BURGLARY RATES AND NEIGHBORHOOD Contextual Characteristics: A Case Study in Hartford, Connecticut

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ABSTRACT

There is a long-standing interest in the spatial relationship between neighborhood contextual characteristics and crime in the U.S., since such relationship allows police and neighborhood stakeholders to better understand the spatial distribution of crime and design prevention programs to reduce crime risk. The objectives of this research are to 1) examine the relationship between burglary rates and contextual characteristics at the neighborhood-level in the city of Hartford, Connecticut and 2) account for spatial spillover effects of burglary crime penetrating neighborhood boundaries. The analysis results of this research show that predictors such as poverty, tenure of housing, residential mobility, and racial/ethnic diversity are significantly associated with burglary rates across the city. Additionally, the use of the Geographically Weighted Regression model for the spatially weighted burglary rates helps better reveal the spatial relationships between burglary crime and contextual factors, since it explained 68.1 percent of the variances of burglary crime, compared with 60.2 percent using the raw burglary rates. The results are discussed, and implications are given in the context of Hartford.

Key words: Burglary, Contextual Characteristics, Hartford, Geographically Weighted Regression

Introduction

A burglary, also called breaking and entering, is committed when someone enters an inhabited dwelling without permission and with the intent to steal or rob property. Although Connecticut has had a dramatic reduction in violent and property crimes over the past decade, burglary is still a common offense in the City of Hartford. According to the Uniform Crime Report (UCR) statistics, Hartford had 738 reported burglaries in 2017, making them the second most common felony offense after larceny (Federal Bureau of Investigation 2017). In 2017, the burglary rate in Hartford was 5.9 per thousand people which was more than twice the Connecticut rate (2.49 per thousand people). In addition, when a household member is present, burglaries can often lead to violent crimes such as assault (15.0 percent), robbery (7.0 percent), and rape (3.0 percent) (Catalano 2010). To better understand burglaries in Hartford, it is worthwhile to examine the burglary crime explanatory factors in different neighborhoods.

As a multi-disciplinary field of research, criminology research always has a wide range of perspectives and often competing theoretical foundations. Its mainstream research has focused on the issue of crime causation or in other words: what produces crime and the criminal? Traditionally, criminologists have long noticed the importance of place in understanding crime. Criminology research has shown that burglary offenses are not spatially randomly distributed, but instead tend to be geographically patterned (Bernasco and Luykx 2003; Malczewski and Poetz, 2005). The spatial patterns of burglaries can be explained by several theories in the criminology field (Brantingham and Brantingham 1984; Evans 1989, Hartnagel 2004; Evans and Herbert 2013).

Some research suggests that burglaries can be explained by crime opportunity theory and, consistent with this argument, criminological studies employ the routine activities hypothesis (Cohen and Felson 1979; Kennedy and Forde 1990; Koening and Linden 2004). The routine activity argument highlights the tendency of burglars to commit offenses inside or near their neighborhoods (Malczewski and Poetz 2005). It suggests that vulnerable neighborhoods are more likely to be located near areas where offenders reside (Herbert and Hyde 1985; Wright Logie and Decker 1995; Wiles and Costello 2000). By contrast, some theories suggest that crime control is directly or indirectly related to the creation of general community instability (Sampson and Groves 1989; Bursik and Grasmick 1993). The area variability hypothesis suggests that neighborhoods with high levels of mixture or heterogeneity are the most vulnerable to crime (Ceccato, Haining, and Signoretta 2002). On the other hand, the local social control hypothesis suggests that well-integrated and socially cohesive neighborhoods with a strong sense of community identity tend to have less crime (Bursik and Grasmick 1993; Hancock 2001). Given the various crime theories, empirical research is needed to investigate the spatial differences in burglary rates and identify neighborhood contextual characteristics that underlie existing spatial differences.

Numerous empirical studies have examined the spatial aspects of urban crime at the neighborhood level using Geographic Information Systems (GIS) techniques and quantitative methods (Sampson, Morenoff, and Gannon-Rowley 2002; Cahill and Mulligan 2003; Townsley 2009). However, the previous studies of neighborhood-level crime are often criticized due to the artificial boundary problem that often arises when aggregating individual crime incidents to neighborhood units using the containment approach (Murray et al. 2001; Ratcliffe 2010; Zhang, Suresh, and Qiu 2012). The issue of this approach is that it completely ignores the impact of crimes committed on or near the border but fall within adjacent neighborhoods (McCord and Ratcliffe 2007; Zhang, Suresh, and Qiu 2012). This paper attempts to tackle the issue by designing a spatial weighting method to count incidents within the boundary of each neighborhood, along with those in close proximity in a case study, using data on burglary crime collected by the Hartford Police Department.

Literature Review

Crime Theories and Ecological Measures

Various research has been done in the criminology field on the socio-economic factors contributing to the level and type of crime experienced in a community. This study of the socio-economic characteristics of burglary criminals and victims can be then extended to a critical analysis of the role of location. As a theoretical foundation in the criminology field, criminal opportunity assumes that opportunity is the necessary condition for crime and that the growing amount of goods in stores and homes and the sharp rise in personal wealth has provided increasing opportunities for criminal activities. Closely related to this concept is the routine activities theory of crime, in which demographic or social class factors contribute to particular activity routines. The theory emphasizes that the occurrence of a burglary requires the simultaneous existence of three elements: 1) the presence of a motivated offender (such as an unemployed person), 2) a suitable target (such as a residential dwelling containing goods which could be easily resold) and, 3) the absence of a capable guardian (homeowner, watchful neighbor, friend or relative) (Clarke and Felson 1993, 9; Knox 1995, 256; Hackler 2000, 169). The routine activities approach "stems from rational choice assumptions and emphasizes the circumstances under which crime is most likely" (Wilcox, Land, and Hunt 2003, 22). While a small number of burglary offenders may choose targets or victims far from their homes, most of them tend to commit crimes in areas that they are familiar with (Ainsworth 2001).

Shaw and McKay (1942) proposed social disorganization theory in their study of communities with high levels of crime. Their study in the City of Chicago illustrates that crime rates were not randomly distributed throughout the city and that the so-called Zone of Transition that is close to the city center has the highest crime rate. The neighborhoods in the Zone of Transition tend to have low socio-economic status, high numbers of ethnic/racial minorities, and high residential mobility (Wilcox, Land, and Hunt 2003, 28). As a result, Shaw and McKay (1942) suggested that the high crime rates were not a function of the personal attributes of the groups residing in the neighborhoods, but rather that "the structural factors of poverty, high heterogeneity, and high mobility created 'social disorganization', and it was community-level social disorganization that was presumed to cause crime" (Wilcox, Land, and Hunt 2003, 28). The area variability and local social control hypotheses have their roots in social disorganization theory (Herbert and Hyde 1985). The area variability hypothesis argues that 'mixed' or heterogenous areas are more likely to experience higher crime rates. The local social control hypothesis suggests that neighborhoods in which social cohesion is low and there is little sense of community are more vulnerable to crime (Bursik and Grasmick 1993; Hancock 2001). In contrast, ordered and well-organized neighborhoods with a strong sense of community identity experience less crime (Sampson, Raudenbush, and Earls 1997).

Empirical research suggests that burglary offences can be explained by variables that quantify "offender" and "target" characteristics. The socio-economic conditions of neighborhoods where offenders live can be characterized by: 1) high unemployment rates (Rountree and Land 2000; Hartnagel 2004), 2) high proportions of low-income households

(Kennedy and Forde 1990; Bursik and Grasmick 1993; Kitchen 2007), 3) low levels of education (Ehrlich 1975; Kitchen 2007), 4) lone-parent families (Bottoms and Wiles 1988; Bowers and Hirschfield 1999), 5) transient populations (Bottoms and Wiles, 1988; Bernasco and Luykx 2003), and 6) ethnicity and race variables measuring the degree of ethnic/race heterogeneity (Miethe and Meier 1994; Bowers and Hirschfield 1999; Ceccato, Haining, and Signoretta 2002). In addition, criminology research suggests a variety of neighborhood attributes that can be used to characterize the risk of burglary, such as the value of dwellings (Kennedy and Forde 1990; Bursik and Grasmick 1993; Paternoster and Bushway 2001), tenure and type of housing (Neustrom and Norton 1995; Ceccato, Haining, and Signoretta 2002), household income (Bursik and Grasmick 1993; Rountree and Land 2000), and residential mobility (Ceccato, Haining, and Signoretta 2002; Hartnagel 2004).

