Residential Burglaries and Neighborhood Socioeconomic Context in London, Ontario: Global and Local Regression Analysis*

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The main aim of this article is to analyze the relationships between the spatial patterns of residential burglaries and the socioeconomic characteristics of neighborhoods in London, Ontario. Relative risk ratios are applied as a measure of the intensity of residential burglary. The variation in the risks of burglary is modeled as a function of contextual neighborhood variables. Following a conventional (global) regression analysis, spatial variations in the relationships are examined using geographically weighted regression (GWR). The GWR results show that there are significant local variations in the relationships between the risk of residential burglary victimization and the average value of dwellings and percentage of the population in multifamily housing. The results are discussed in the context of four hypotheses, which may explain geographical variations in residential burglary. The practical implication of the GWR analysis is that different crime prevention policies should be implemented in different neighborhoods of the city. **Key Words: residential burglary, neighborhood socioeconomic characteristics, global and local regression analysis, London, Ontario.**

Introduction

Research into the spatial patterning of residential burglary can be organized around several hypotheses (Brantingham and Brantingham 1984; Evans 1989; Herbert 2002; Hartnagel 2004). There is much evidence to show that residential burglary is largely a crime of opportunity. Consistent with this argument, criminological studies employ the *routine activities hypothesis* (Cohen and Felson 1979; Kennedy and Forde 1990; Koening and Linden 2004). This approach is based on the premise that the act of burglary requires three elements: motivated offenders, suitable targets, and the absence of capable guardians. The three factors must be present simultaneously for a burglary to occur. The routine activity argument also highlights the tendency of burglars to commit offences in their neighborhoods. It suggests that vulnerable communities are located close to areas where offenders live (T. S. Smith 1976; Herbert and Hyde 1985; Wright, Logie, and Decker 1995; Wiles and Costello 2000). Another explanation may be based on the *area affluence/deprivation hypothesis*, which suggests that affluent neighborhoods tend to have relatively less residential burglary than disadvantaged communities (Sampson and Wooldredge 1987; Kennedy and Forde 1990; Miethe and Meier 1994). It is often argued that economic deprivation directly causes crime because of the incentive to make gains illegally (Bursik and Grasmick 1993). By contrast, some theories claim that the effect is indirect via the creation of general community instability (Sampson and Groves 1989; Bursik and Grasmick 1993). Accordingly, the *area variability hypothesis* suggests that socially mixed neighborhoods with high population turnover experience more crime (Ceccato, Haining, and Signoretta 2002; Herbert 2002; Haining 2003, 367–76). On the other hand, the *local social control hypothesis* suggests that ordered and well-organized neighborhoods with a strong sense of community identity experience less crime (Bursik and Grasmick

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1993; Hancock 2001; Herbert 2002). These four hypotheses provide the basis for analyzing the relationships between risks of residential burglary and neighborhood contextual variables in London, Ontario.

While contextual studies have advanced knowledge on the relationships between the level of crime and neighborhood characteristics, many of them are limited in several respects (for a critical and comprehensive overview, see Anselin et al. 2000; Rountree and Land 2000; Pratt 2001). One of the limitations is that the neighborhood is the sole contextual unit under study, while the broader social climate (e.g., the city or region in which the neighborhoods are located) and the local relationships (e.g., the nature of the relationships may be different in different parts of the study area) are largely ignored. Many contextual studies on residential burglary are hampered by their use of conventional linear regression modeling techniques (Anselin et al. 2000; Rountree and Land 2000), which may be inappropriate for analyzing spatial data because of the violation of important assumptions of conventional regression procedures (e.g., assumptions related to independence of errors and error variance homogeneity). Several spatial modeling approaches for examining the effects of contextual characteristics on burglary rates have been proposed to avoid this problem (e.g., Anselin et al. 2000; Ceccato, Haining, and Signoretta 2002; Haining 2003). We suggest that geographical weighted regression (GWR) (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Charlton, and Brunsdon 2002) can provide a useful method for analyzing the spatial nonstationarity of the relationships between residential burglaries and neighborhood contextual characteristics.

This article is organized into four sections. The next section describes the data sets used in this study. Then, we provide a discussion on the spatial pattern of residential burglary in London, Ontario, and the contextual variables that might explain the geographical variation in residential burglary. Following this, we present the results of a global regression model relating the relative risks of residential burglary to the neighborhoods' contextual characteristics. After pointing out the possible flaws in the global regression modeling, we discuss the results of a local analysis using GWR. The final section presents concluding remarks.

