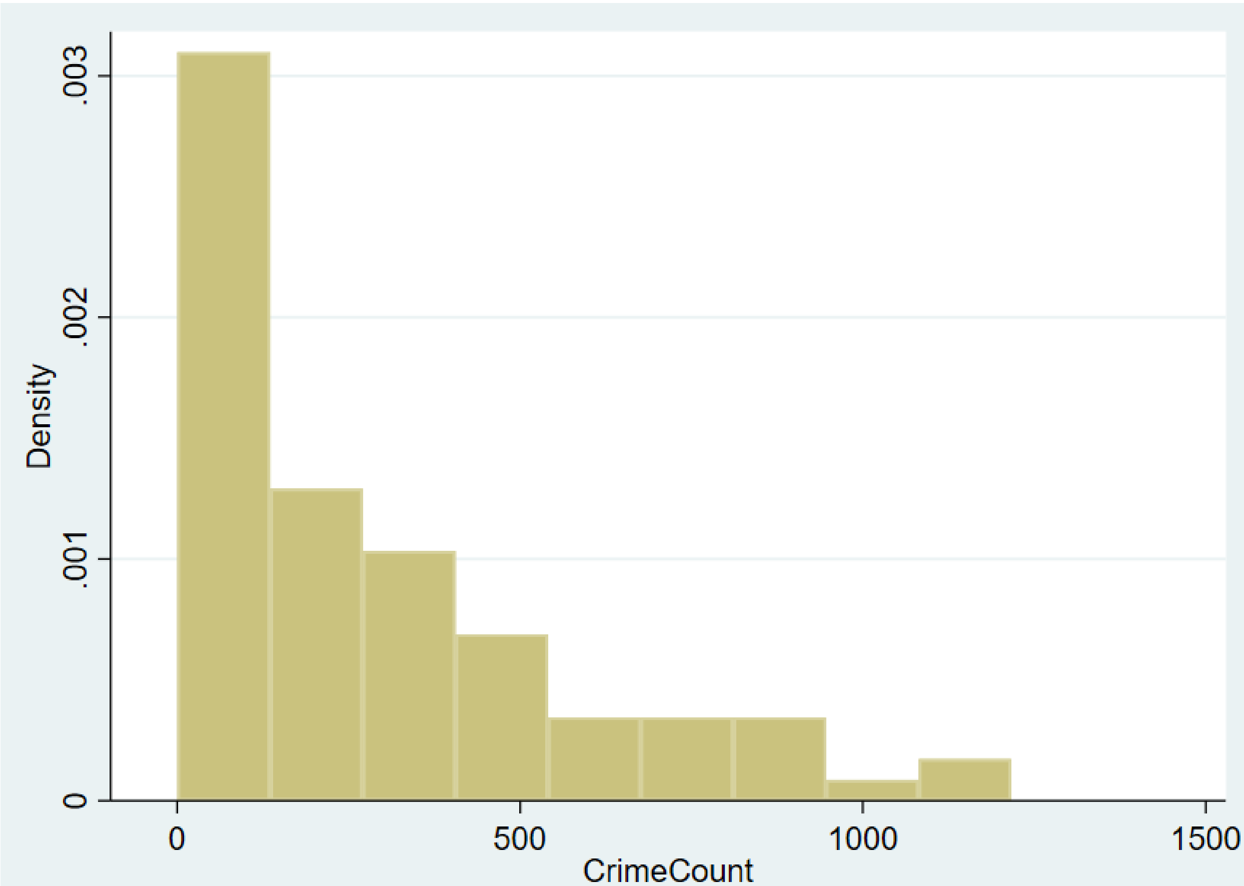

Figure A-1. Histogram of Crime Count Four-Year (2016-2019) Average

```
. poisson CrimeCount ConcentratedDisadvantage Eviction Foreclosure SubprimeLoan P
> ercentUnoccupied MeidanGrossRent MedianHomeValue
note: you are responsible for interpretation of noncount dep. variable.

Iteration 0:   log likelihood = -7303.4134
Iteration 1:   log likelihood = -7235.0095
Iteration 2:   log likelihood =  -7234.781
Iteration 3:   log likelihood =  -7234.781

Poisson regression                                  Number of obs =        86
                                                    LR chi2(7)    =  10856.76
                                                    Prob > chi2   =    0.0000
Log likelihood = -7234.781                          Pseudo R2     =    0.4287
```