Previous Research on Burglary Crime

Rengert (1991) proposed a model which assumed that most property criminals have a choice between several alternative opportunities and considered site characteristics in relation to all possible alternatives within the system. In the study, most of the Philadelphia burglars lived in the central parts of the city and most of the burglaries were committed there. Rountree and Land (2000) presented a study that addresses the potential generalizability of empirical relationships from multilevel (individual- and neighborhood-level) models of burglary victimization across three cities by comparing the effects of individual-level sociodemographic and routine-activity variables, neighborhood-level social disorganization and concentration-of-poverty variables, and micro–macro interactions using data from Rochester, St. Louis, and Tampa-St. Petersburg. The study shows that 1) mean burglary victimization risk changes significantly across neighborhoods in all cities examined, but the individual-level covariates of risk do not vary in their effects across neighborhood or city contexts; and 2) much of the variability in burglary risk across neighborhoods is accounted for by the inclusion of neighborhood-level covariates. Chamberlain and Hipp (2015) examined how variations in inequality across larger areas might impact crime rates in neighborhoods. The research shows that disadvantage in the focal neighborhood and nearby neighborhoods increase neighborhood violent crime, which is consistent with social disorganization theory. Johnson et al. (2007) analyzed space–time patterns of burglary in ten areas, located in five different countries. In this study, while the precise patterns vary, for all areas, houses within 200 meters of a burgled home were at an elevated risk of burglary for a period of at least two weeks. Frith and Johnson (2017) modeled burglary offender spatial decision-making at the street segment level. In the research, as predicted by crime pattern theory, novel metrics concerning offender familiarity and effort are significant predictors of residential burglary location choices.

Crime Aggregation and Artificial Unit Problems

In crime research, census boundaries (e.g., census tracts or census block groups) are widely used as the approximation of neighborhoods, but they don't exactly match the underlying patterns of urban crime (Brantingham 2009; Zhang, Suresh, and Qiu 2012). Additionally, point-in-polygon aggregation of crime points is often used to calculate the total number of crime incidents inside each urban neighborhood (Ratcliffe 2010). The method is an easy and convenient way to link crime incidents to corresponding areal units, but the distribution of crime does not necessarily correspond to those predefined neighborhood boundaries (Eck 2005; Paulsen and Robinson 2009; Zhang, Suresh, and Qiu 2012). As a result, it is questionable to use the point-in-polygon spatial operation to summarize crime incidents in urban neighborhoods, because the method completely ignores the influence of crime incidents committed on or near neighborhood borders but fall in adjoining neighborhoods (Zhang, Suresh, and Qiu 2012). In other words, the point-in-polygon spatial operation significantly underestimates the real risk of neighborhood crime (McLafferty, Williamson, and McGuire 1999; Zhang and Song 2014). To quantify the real risk of neighborhood crime, recent studies created buffer rings around urban neighborhoods to count the total number of crime incidents (McCord and Ratcliffe 2007; Zhang, Suresh, and Qiu 2012). However, the buffering method overestimated the real risk of neighborhood crime, since crime incidents can be repeatedly counted by adjoining neighborhoods (Zhang, Suresh, and Qiu 2012). In addition, Zhang and Song (2014) proposed a method to calculate the risk of crime for each areal unit by taking crime incidents in adjacent units into consideration. The research results were generated based on a queen-based spatial contiguity weight matrix which only considers spatial units as neighbors when they share a common edge or vertex. As shown in Figure 1, Unit A will not be considered as a neighbor for Unit D if neighbors are defined by a queen-based spatial contiguity algorithm, since they don't share a common edge or vertex.

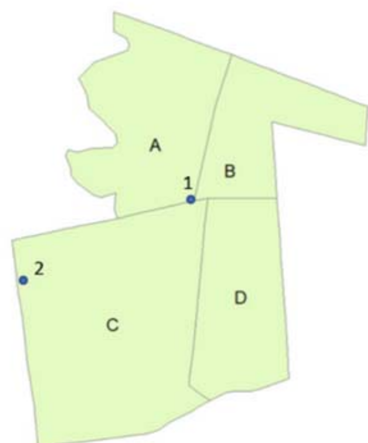

Figure 1: An example of four hypothetical neighborhoods

By using this algorithm, although the Crime Incident #1 is much closer to Unit D than Crime Incident #2, the Crime Incident #1 is not taken into consideration in the calculation of the real risk of crime for Unit D, but Crime Incident #2 is. In other words, the real crime risk for Unit D is underestimated to some extent when a queen-based spatial contiguity weight matrix was used in the calculation, because the crime risk from nearby Unit A is excluded from the analysis. Additionally, Zhang and Song's (2014) study aggregates crime incidents at the centroids of neighboring units and assumes that their physical distances to the target unit are the same in the process of calculating the spatial weights. To address these weaknesses, this study proposes a new and improved method to quantify burglary risk for each areal unit by taking crime occurrences in adjacent units into consideration.

Methodology

Study Area

The City of Hartford, located at the center of Connecticut (Figure 2), is one of America's oldest cities. Founded in 1635, it is currently the capital city of Connecticut and has the nickname "Insurance Capital of the World" as it hosts many headquarters or large offices of insurance companies (i.e. The Hartford and Travelers) and insurance is the region's major industry. The 2020 U.S. Census shows that Hartford is the fourth-largest city in Connecticut with a total population of 121,054, behind the coastal cities of Bridgeport, New Haven, and Stamford (U.S. Census Bureau 2020). Hartford is home to some of the largest corporations in Connecticut that provide over 65,000 jobs. The city provides the widest range of housing options – from a historic Victorian home in the West End to a converted factory loft apartment in the southwest of the city; from a luxury downtown apartment to a starter home beside the University of Hartford; or from townhouses in South Downtown to two- and three-family homes in the South End.

The city of Hartford has a total area of 18.0 square miles, of which 17.3 square miles is land and 0.7 square miles is water. The Connecticut River, located on the east side of the city, forms the boundary between Hartford and East Hartford. The Park River originally divided Hartford into northern and southern sections and was a major element of Bushnell Park, but the river was nearly completely buried by flood control projects in the 1940s. The intersection of Highway I-84 and I-91 is located in downtown Hartford. In addition, two other highways service the city: CR-2, an expressway that runs from downtown Hartford to Westerly, Rhode Island, and the Wilbur Cross Highway segment of CR-15, which skirts the southeastern part of the city near Brainard Airport. The City of Hartford is an important study area for burglary crime for two reasons. First, its crime rate in 2017 was higher than 95.0 percent of all U.S. cities (Federal Bureau of Investigation 2017) and the high crime rate led to the population loss in the past (Sauter, Stebbins, and Comen 2017). Second, burglary crime in Hartford was the second highest felony offense in 2017.

Data Preparations

This study is based on the Hartford Police Department's datasets for each year in the five-year period between January 1st, 2013 and December 31st, 2017 (Hartford Data 2019). The five-year crime data is used in this study, because it not only provides insights on recent burglary offenses in Hartford, but also aligns with the most recent American Community Survey five-year estimates for 2013-2017 (U.S. Census Bureau 2017). The data consisted of 3,523 burglary incidents in the City of Hartford, Connecticut during the five-year period. Each incident was added into ArcGIS 10.6.1 (Environmental System Research Institute 2018) based on the x and y coordinates included in the dataset. The burglary point layer was spatially joined with a shapefile consisting of ninety-six Census Block Groups (CBGs) in Hartford. This enabled the