Data

This study is based on the London Police Department's datasets for each year in the period 1998–2001. The data consisted of 8,534 residential burglary incidents (break-and-entries) in the urban area of London, Ontario. We encountered the following data quality problems: (1) missing geographical coordinates, (2) location errors associated with geographical coordinates (burglary incidents references to the midpoint of streets), (3) incorrect or incomplete street addresses, (4) duplicate records, and (5) underreporting associated with the classification of incidences according to the most serious offence; for example, if there is a break-and-enter with violence involved, the incident was classified according to the crime that carried the longest maximum sentence, which would be the violent offence; this resulted in an underrepresentation of less serious offences such as burglaries (Statistics Canada 2002). It was possible to check the quality of the data with respect to all but the last problem. After removing records because of quality problems, a total of 8,494 burglary incidences were included into the analysis. The incidents were aggregated based on a geographical frame consisting of 481 Enumeration Areas (EAs) for the 1996 Population Census (Statistics Canada 2003). The burglary dataset (point data) was integrated with the socioeconomic datasets (polygon/area data). There are two data problems with using EAs for analyzing neighborhood characteristics: (1) data on some socioeconomic variables were not released by Statistics Canada due to confidentiality requirements, and (2) some EAs did not have residential dwellings and therefore were irrelevant for analyzing residential burglary. In total, there was 32 EAs with missing data. These areas were eliminated from the analysis. The data were stored, manipulated, and analyzed using ArcView GIS 3.2 (ESRI 1996).

Spatial Pattern of Residential Burglaries

London is located in the southwest portion of Ontario, midway between Toronto, Ontario, and Detroit, Michigan (see Figure 1). It has a population of approximately 340,000. Figure 2 shows the spatial pattern of the relative risk of residential burglary ratios (RR_i) in London.[1] Three features of the spatial pattern deserve attention (for details, see Malczewski, Poetz, and Ianuzzi 2004). First, the highest RR_i values tend to concentrate in areas adjacent to the center of the city or core area. On the other hand, the lowest relative risk values tend to be located in the peripheral areas (a similar pattern of crime in London was observed by Jarvis and Messinger 1974). This finding is supported by the literature, which suggests that the intensity of crime tends to decrease with increasing distance from the city's center (e.g., Brantingham and Brantingham 1984; Bowers and Hirschfield 1999; Kohfeld and Sprague 1988).

Second, the spatial pattern of residential burglaries in London is characterized by a west–east division. In general, the relative risks of residential burglary tend to be higher in the eastern portion of the city. This observation suggests that the pattern of crime in London can be described using the notion of the *dual city*, which identifies a polarization of the city into two distinct spatial units according to socioeconomic status (Malczewski, Poetz, and Ianuzzi 2004). In London, one can identify the contrast between the west of Adelaide St. areas of low relative burglary risks/high socioeconomic status and the east of Adelaide St. neighborhoods of high risks/low socioeconomic status (see Figures 1 and 2).

Third, there are pockets of elevated risk of residential burglary in the area adjacent to the University of Western Ontario (UWO) campus in the northwest sector of the city. A distinctive feature of this area is that it contains a relatively large proportion of rented accommodation with overrepresentations of young people (mostly university students), and transient populations. The presence of a large student community might be a factor contributing to the spatial pattern of residential burglary (see Bottoms and Wiles 1988; Henson and Stone 1999).