CrimeCount	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Concentrated~e	.1447016	.0122661	11.80	0.000	.1206606	.1687427
Eviction	.0090285	.0004635	19.48	0.000	.00812	.009937
Foreclosure	.0339747	.0032753	10.37	0.000	.0275552	.0403941
SubprimeLoan	-.0252435	.0031788	-7.94	0.000	-.0314738	-.0190133
PercentUnocc~d	.0431732	.0015425	27.99	0.000	.04015	.0461964
MeidanGrossR~t	-.1437847	.0048999	-29.34	0.000	-.1533884	-.1341811
MedianHomeVa~e	.0013718	.0001239	11.07	0.000	.0011289	.0016146
_cons	5.926996	.0557664	106.28	0.000	5.817696	6.036296

Figure A-2. Poisson Regression Model for Crime Count Four-Year (2016-2019) Average

```
. estat gof

         Deviance goodness-of-fit =   13904.2
         Prob > chi2(78)          =    0.0000

         Pearson goodness-of-fit  =  14972.38
         Prob > chi2(78)          =    0.0000

.
```

Figure A-3. Goodness of Fit Statistic Test for Poisson Regression Crime Count Four-Year (2016-2019) Average

```
. nbreg CrimeCount ConcentratedDisadvantage Eviction Foreclosure SubprimeLoan Per
> centUnoccupied MeidanGrossRent MedianHomeValue
note: you are responsible for interpretation of non-count dep. variable

Fitting Poisson model:

Iteration 0:   log likelihood = -7303.4134
Iteration 1:   log likelihood = -7235.0095
Iteration 2:   log likelihood =  -7234.781
Iteration 3:   log likelihood =  -7234.781

Fitting constant-only model:

Iteration 0:   log likelihood = -573.60799
Iteration 1:   log likelihood = -567.82087
Iteration 2:   log likelihood = -567.81184
Iteration 3:   log likelihood = -567.81184

Fitting full model:

Iteration 0:   log likelihood = -555.21151
Iteration 1:   log likelihood = -549.76464
Iteration 2:   log likelihood = -549.60253
Iteration 3:   log likelihood = -549.60219
Iteration 4:   log likelihood = -549.60219
```

Figure A-4. Negative Binomial Regression Model for Crime Count Four-Year (2016-2019) Average

```
Negative binomial regression                            Number of obs =      86
                                                        LR chi2(7)    =   36.42
Dispersion: mean                                        Prob > chi2   =  0.0000
Log likelihood = -549.60219                             Pseudo R2     =  0.0321
```

CrimeCount	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Concentrated~e	.1181941	.2500052	0.47	0.636	-.371807	.6081952
Eviction	.0140517	.0118117	1.19	0.234	-.0090989	.0372023
Foreclosure	.0558199	.0539142	1.04	0.301	-.04985	.1614898
SubprimeLoan	-.0640614	.0517689	-1.24	0.216	-.1655265	.0374037
PercentUnocc~d	.0671375	.0356577	1.88	0.060	-.0027503	.1370254
MeidanGrossR~t	-.174058	.0750111	-2.32	0.020	-.321077	-.027039
MedianHomeVa~e	.0010108	.0023036	0.44	0.661	-.0035042	.0055257
_cons	5.94192	.9276545	6.41	0.000	4.123751	7.760089
/lnalpha	.0961029	.1378127			-.174005	.3662108
alpha	1.100872	.1517142			.8402927	1.442259

```
LR test of alpha=0: chibar2(01) = 1.3e+04                Prob >= chibar2 = 0.000
```

Figure A-5. Negative Binomial Regression Model for Crime Count Four-Year (2016-2019) Average

APPENDIX B

CHOOSING BETWEEN NON-ADJUSTED NEGATIVE BINOMIAL REGRESSION, AND ZERO-INFLATED NEGATIVE BINOMIAL REGRESSION

Table B-1. AIC Model Comparison for Negative Binomial Regression Model and Zero-Inflated Negative Binomial Regression Model

Variables	Negative Bonomial Regression Model *irr/se*	Zero-inlfated Negative Binomial Regression Model *irr/se*
Concentrate Disadvantage	1.13	1.13
	(0.28)	(0.28)
Eviction	1.01	1.01
	(0.01)	(0.01)
Foreclosure	1.06	1.06
	(0.06)	(0.06)
Subprime Loan	0.94	0.94
	(0.05)	(0.05)
Percent of Unoccupied	1.07	1.07
Housing Units	(0.04)	(0.04)
Median Gross Rent	0.84*	0.84*
	(0.06)	(0.06)
Median Home Value	1.00	1.00
	(0.00)	(0.00)
Constant	380.67***	380.66***
	(353.13)	(353.12)
Inflate (Crime Count)	N/A	1.05e-17
		(47.87)
F (7, 87)/LR chi^2(7)	36.42***	36.42***
R-squared/Pseudo R-squared	0.03	.
AIC	1117.20	1121.20
N	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