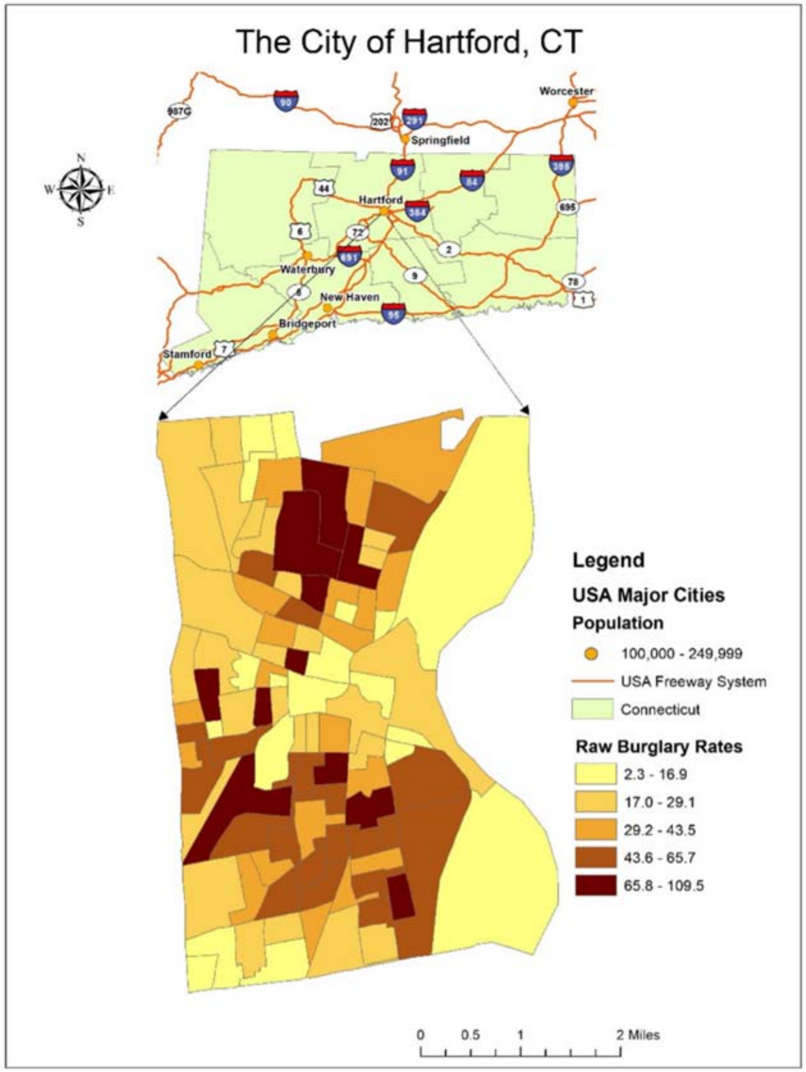

Figure 2: Study Area

computation of the total number of burglaries for each CBG. In this research, CBGs are used as the approximation of neighborhoods, since Hartford does not have well defined neighborhood boundaries, and CBGs are one of the most widely used geographic boundaries which can be used to compile the burglary data and neighborhood demographic and socio-economic characteristics data. A CBG usually contains between 600 and 3,000 people and its boundary never crosses the boundaries of different states or counties (Iceland and Steinmetz 2003). In addition, CBGs are used to represent neighborhoods, since they are designed to be relatively homogeneous with respect to population demographics and socio-economic characteristics.

In this study, the raw counts of burglaries in each CBG were added to those of adjacent CBGs in order to account for the spillover crime risk from adjoining CBGs. This calculation is necessary, because the actual risk of burglary crime in a given CBG is determined not only by its own frequency of crime incidents, but also affected by crimes in neighboring areas (Bernasco and Luykx 2003; Downey 2003; Zhang and Song 2014). Consequently, when small geographic units such as CBGs are used, a more accurate measure of the risk of crime for each areal unit needs to take crime occurrences in adjacent units into consideration (Wang and Arnold 2008; Zhang and Song 2014). A new measure for spatially averaged counts of burglaries was calculated below.

$$B_i^w = \frac{B_{io} + \sum_{jk}^{mn} B_{jk} SW_{ijk}}{1 + \sum_{jk=1}^{mn} SW_{ijk}}$$

where B_{io} is the observed number of burglaries in a CBG i and it is calculated by using ¬the point-in-polygon approach (Ratcliffe 2010). It should be noted that $i \in C1 = \{1,2,\ldots,q\}$ which is the index set of locations of q observations (i.e. all CBGs in Hartford). B_{jk} is the kth observed burglary incident in neighboring area j. m is the number of neighboring CBGs for a CBG i which is determined by distance-band (GeoDa 2020), so $j \in C_2 = \{1,2,\ldots,m\}$. n is the number of observed burglaries in neighboring area j, so $k \in C_3 = \{1,2,\ldots,n\}$. It this study, 0.5 mile is used as the critical distance in the search of neighboring CBGs. The critical distance of 0.5 mile was chosen, because the distance from the typical American's house to the edge of its neighborhood is between 520 and 1,060 meters with an average of 790 meters or about 0.5 mile according to the U.S. Census Bureau's research on the perceived size of a typical U.S. neighborhood (Donaldson 2013). Accordingly, Wijk is a spatial weight based on the spatial relationship between area i and the observed burglary incident k in neighbor unit j. Wijk = 0, if an area j is outside of a critical distance band from the target area i. If an area j is within the critical distance band – 0.5 mile – from i, W_{ijk} is calculated below:

$$w_{ijk} = \frac{\frac{1}{d_{ijk}}}{\sum_{jk=1}^{mn} \frac{1}{d_{ijk}}}$$

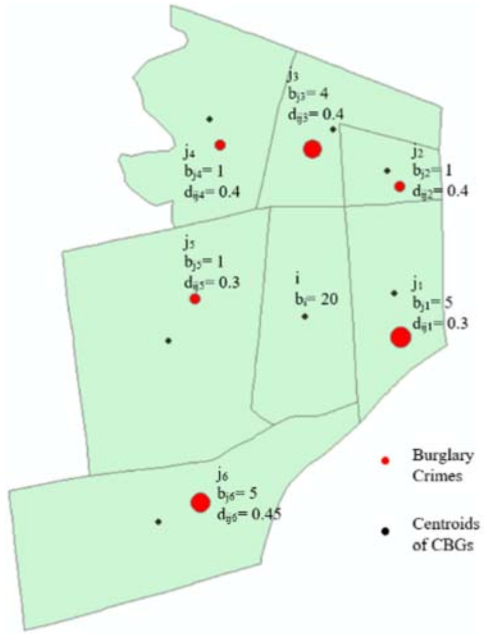

Figure 3. An example of seven hypothetical neighborhoods

Where d_{ijk} is the straight-line distance from the centroid of target area neighborhood i to the kth observed burglary incident in the neighboring area j and it was calculated using point distance function provided by ArcGIS10.6.1 (Environmental System Research Institute 2018). An inverse-distance weighting method was used to give the closest burglary incident the highest weight. Thus, the level of burglary risk in target neighborhood i is positively associated with each burglary incident in an adjacent area, but negatively affected by the physical distance (d_{ijk}) between target neighborhood i and observed burglary incident B_{jk}. To illustrate the new method, a simplified example is given in Figure 3 for demonstration purposes.

It should be noted that in reality, there can be multiple burglaries in multiple locations in a neighboring unit. The target area i has six neighborhood units which was determined by distance-band (GeoDa 2020). Each of which has an observed number of burglaries (B_{jk}) and a different crime-to-centroid distance to the target neighborhood i. The observed number of burglaries within the target neighborhood was twenty. In this example, the spatial weight of adjacent observed burglary crime j_1 was computed as

$$w_{ij1} = \frac{\frac{1}{0.3}}{\frac{1}{0.3}+\frac{1}{0.4}+\frac{1}{0.4}+\frac{1}{0.4}+\frac{1}{0.3}+\frac{1}{0.45}} = 0.203$$

The spatial weights of other five adjacent observed burglary crimes were calculated in the same way, with $W_{ij2} = 0.153$, $W_{ij3} = 0.153$, $W_{ij4} = 0.153$, $W_{ij5} = 0.203$, and $W_{ij6} = 0.136$. The spatially averaged number of burglaries for target area i was then calculated as:

$$B_i^w = \frac{20 + 5*0.203 + 1*0.153 + 4*0.153 + 1*0.153 + 1*0.203 + 5*0.136}{1 + (0.203 + 0.153 + 0.153 + 0.153 + 0.203 + 0.136)} = 22.81$$

Then, the burglary rates were calculated by dividing the total raw counts and spatially averaged counts by residential population in each CBG and multiplying by 1,000. The descriptive statistics for the two dependent variables – raw burglary rates and spatially weighted burglary rates are shown in Table 1 below.