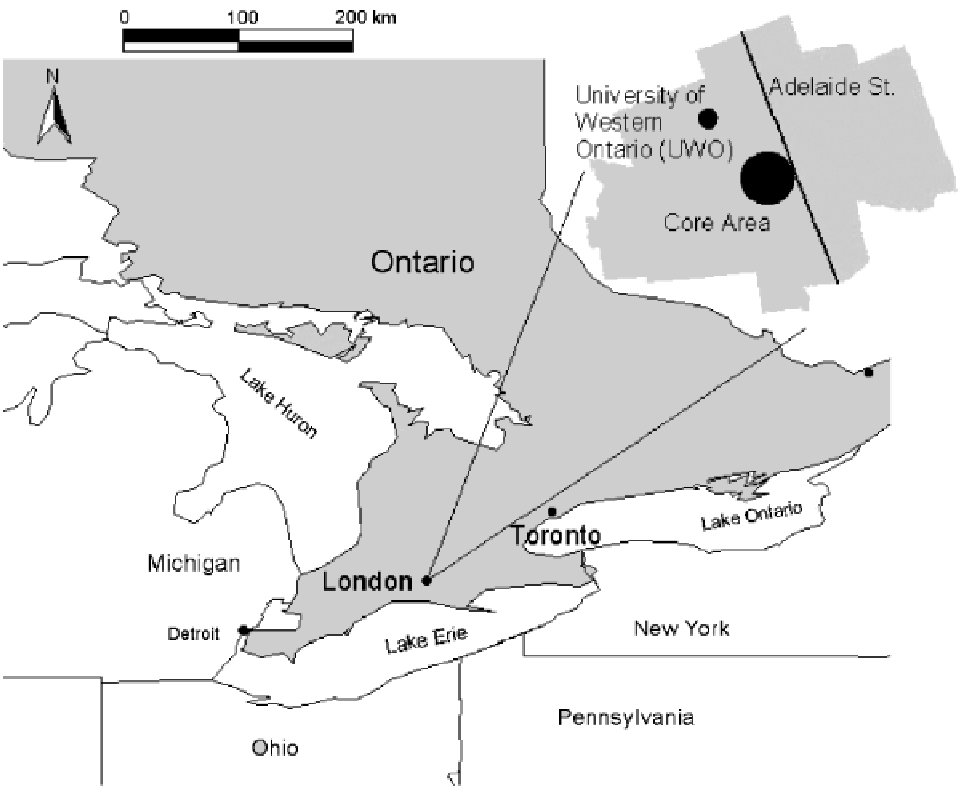

Figure 1 *Location of London, Ontario.*

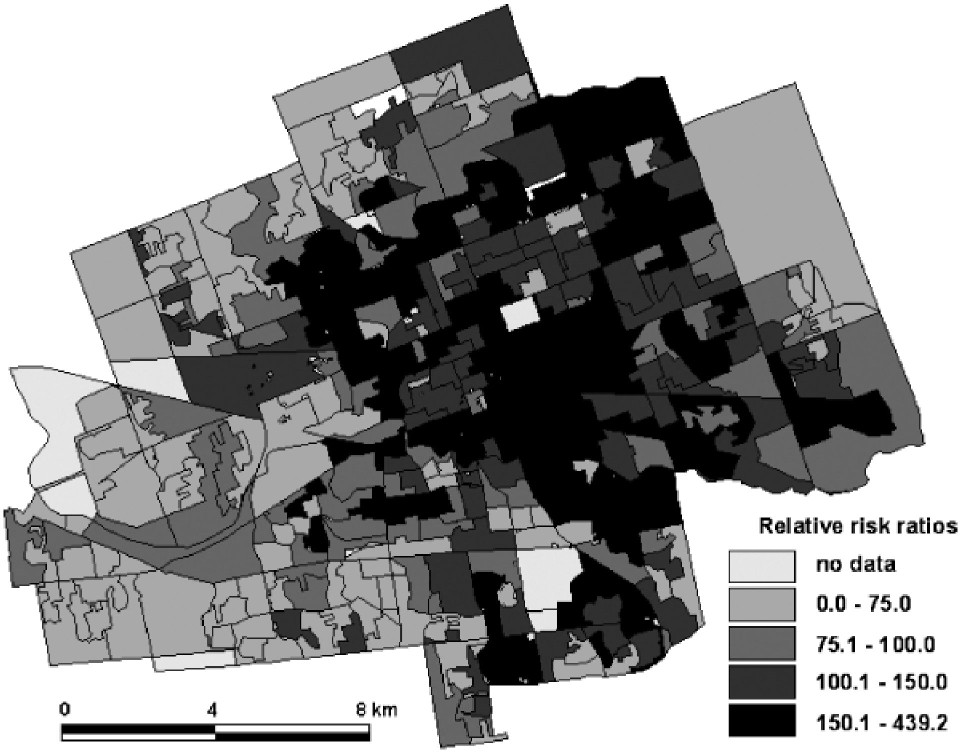

Figure 2 *Relative risk of residential burglary in London, Ontario, by enumeration area in 1998–2001.*