APPENDIX C

NEGATIVE BINOMIAL REGRESSION RESULTS OF CONCENTRATED DISADVANTAGE INDEX AND HOUSING MARKET VARIABLES ON CRIME COUNT

Table C-1. Negative Binomial Regression Results for Concentrated Disadvantage and Eviction Index on Crime Count

	Model 1	Model 2
	irr/se	*irr/se*
Sampson’s concentrated disadvantage index	1.29	N/A
	(0.30)	
New concentrated disadvantage index	N/A	1.37
		(0.33)
Percent of unoccupied housing units	1.07*	1.07
	(0.04)	(0.04)
Median gross rent	0.82**	0.82**
	(0.06)	(0.06)
Median home value	1.00	1.00
	(0.00)	(0.00)
Constant	685.18***	637.34***
	(504.81)	(474.16)
LR Chi-squared (4)	33.02***	33.48***
Pseudo R-squared	0.03	0.03
N	86	86

Ϯ=p<.10; *=p < .05; **=p < .01; ***=p < .001

Table C-2. Negative Binomial Regression Results for Concentrated Disadvantage and Foreclosure Index on Crime Count

	Model 1	Model 2
	irr/se	*irr/se*
Sampson's concentrated disadvantage index	1.29 (0.30)	N/A
New concentrated disadvantage index	N/A	1.41 (0.37)
Percent of unoccupied housing units	1.07* (0.04)	1.07* (0.04)
Median gross rent	0.82** (0.06)	0.82** (0.06)
Median home value	1.00 (0.00)	1.00 (0.00)
Constant	685.18*** (504.81)	604.20*** (457.14)
LR Chi-squared (4)	33.02***	33.53***
Pseudo R-squared	0.03	0.03
N	86	86

Ϯ=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

Table C-3. Negative Binomial Regression Results for Concentrated Disadvantage and Subprime Loan Index on Crime Count

	Model 1	Model 2
	irr/se	*irr/se*
Sampson's concentrated disadvantage index	1.29 (0.30)	N/A
New concentrated disadvantage index	N/A	1.38 (0.34)
Percent of unoccupied housing units	1.07* (0.04)	1.07 (0.04)
Median gross rent	0.82** (0.06)	0.82** (0.06)
Median home value	1.00 (0.00)	1.00 (0.00)
Constant	685.18*** (504.81)	673.24*** (493.58)
LR Chi-squared (4)	33.02***	33.49***
Pseudo R-squared	0.03	0.03
N	86	86

†=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

APPENDIX D

DETERMINING MODELS FOR SPATIAL ANALYSIS BETWEEN SPATIAL LAG MODEL AND SPATIAL ERROR MODEL AND OLS REGRESSION MODEL DIAGNOISTIC

To examine whether to use spatial lag model or spatial error model to answer research question 3, I develop three steps to determine. First, I check if the residuals of the OLS regression (crime rate) violate the assumption of normality. Second, I examine global Moran's I statistic to investigate if there is spatial dependence in the dependent variable of crime rate. Third, I conduct regression diagnostics in models of crime rate to check which spatial models (spatial lag or spatial error) is appropriate for my data. Last, I compare AIC values of the OLS regression model with AIC values of the spatial whichever fits the data in the third step.

Figure D-1 displays the skewness and kurtosis statistics results for the dependent variable crime rate. The results show that both skewness and kurtosis test have values less than 0.05, indicating that the crime rate variables is skewed and kurtosis. The joint Prob>chi^2 value indicates a joint test where a value less than .05 indicates non-normality. Figure D-2 displays the histogram of crime rate. As we visualize the histogram graph, crime rate is skewed to the left, and it shows no evidence of normality.

The global Moran's I test statistic is shows in Figures 3-3 and 3-4 of Chapter 3. The results show that crime rate is spatially patterned in the city of Knoxville. The test statistic of global Moran's I is 0.5452, well to the right of the reference distribution. The z-score that correspond to computed Moran's I (0.5452) is 9.2498. This suggest a strong rejection of the null hypothesis that there is spatial randomness (no spatial autocorrelation) and I conclude that crimes across census tract in Knoxville are spatially clustered, meaning that crime and victimization in Knoxville occurs more often in some census tracts, while in other census tracts, it does not occur very often.