	Min	Max	Median	Interquartile Range	Standard Deviation
Raw burglary rates: raw burglary counts per 1,000 people	2.8	109.5	26.0	16.5	16.2
Spatially weighted Burglary rates: spatially weighted burglary counts per 1,000 people	3.1	114.5	27.2	16.8	15.6

Table 1. Descriptive Statistics for the Dependent Variables – Burglary Rates

This study considers ten socio-economic characteristics as the potential explanatory variables (see Table 2). The ten contextual variables at CBG level were chosen to reflect the key dimensions underlying the variation in the risk of burglary as suggested by the crime theories as well as variables used in previous empirical research (see literature review for detail). The demographic and socio-economic variables such as residential population, education, income, poverty, house price, tenure of housing, type of housing, residential mobility, racial and ethnic population, and household type were taken from the American Community Survey five-year estimates for 2013-2017 (U.S. Census Bureau 2017). The education variable was quantified by the percentage of people aged twenty-five to sixty-four without a college degree or above. The income variable was determined by the median household income. The poverty variable was calculated as the percentage of people living under the poverty line. The home price variable was measured as the median house value. Tenure of housing was quantified by the percentage of renters in the population. Type of housing was calculated by two measures: 1) Percentage of single unit dwellings and 2) Percentage of multiple unit dwellings. Residential mobility was determined by the percentage of people lived elsewhere twelve months ago. The household type variable was calculated by the percentage of single female headed households. The racial/ethnic diversity variable was measured using Shannon equitability index (Shannon and Weaver 1949) based on eight racial/ethnic groups' population in CBGs in Hartford, including Hispanic, Non-Hispanic White alone, Non-Hispanic Black alone, Non-Hispanic Asian alone, Non-Hispanic American Indian and Alaska Native alone, Non-Hispanic Native Hawaiian and Other Pacific Islander alone, Non-Hispanic other race alone, and Non-Hispanic two or more races. Population data for these eight racial/ethnic groups were collected from American Community Survey five-year estimates for 2013-2017 (U.S. Census Bureau 2017). Shannon's index, which originated in ecology research, not only accounts for both abundance and evenness of the species present, but also has implications for the relative racial/ethnic heterogeneity of human populations (White 1986). The Shannon diversity index is calculated using the following equation in Excel:

$$H = -\sum_{l=1}^{s} p_l \, lnp_l$$

Where S is total number of racial/ethnic groups in the community, p_l is the proportion of the l_{th} racial/ethnic group to the total population.

Then, the Shannon equitability index (E_H) can be then generated by dividing H by H_{max}, which has a value between 0 (no diversity or a neighborhood is completely dominated by one racial/ethnic group) and 1 (perfectly diverse or all racial/ethnic groups are equally represented in the neighborhood). Then, the demographic and socioeconomic datasets were joined with the CBGs file and stored for further analysis using ArcGIS 10.6.1 (Environmental System Research Institute 2018). There is one data problem with using census block groups for analyzing neighborhood socio-economic characteristics. One census block group in Hartford has no reported demographic and socio-economic data. This potentially is a data suppression issue, since the census bureau does not report all sub-national data if the American Community Survey estimates have a disclosure risk or an unacceptable level of statistical reliability. As a result, this census block group was excluded from further analysis. The descriptive statistics for each explanatory variable and the correlation among them are shown in Table 2 and 3 respectively. An analysis of the Pearson's correlations indicates that all independent variables were statistically significantly (at least at 0.05 level) correlated with the two dependent variables (i.e., raw burglary rates and spatially weighted burglary rates).

Variables	**Min**	**Max**	**Median**	**Interquartile Range**	**Standard Deviation**
Education: percent of people aged twenty-five to sixty-four without a college degree or above	8.2	90.2	62.8	19.1	16.3
Income: median household income	11,140	100,526	31,809	23,750	19,507
Poverty: percent of people living under the poverty line	1.7	66.5	29.8	22.8	15.6
House price: median house value	74,684	289,144	122,985	72,581	41,254
Tenure of housing: percent of renters in the residential population	0.0	100.0	78.9	30.6	24.9
Type of housing I: percent of single-unit dwellings	0.0	100.0	12.6	23.7	25.9
Type of housing II: percent of multiple-unit dwellings	0.0	100.0	87.3	23.7	25.9
Residential mobility: percent of people who lived elsewhere twelve months ago	0.0	40.1	13.2	10.3	9.2
Racial/ethnic diversity **Index**: Shannon equitability index	6.0	82.3	39.7	26.7	21.5
Household type percent of single female headed households	4.5	42.4	29.8	18.1	19.3

Table 2. Descriptive Statistics for the Explanatory Variables.

Variables	Education	Income	Poverty	House price	Tenure of housing	Type of housing I	Type of housing II	Residential mobility	Racial/ ethnic diversity	Household type
Raw burglary rates	-0.25*	-0.40**	0.54**	-0.48**	-0.42**	-0.22*	0.35*	0.46*	0.52**	0.28*
Spatially weighted Burglary rates	-0.31**	-0.45**	0.62**	-0.52**	-0.53**	-0.26*	0.47**	0.51**	0.65**	0.37*
Education		0.38**	-0.46**	0.32**	-0.30*	0.41**	0.03	0.125	-0.39**	-0.42**
Income			-0.51**	0.41**	-0.35*	0.36**	-0.15	-0.31*	-0.36**	-0.47**
Poverty				-0.46**	0.30*	-0.33*	0.10	0.34**	0.49**	0.51**
House price					-0.40**	0.37**	0.12	-0.43**	-0.45**	-0.57**
Tenure of housing						-0.34*	0.44**	0.46**	0.51**	0.38**
Type of housing I							-0.31*	-0.38**	-0.45**	-0.51**
Type of housing II								0.40**	0.30*	0.32*
Residential mobility									0.46**	0.54**
Racial/ethnic diversity										0.58**

* $p < 0.05$; ** $p < 0.01$

Table 3. A Pearson's Correlation Matrix of Dependent and Independent Variables

Geographically Weighted Regression Model Building

Many early contextual studies on crime patterns are criticized for their use of global regression modeling techniques, such as Ordinary Least Squares or OLS regression (Malczewski and Poetz 2005), because the regression method violates some basic assumptions when spatial data is used (e.g., independence of observations and spatial stationarity of the relationship between independent and dependent variables). Geographically Weighted Regression or GWR (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Brunsdon, and Charlton 2002) relaxes these assumptions and enables the analysis of spatially clustered data. GWR is often considered as an extension of OLS regression, since it allows local parameters instead of global parameters to be estimated, hence making it possible to model spatial variations within the data (Fotheringham, Brunsdon, and Charlton 2002). Unlike OLS regression, which produces a single global model across space, GWR simultaneously conducts multiple regressions for different data units so that there is one regression model per spatial data unit (e.g. a census block group) (Hipp and Chalise 2015). In a GWR model, observations near a particular data unit will have more influence in the estimation than observations further away (Hipp and Chalise

2015). Given the weaknesses of OLS regression and strength of GWR, this research uses GWR for analyzing the spatial non-stationarity relationship between burglary rates and neighborhood contextual characteristics in the City of Hartford.

The first step is to examine the spatial heterogeneity of the dependent variables: raw burglary rates and spatially weighted burglary rates. If the burglary rates are not spatially clustered, there is no need to build a spatially explicit model. The Moran's *I* Index (Anselin 1995) provided by ArcGIS 10.6.1 (Environmental System Research Institute 2018) was used to identify the clustering of burglary rates across CBGs in the City of Hartford. Moran's *I* ranges from −1.0, perfectly dispersed (e.g., a checkerboard pattern), to a +1.0, perfectly clustered. In this research, Moran's *I* scores (0.246 and 0.348) and p values (0.0002 and 0.0001) were generated, indicating burglary rates are spatially clustered and the result is statistically significant. A Local Moran's *I* Cluster Analysis of burglary rates was conducted, and the results are shown in Figure 4 below.

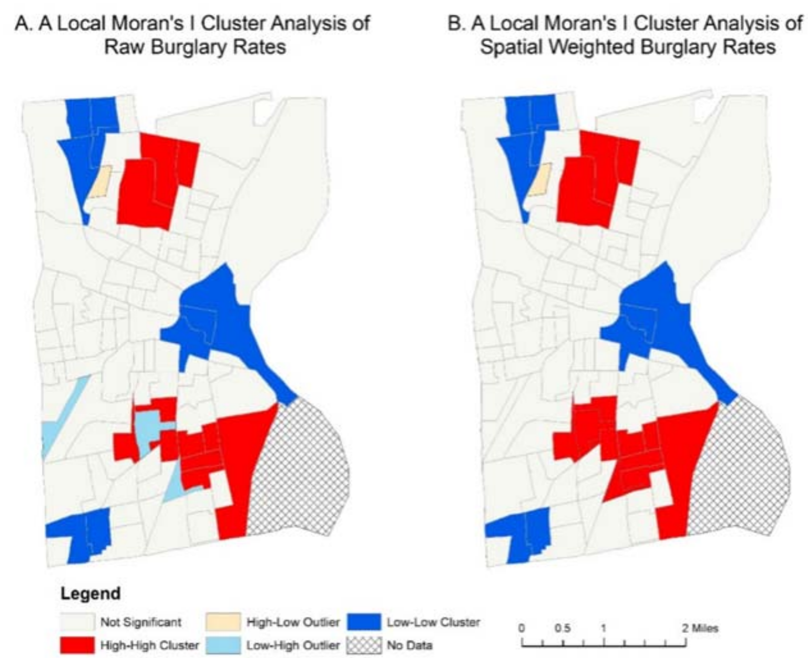

Figure 4. A Local Moran's *I* Cluster Analysis of Burglary Rates

In Figure 4, the maps demonstrate five different types of spatial clustering: (1) high-high, for neighborhoods with high burglary rates that are in close proximity to neighborhoods with high burglary rates; (2) low-low, for neighborhoods with low burglary rates that are in close proximity to neighborhoods with low rates; (3) high-low (known as spatial outliers), for neighborhoods with high burglary rates, but are proximate to neighborhoods with low rates; (4) low-high (also known as spatial outliers), for neighborhoods with low burglary rates, yet are in close in proximity to neighborhoods with high rates; (5) not significant, for neighborhoods where there is no significant spatial clustering. As shown in Figure 4, low-low spatial clusters were found in neighborhoods located in the east, northwest, and southwest of Hartford, while high-high spatial clusters are overlapped with CBGs located in the southeast and north of the city.

The OLS multivariate model (Aiken and West 1991) in SPSS 25 was then used to conduct initial data exploration and model specification. Two factors motivated the decision to first specify the OLS model: 1) to identify explanatory variables significantly correlated with the dependent variable (burglary rates) before specifying the GWR model; and 2) the GWR software used for spatial analysis does not provide a variance inflation factor (VIF) to measure multicollinearity. If the standard regression equation in the investigation of burglary rates is given by:

$$Y_i = \beta_0 + \sum_p \beta_p x_{pi} + \varepsilon_i$$

where Y_i is the burglary rate at CBG i, β_0 is a constant term (i.e., the intercept), β_p measures the relationship between the independent variable x_p and Y for the set of i CBGs, and ε_i is the error associated with CBG i. It should be noted that $i \in C_1 = \{1,2,\ldots,q\}$ which is the index set of locations of n observations (i.e. all CBGs in Hartford).

It should also be noted that the above equation "results in one parameter estimate for each variable included" (Cahill and Mulligan 2007). The summary of the OLS analysis results is presented in Table 4 below. In the OLS regression, only variables significantly correlated with the dependent variables were included. The OLS models are significant (F = 16.859 and 19.756, $p < 0.05$). The adjusted R^2 values are 0.389 and 0.446 which means that the models explained 38.9 percent and 44.6 percent of the variance in neighborhood-level burglary rates. The VIF for all variables was less than 3.0, a commonly used cutoff point, suggesting no severe multicollinearity issue was detected among the explanatory variables (Table 4).

As shown in Table 4, there is a positive and significant relationship between burglary rates and the following variables: the percent of people living under the poverty line, percent of the renters in the residential population, percent of people who lived elsewhere twelve months ago, and Shannon equitability index. In other words, the burglary rates tend to be higher in a neighborhood where the percent of people living under the poverty line, the renters in the residential population, and people who lived elsewhere twelve months ago are also higher. In addition, the higher the Shannon equitability index in a neighborhood, the higher the burglary rates in that neighborhood. The rest of the explanatory variables are insignificantly related to burglary rates in this study. The residuals of the OLS model were spatially auto-correlated (Moran's I = 0.18 and 0.23; $p < 0.05$). In other words, the OLS model overestimated burglary risks for some neighborhoods, while it underestimated the risks for some others.

Variables	OLS model – raw burglary rates			OLS model – spatially weighted burglary rates		
	β	SE value	VIF	β	SE value	VIF
Intercept	-1.057	1.886	-----	2.231	1.754	-----
Poverty: percent of people living under the poverty line	0.492*	0.141	2.794	0.622**	0.126	1.992
Tenure of housing II: percent of renters in the residential population	0.401*	0.031	1.589	0.461*	0.012	2.857
Residential mobility: percent of people who lived elsewhere twelve months ago	0.284*	0.121	1.357	0.354*	0.100	1.557
Racial/ethnic diversity Index: Shannon equitability index	0.621**	0.219	2.478	0.761**	0.115	2.048

Table 4. Results from Ordinary Least Square Model of Neighborhood-Level Burglary Rates

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Then, the same set of variables was then used to specify a GWR model using the GWR4 software (GWR4 2015). GWR is a modeling technique used to explore spatial non-stationarity (Brunsdon, Fotheringham, and Charlton 1996). The "main characteristic of GWR is that it allows regression coefficients to vary across space, and so the values of the parameters can vary between locations" (Mateu 2010, 453). In other words, instead of estimating a single parameter for each variable, GWR estimates local parameters. By estimating a parameter for each data location (i.e. neighborhood) in the City of Hartford, the GWR equation would only alter the OLS equation as follows:

$$Y_i = \beta_{0i} + \sum_p \beta_{pi} x_{pi} + \varepsilon_i$$

where Y_i is the burglary rate at CBG i, β_{0i} is the constant term at CBG i, x_{pi} is the explanatory variable (i.e. poverty, tenure of housing, residential mobility, racial/ethnic diversity) at CBG i, β_{pi} is the value of the parameter for the corresponding explanatory variable at CBG i, and ε_i is the error term at CBG i. It should be noted that $i \in C_1 = \{1,2,\ldots,q\}$ which is the index set of locations of n observations (i.e. all CBGs in the City of Hartford).

GWR becomes useful when "a single global model cannot explain the relationship between some sets of variables" (Brunsdon, Fotheringham, and Charlton 1996, 281). In the

GWR model, a continuous surface of parameter values is estimated under the assumption that locations closer to i will have more influence on the estimation of the parameter $\hat{\beta}_i$ for that location. Consequently, GWR allows researchers to explore "spatial non-stationarity by calibrating a multiple regression model which allows different relationships to exist at different geographical locations" (Leung, Mei, and Zhuang 2000). The GWR model was used to explore the macro-level spatial non-stationarity of the statistical relationship among burglary rates and the predictors including poverty, residential mobility, tenure of housing, racial/ethnic diversity.

While conducting the GWR, the continuous (Gaussian) model and the adaptive kernel were used, which was produced using the bi-square weighting function. The adaptive kernel uses varying spatial areas, but a fixed number of observations for each estimation. It is the most appropriate technique when the distribution of observations varies across space. In this case, observations (neighborhoods) are much smaller and closer together in the center of the city than they are at the edge. Finally, a process that minimizes the Akaike Information Criteria (AIC) was used to determine the best kernel bandwidth. The parameter estimates and t values produced by the software were exported and mapped using ArcGIS 10.6.1 (Environmental System Research Institute 2018).

Results

Summary statistics of the two GWR models are presented in Table 5. Compared with the results of the OLS models, using GWR significantly improved the explanatory performance by much larger adjusted R2 values (for both measures). The GWR model that adopted spatially weighted burglary rates explained 68.1 percent of the total variation in the dependent variable and it was a much better fit than using the measure of raw burglary rates which accounted for 60.2 percent of the variance (Table 5). A Local Moran's I cluster analysis (Anselin 1995) was conducted for the residuals of the two GWR models as a diagnostic for the collinearity in GWR residuals. There were no violations of residual independence (Table 5). The GWR models generated β coefficients for each neighborhood (see Table 6,Figures 5 A-D, and Figures 6 A-D), adjusted local R^2 value (see Figures 5E and 6E) and t values for each neighborhood (see Figures 7 and 8).