The regression diagnostic tests are displayed in Figures 4-8, 4-9, 5-8, 5-9, 6-8, and 6-9. All diagnostic tests indicated that spatial lag model is better than spatial error model, since the spatial lag test is more significant than the spatial error test (under the situation of both tests are significant, I chose the one that is more significant). Also, the test statistic of spatial lag is larger than the spatial error. Therefore, I chose the spatial lag model.

Table D-1 displays the AIC values of OLS model and spatial lag model. As is shown in the table, OLS regression has the AIC value of 581.26. and the AIC value of spatial lag model is 567.01. As the AIC of spatial lag model is smaller than the AIC of OLS regression model. I conclude that spatial lag model is more efficient.

```
. sktest CrimeRate

Skewness and kurtosis tests for normality
                                                          ─────── Joint test ───────
    Variable │        Obs   Pr(skewness)   Pr(kurtosis)   Adj chi2(2)   Prob>chi2
─────────────┼──────────────────────────────────────────────────────────────────────
   CrimeRate │         86         0.0000         0.0007         27.96      0.0000

. hist CrimeRate
(bin=9, start=.0086192, width=4.9281749)
```

Figure D-1. Skewness and Kurtosis Test for Dependent Variable Crime Rate

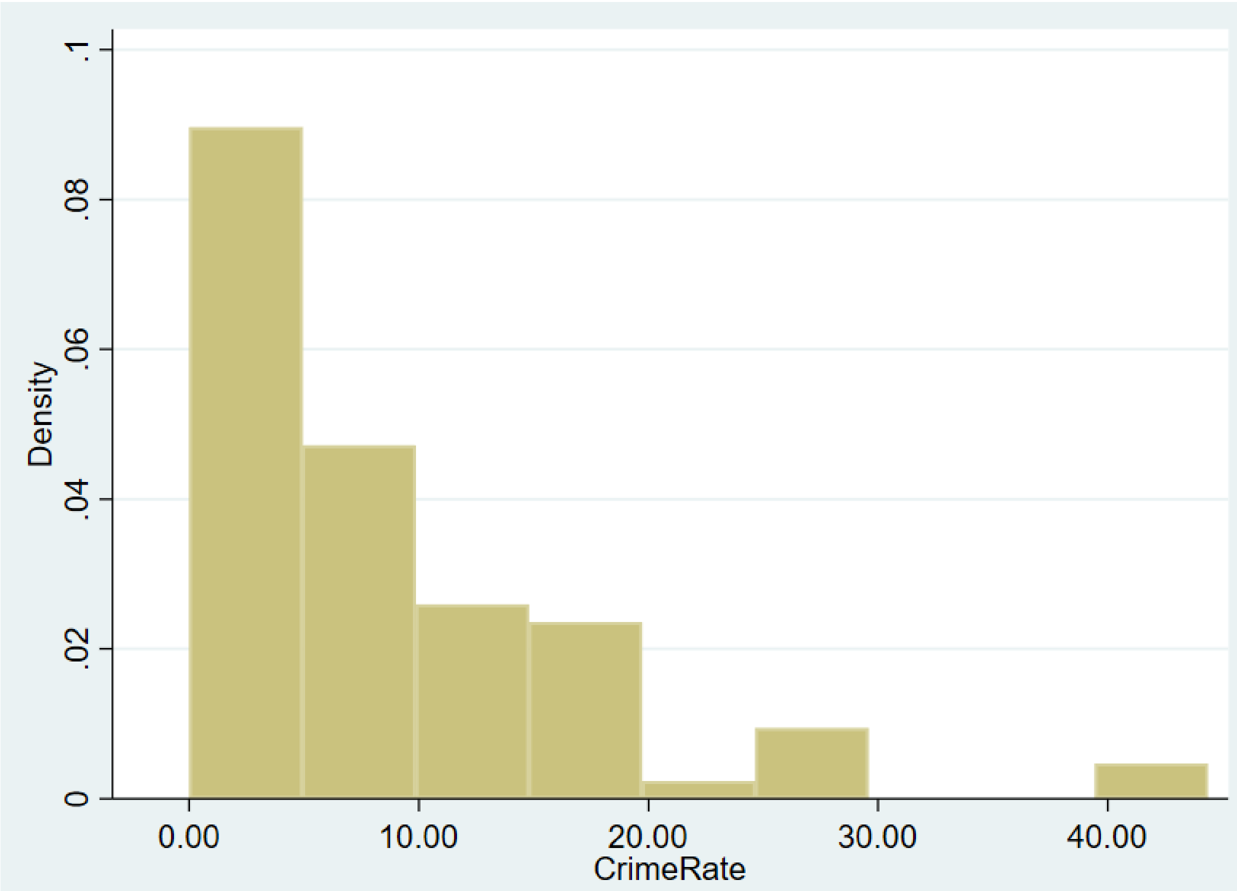

Figure D-2. Histogram of Crime Rate

Table D-1. AIC Model Comparison for OLS Regression Model and Spatial Lag Model

Variables	OLS Regression Model	Spatial Lag Model
	Coef/se	*Coef/se*
Concentrate Disadvantage	4.61**	2.51
	(1.53)	(1.34)
Eviction	0.00	0.02
	(0.07)	(0.06)
Foreclosure	-0.19	-0.14
	(0.36)	(0.31)
Subprime Loan	-0.26	-0.30
	(0.32)	(0.27)
Percent of Unoccupied	0.56**	0.41*
Housing Units	(0.20)	(0.17)
Median Gross Rent	-0.71	-0.43
	(0.43)	(0.37)
Median Home Value	0.01	0.01
	(0.01)	(0.01)
Spatial Lag Term (Rho)	N/A	0.48***
		(0.11)
Constant	9.19	3.70
	(5.27)	(4.62)
F(7, 87)	11.71***	N/A
R-squared	0.51	0.62
AIC	581.26	567.01
N	86	86

†=*p*<.10; *=*p* < .05; **=*p* < .01; ***=*p* < .001

APPENDIX E

DESCRIPTIVE STATISTICS OF THE VARIABLES USED ADDRESSING THE RESEARCH QUESTIONS, VALUES BY YEAR FROM 2016-2019