Statistics	GWR model – raw burglary rates	GWR model – spatially weighted burglary rates
Adjusted R^2	0.602	0.681
Akaike Information Criterion(AIC)	851.63	749.18
Moran's I for residuals	0.02	0.01

Table 5. Results from Geographically Weighted Regression

Variables	*β* coefficients of GWR model – raw burglary rates		*β* coefficients of GWR model – spatially weighted burglary rates	
	Min	Max	Min	Max
Intercept	-0.641	1.761	-0.523	2.413
Poverty: percent of people living under the poverty line	-0.681	1.922	-0.415	2.626
Tenure of housing II: percent of renters in the residential population	-1.382	2.375	-1.121	3.025
Residential mobility: percent of people lived elsewhere twelve months ago	-1.245	1.644	-1.021	2.315
Racial/ethnic diversity Index: Shannon equitability index	-1.465	2.231	-1.204	2.615

Table 6. β coefficients from GWR Models of Neighborhood-Level Burglary Rates in Hartford

Variables	GWR model – raw burglary rates			GWR model – spatially weighted burglary rates		
	$-1.96 \leq t^* \leq 1.96$	$1.96 \leq t^* \leq 2.58$	$t^* > 2.58$	$-1.96 \leq t^* \leq 1.96$	$1.96 \leq t^* \leq 2.58$	$t^* > 2.58$
Intercept	-----	-----	-----	-----	-----	-----
Poverty: percent of people living under the poverty line	75.8	18.9	5.3	69.5	22.1	8.4
Tenure of housing II: percent of renters in the residential population	62.1	34.7	3.2	55.8	33.7	10.5
Residential mobility: percent of people lived elsewhere twelve months ago	65.2	27.4	7.4	52.7	35.7	11.6
Racial/ethnic diversity Index: Shannon equitability index	85.2	9.5	5.3	74.8	18.9	6.3

* 1.96 and 2.58 are the cut-off values for *t*-test. When $|t| > 1.96$, the *β* coefficient estimate for a variable is significant at a significance level of 0.05. When $|t| > 2.58$, the *β* coefficient estimate for a variable is significant at a significance level of 0.01.

Table 7. Percentage of Neighborhoods by 95.0 percent of t Statistics in Hartford

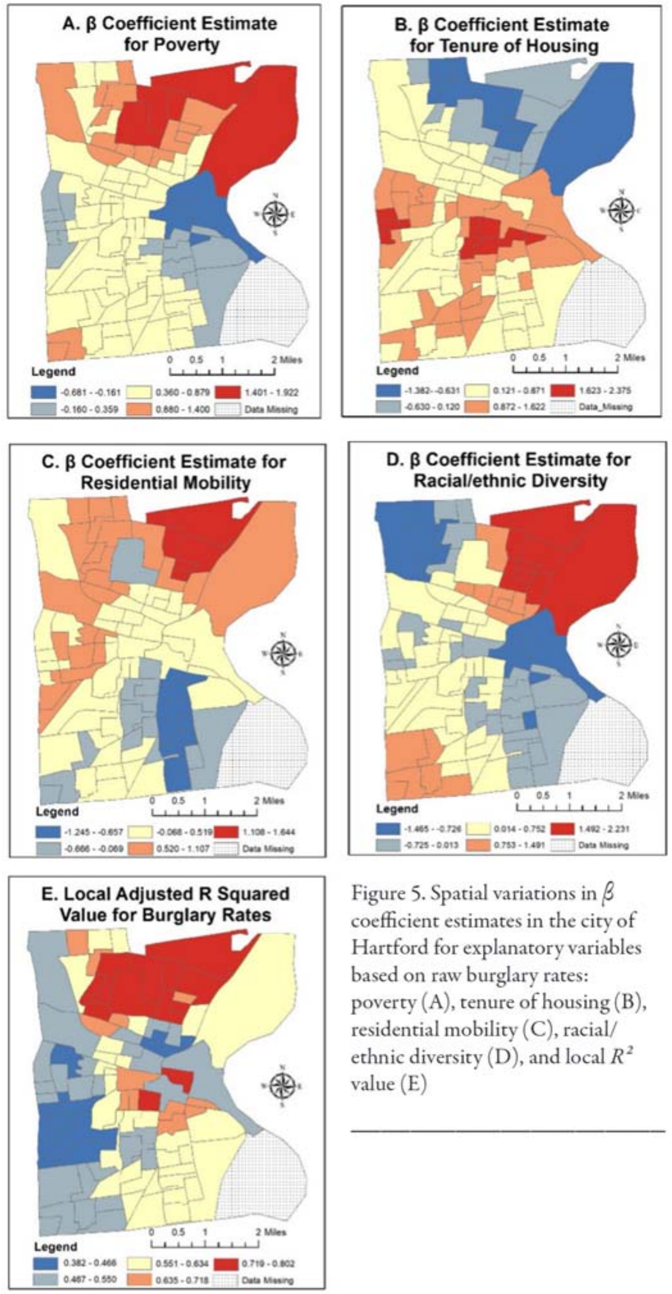

Figure 5. Spatial variations in β coefficient estimates in the city of Hartford for explanatory variables based on raw burglary rates: poverty (A), tenure of housing (B), residential mobility (C), racial/ethnic diversity (D), and local R^2 value (E)

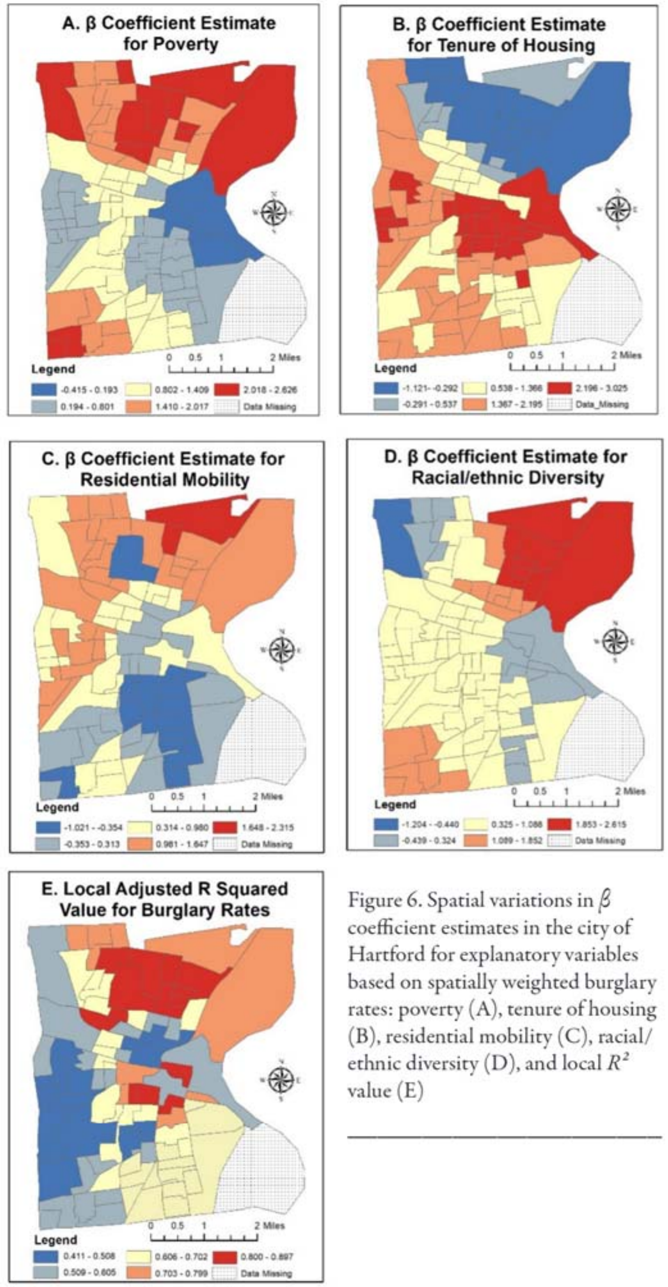

Figure 6. Spatial variations in β coefficient estimates in the city of Hartford for explanatory variables based on spatially weighted burglary rates: poverty (A), tenure of housing (B), residential mobility (C), racial/ethnic diversity (D), and local R^2 value (E)

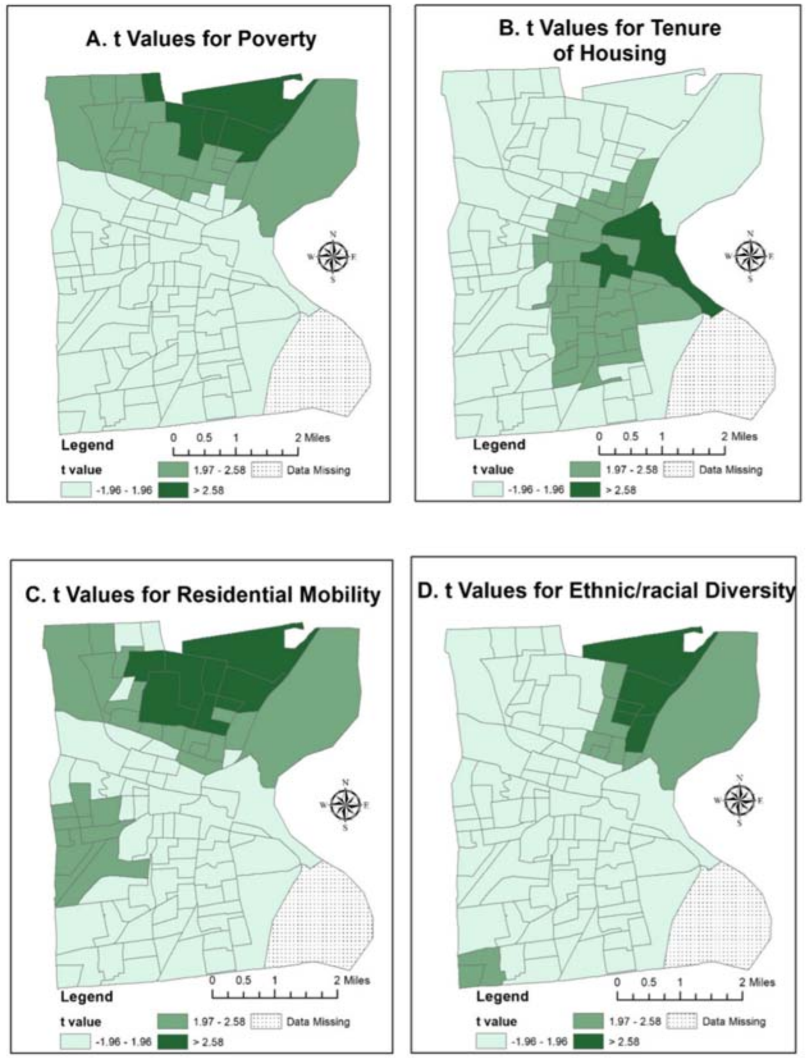

Figure 7. Spatial variations in t values in Hartford for explanatory variables based on raw burglary rates: poverty (A), tenure of housing (B), residential mobility (C), racial/ethnic diversity (D). Note: 1.96 and 2.58 are the cut-off values for t-test. When $|t| > 1.96$, the β coefficient estimate for a variable is significant at a significance level of 0.05. When $|t| > 2.58$, the β coefficient estimate for a variable is significant at a significance level of 0.01.

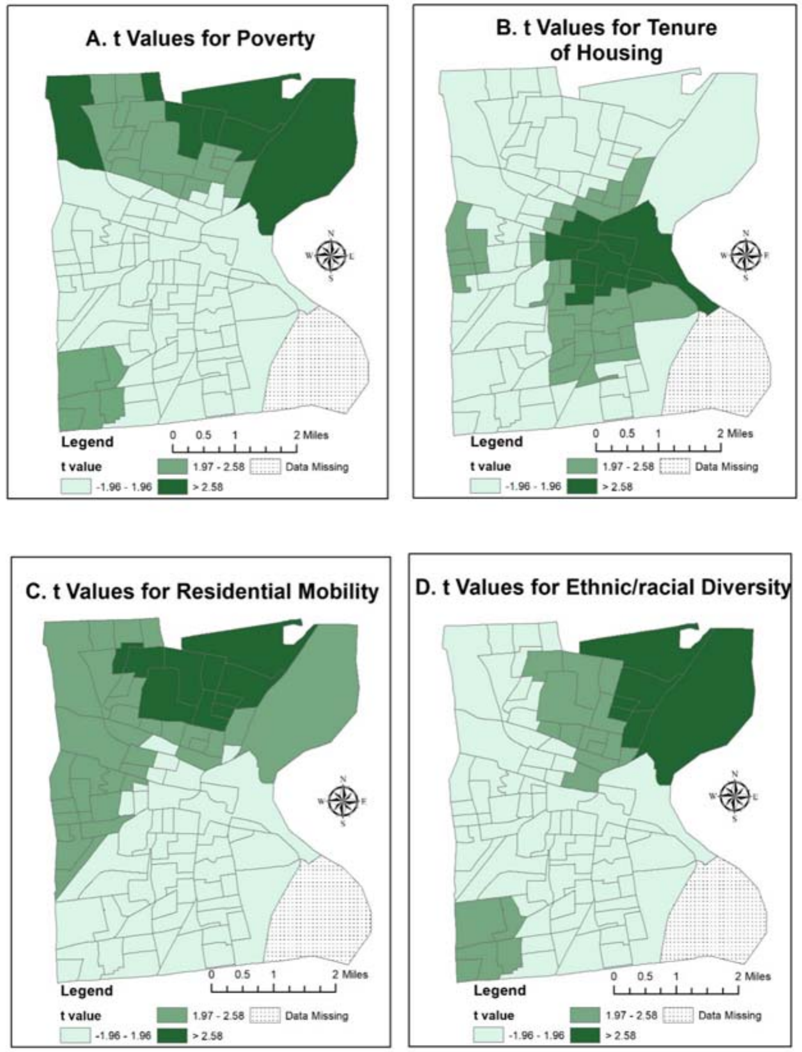

Figure 8. Spatial variations in t values in Hartford for explanatory variables based on spatially weighted burglary rates poverty (A), tenure of housing (B), residential mobility (C), racial/ethnic diversity (D). Note: 1.96 and 2.58 are the cut-off values for t-test. When $|t| > 1.96$, the β coefficient estimate for a variable is significant at a significance level of 0.05. When $|t| > 2.58$, the β coefficient estimate for a variable is significant at a significance level of 0.01.

Discussion

As shown in Table 6, Figure 5A, and Figure 6A, poverty, defined by the percentage of people living under the poverty line, is mainly positively associated with neighborhood-level burglary rates across the city. However, there are some outliers demonstrating that the predictor is negatively but insignificantly associated with burglary rates at the west and southeast ends of the city (Figure 5A and 6A). This finding supports previous research which shows that households with low income suffer a 60.0 percent greater chance of burglary than high-income ones (Levitt 1999) and property crimes like burglary are also more prevalent in poor neighborhoods than their wealthy counterparts (Dong 2020). Given the high poverty rate in Hartford and its positive association with burglary rates, regeneration initiatives and antipoverty programs aimed at re-allocation of economic resources and job creation should be established in the high poverty neighborhoods in Hartford.

As shown in Table 6, Figure 5B, and Figure 6B, tenure of housing, defined by the percentage of renters in the residential population, is mainly positively associated with neighborhood-level burglary rates across the city. However, there are some outliers demonstrating that the predictor is negatively but insignificantly associated with burglary rates at the north ends of the city (Figure 5B and 6B). This finding supports previous research which suggests that renters are 85.0 percent more likely than owners to be burglary victims (National Crime Prevention Council 2019). In Hartford, just 24.0 percent of the homes are occupied by a homeowner, compared to 67.0 percent statewide. In the center of Hartford, almost 100.0 percent of the residents are living in a rental home, so the area is highly and significantly correlated with raw or spatially weighted burglary rates (see Figures 5B, 6B, 7B, and 8B).