Table E-1. Descriptive Statistics

Variables	Mean	SD
Dependent Variable		
Crime Rate (2016)	8.59	9.51
Crime Rate (2017)	8.88	10.15
Crime Rate (2018)	8.29	9.18
Crime Rate (2019)	7.79	8.86
Independent Variables		
Eviction Count (2016)	17.35	18.82
Eviction Count (2017)	16.38	16.30
Eviction Count (2018)	16.97	16.98
Eviction Count (2019)	15.20	13.87
Foreclosure Count (2016)	5.01	3.86
Foreclosure Count (2017)	3.87	3.59
Foreclosure Count (2018)	3.56	3.02
Foreclosure Count (2019)	2.42	2.18
Subprime Loan Count (2018)	3.05	2.50
Subprime Loan Count (2019)	4.73	3.49
Percent Poverty (2016)	24.04	17.28
Percent Poverty (2017)	24.18	17.77
Percent Poverty (2018)	23.89	17.82
Percent Poverty (2019)	22.87	16.76
Percent Female-Headed Household	8.37	6.03
Percent of Government Welfare (2016)	32.35	25.50
Percent of Government Welfare (2017)	29.57	24.10
Percent of Government Welfare (2018)	28.96	24.79
Percent of Government Welfare (2019)	28.26	24.43
Percent Unemployment (2016)	6.93	4.93
Percent Unemployment (2017)	6.02	4.55
Percent Unemployment (2018)	5.31	4.18
Percent Unemployment (2019)	4.61	3.60

Table E-1 (Continued)

Variables	Mean	SD
Percent of Children under 18 Years (2016)	32.26	21.80
Percent of Children under 18 Years (2017)	31.46	22.11
Percent of Children under 18 Years (2018)	33.84	23.05
Percent of Children under 18 Years (2019)	35.25	23.38
Percent Black (2016)	12.37	16.45
Percent Black (2017)	12.32	16.63
Percent Black (2018)	12.63	16.89
Percent Black (2019)	12.56	16.32
Control Variables		
Percent of Unoccupied Housing Units (2016)	9.13	4.92
Percent of Unoccupied Housing Units (2017)	9.39	4.97
Percent of Unoccupied Housing Units (2018)	9.75	5.24
Percent of Unoccupied Housing Units (2019)	9.53	5.22
Median Gross Rent (*100) (2016)	8.45	1.94
Median Gross Rent (*100) (2017)	8.67	2.14
Median Gross Rent (*100) (2018)	8.96	2.25
Median Gross Rent (*100) (2019)	9.28	2.35
Median Home Value (*1000) (2016)	161.214	82.691
Median Home Value (*1000) (2017)	167.372	87.740
Median Home Value (*1000) (2018)	172.378	90.749
Median Home Value (*1000) (2019)	182.011	96.044

VITA

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