As demonstrated in Table 6, Figure 5C, and Figure 6C, residential mobility, defined by the percentage of people who lived elsewhere twelve months ago, is mostly positively associated with neighborhood-level burglary rates across the city, although there are some outliers demonstrating that the predictor is negatively but insignificantly associated with burglary rates in southern Hartford (Figure 5C and 6C). As illustrated in Table 6, Figure 5D, and Figure 6D, racial/ethic diversity, defined by Shannon equitability index, is largely positively associated with neighborhood-level burglary rates, although there are some outliers demonstrating that the predictors are negatively but mostly insignificantly associated with burglary rates in northwestern and eastern Hartford (Figure 5D and 6D). These findings are consistent with previous research findings which suggest that residential instability and racial/ethnic heterogeneity weaken residents' attachment to the neighborhood and impedes informal social control and order maintenance, so crime rates are high in neighborhoods where residential mobility and racial/ethnic heterogeneity are high. For example, Sampson, Raudenbush, and Earls (1997) suggest that residential instability and racial/ethnic heterogeneity are major structural conditions that undermine collective efficacy, in turn fostering increased crime. Additionally, empirical research shows that poverty and disorder tend to be highly correlated with racial/ethnic diversity (Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997). Disorder and poverty negatively influence individuals' ability and willingness to engage in social activities with neighbors, so they could exacerbate the feeling of powerlessness and mistrust, and worsen inter-personal relationships (Sampson, Raudenbush, and Earls 1997; Marschall and Stolle 2004) which undermines collective efficacy for people living in neighborhoods with high level of racial/ethnic diversity and in turn boost crime in the neighborhoods. To enhance collective efficacy, comprised of social cohesion and control, in neighborhoods with high residential mobility and racial/ethnic diversity in Hartford, stakeholders from local communities should first be engaged to identify burglary problems, craft solutions and assess responses. Then, intervention measures should be focused on 1) surveying local residents to learn how they feel about their neighborhoods; 2) involving stakeholders to use the data gathered in community surveys to identify problems and common targets, craft solutions, and assess responses; 3) encouraging the local residents to participate in neighborhood watch or citizen patrol programs; and 4) avoiding racial profiling practice in high crime neighborhoods. Guided by problem-oriented policing strategies, crime statistics would dictate that a relatively greater number of residents will be stopped, searched, and/or eventually arrested in neighbourhoods with concentrated disadvantage, high residential mobility, and high racial/ethnic diversity in the future. This practice can lead to a vicious cycle that even the strictest law enforcement advocates would admit is patently unfair.

As shown in Table 6 and Figures 5-8, the change in magnitude and direction of the coefficients suggests spatial non-stationarity of the relationship between the burglary rates (i.e. both raw burglary rates and spatially weighted burglary rates) and the predictors. The variation in parameter estimates from GWR suggests the necessity of applying this spatial statistical tool to future crime studies that would be restricted by using global OLS models, since GWR provides insights on how a particular explanatory variable influences the crime rates across the study area. For example, as shown in Figures 6B and 8B, tenure of housing, defined by the percentage of renters in the residential population, had the greatest effect in neighborhoods located in the center-eastern Hartford. As illustrated in Figures 6D and 8D, in neighborhoods located in the northeastern and southwestern of Hartford, the racial/ethnic diversity variable had a greater association with burglary rates.

The importance of using spatial statistical tools such as GWR in future crime studies can also be confirmed by the local R^2 value (see Figure 5E and 6E). The adjusted R^2 for the two GWR models ranged from 0.382 and 0.802 and from 0.411 to 0.897, with an average of 0.602 and 0.681 respectively, while the adjusted R^2 in the OLS models were 0.389 and 0.446. The OLS R^2 values mask a wide distribution of local associations between the explanatory variables and burglary rates. In other words, without GWR, the OLS model would be unable to estimate the variance of local associations. For example, in the northern and center Hartford, the GWR model explained up to 89.7 percent of the variance in the spatially weighted burglary rates, indicating the measures of social disorganization theory better explained the variances in the burglary rates there. However, among neighborhoods clustered in the west of the city, the model did not explain much of the variance (about 41.1– 50.8 percent), suggesting social disorganization theory measures were not effective in explaining the patterns of burglary crime in the suburban neighborhoods in western Hartford. Such spatial variation would have been neglected with the OLS model alone. Likewise, as shown in Table 5, the GWR model adopted spatially weighted burglary rates generates a much smaller Akaike information criterion (AIC) value (i.e. 749.18) than the one adopted raw burglary rates (i.e. 851.63), indicating a significant improvement in predicting the variation of burglary crime.

It should be noted the spatially weighted count method not only leads to a better fit GWR model than using the measure of raw crime counts, but it also has two major advantages compared with the ones proposed by past research (Zhang, Suresh, and Qiu 2012; Zhang and Song 2014). First, it uses a pre-defined critical search distance band instead of queen-based spatial contiguity (i.e. sharing either sides or common vertices with the focus area) to search for neighboring units. The rationale behind this change is that the crime risk of spatial spillover effect should be accounted based on a physical distance, not spatial connectivity. Second, it directly weights burglary incidents in adjoining units based on the inverse distance from the incidents to the targeting neighborhood, where the previous research aggregates burglary incidents into the centroids of adjoining units (Zhang, Suresh, and Qiu 2012; Zhang and Song 2014) and weights them based on the inverse distance from the centroids of adjoining neighborhoods to the targeting neighborhood. This new method allows different burglary incidents in an adjoining unit to pose a different level of risk to the targeting unit based on their distances to the unit rather than assuming different burglary incidents in an adjoining unit pose the same level of risk to the targeting unit. Additionally, the calculated *t* statistics (see Table 7) for the local parameters indicate that the GWR model for spatially weighted burglary rates has more significant coefficients (i.e., *t* values were larger than 1.96 or 2.58, the critical value for the significance level of 0.05 and 0.01) than the model for raw burglary rates. In other words, spatially weighted burglary rates are better correlated with the explanatory variables with a high confidence level in the GWR model than raw burglary rates. It is worthwhile to note the fundamental differences between the spatially weighted count method used in this study aiming to account for the spillover crime risk from adjoining CBGs and a spatial lag or spatial error used in the spatial regression model. A spatial lag averages the neighboring values of a location and accounts for autocorrelation in the spatial regression model with the weight matrix. However, the spatially weighted count of crime in this study is used as a dependent variable to account for the negative crime spillover effect from adjoining neighborhoods.

This study is not without limitations. The first group of limitations is associated with geographic boundary effect, such as edge effect. It should be noted that the statistical relationships drawn from areal data must be carefully interpreted. Robinson (1950) long ago suggested the data scale/boundary problem and clearly explained that inferring individual level relationships from macro-level correlations is inappropriate. In this study, CBG boundaries were used as an approximation of neighborhoods and the relationships between burglary rates and contextual characteristics at the neighborhood-level thus cannot be interpreted as and/or applied to individual-level relationships. In addition, the GWR model is restricted by the edge effect, whereby CBGs located on the edges of Hartford do not have the 360° influence of CBGs in the city's interior.

The second group of limitations is related to crime data. It should be noted that the crime dataset prepared by Hartford police may underestimate the burglary offenses to some extent, because only the most serious offenses are recorded per incident of crime according to the UCR classification rule. For example, if there was a burglary with a murder involved, the incident would then be classified according to the crime that carried the longest maximum sentence, which would be the murder offense. Such a classification rule results in an underrepresentation of less serious offenses such as the burglary in the above example. In addition, the local R^2 values accounted for up to 89.7 percent of neighborhood-level burglary rates, which means that other risk factors associated with burglary crime need to be added into the GWR model.

Conclusions

This research analyzed the spatial distribution and correlations of burglary rates in Hartford. Specifically, this study incorporated demographic and socio-economic correlates with burglary rates. The relationship between the crime rate and predictors is not new (i.e. Sampson, Raudenbush, and Earls 1997; Rountree and Land 2000; Malczewski and Poetz 2005; Zhang and Song 2014)), but little research has been done to investigate the spatial heterogeneity of the relationships in the City of Hartford. Additionally, there are a few studies attempting to quantify for each areal unit by taking crime incidents in adjacent units (or spillover effect) into consideration. This research contributes to the existing literature in two ways. First, it uses a distance-based approach to search neighboring units and quantify the risk of burglaries in each CBG by adding those of adjacent CBGs to account for the spillover crime risk from adjoining CBGs. The GWR model for the spatially weighted burglary rates explained 68.1 percent of the variances of burglary crime, proving that it fits much better than using the raw burglary rates. Second, it shows that there is a significant correlation between burglary rates and the explanatory contextual variables, and this relationship has a spatial but nonstationary association in the City of Hartford. This study presents an initial and exploratory step towards better understanding of burglary, but much more in-depth work remains before criminology researchers and law enforcement understand why these spatial variations exist and why explanatory factors, such as poverty, tenure of housing, residential mobility, racial/ethnic diversity have very low explanatory effects in some neighborhoods but explain up to 89.7 percent of burglary rates in others in Hartford.

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