Explanatory Variables

This study considers twelve contextual characteristics as the potential explanatory variables (see Table 1). The choice of these variables was based on a review of the relevant literature. Contextual variables were chosen to reflect the key dimensions underlying the variation in the risk of residential burglary as suggested by the hypothesis presented in the Introduction. To this end, it is important to distinguish between the variables that measure "offender" characteristics and "target" attributes. The former include variables that may explain why an individual would commit a crime. Specifically, empirical research suggests that the contextual characteristics of neighborhoods in which offenders live include: high unemployment rates (Kohfeld and Sprague 1988; Neustrom and Norton 1995; Rountree and Land 2000; Hartnagel 2004), high proportions of low-income households (Kennedy and Forde 1990; Bursik

Table 1 *Explanatory Variables*

Symbol	Description
x_1	Percentage of population with less than a grade 9 education (population 15 years and over)
x_2	Average value of dwelling in $10,000's
x_3	Average household income in $10,000's
x_4	Percentage of population without income (population 15 years and over)
x_5	Unemployment rate (population 15 years and over)
x_6	Percentage of single-family houses (total number of occupied dwellings)
x_7	Percentage of multi-family dwellings (total number of occupied dwellings)
x_8	Percentage of rented dwellings (total number of dwellings)
x_9	Percentage of movers within the last five year (total population)
x_{10}	Percentage of population who have immigrated since 1961 (total population)
x_{11}	Percentage of visible minority population (total population)
x_{12}	Percentage of lone-parent's households (total number of households)

Source: Statistics Canada 2002.

and Grasmick 1993; Pratt 2001), low levels of education (Ehrlich 1975; Pratt 2001), lone-parent families (Bottoms and Wiles 1988; Bowers and Hirschfield 1999), transient populations (Bottoms and Wiles 1988; Bernasco and Luykx 2003), and ethnicity and race variables measuring the degree of ethnic/race heterogeneity (D. A. Smith and Jarjoura 1989; Miethe and Meier 1994; Bowers and Hirschfield 1999; Ceccato, Haining, and Signoretta 2002).

On the other hand, the relevant literature suggests a wide range of possible factors contributing to the attractiveness of a neighborhood as a target for residential burglary. The most often studied neighborhood attributes associated with the risk of residential burglary include: the value of dwellings (Kohfeld and Sprague 1988; 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 (Pettiway 1982; Sampson and Groves 1989; Pratt 2001; Ceccato, Haining, and Signoretta 2002; Hartnagel 2004).

It is important to note that some of the factors (e.g., the level of unemployment and population without income) may serve as both offender and target variables. Previous research on the relationships between unemployment rates/low-income factors and burglary rates has produced conflicting results (Neustrom and Norton 1995; Rountree and Land 2000; Pratt 2001). The unemployment/low-income factors act both to increase motivation to commit crimes and to decrease opportunities for offending (Neustrom and Norton 1995). Thus, the former hypothesis relates the unemployment/low-income factors to the offenders. It suggests that neighborhoods with a high proportion of unemployed and low-income households experience a high level of crime (Kohfeld and Sprague 1988; Evans 1989). The latter hypothesis suggests that these factors are negatively related to crime rates because of a low attractiveness of the targets located in high-unemployment/low-income neighborhoods. Accordingly, it is argued that affluent areas (high income, low unemployment, high-value, detached houses, etc.) are expected to have a relatively low level of crime (Evans 1989; Bursik and Grasmick 1993).

Residential Burglaries and Neighborhood Characteristics: Regression Analysis

Global Multiple Regression

In order to examine relationships between the risks of residential burglary and socioeconomic characteristics of neighborhoods, we calibrated a global, multiple-linear regression model.[2] The RR_i ratios constituted the dependent variable in the model. Given the twelve independent variables under consideration, one can generate $2^{12}-1 = 4{,}095$ regression models. There are a number of methods for selecting the best model (Miller 1990; Selvin 1998). We use the Akaike Information Criterion (AIC) procedure for selecting the "best" subset of the independent variables to be included into the multiple regression analysis (Akaike 1981; Miller 1990; Insightful Corporation 2001). Table 2 shows the best models (subsets of the independent variables). The minimum AIC value of 5031.1 is obtained for a model with five independent variables. Thus, the best global multiple regression model includes the following variables: x_1, x_2, x_5, x_7, and x_8. The parameters of the model were estimated using the ordinary least squares (OLS) method (see, e.g., Selvin 1998; Insightful Corporation 2001). The results are given in Table 3. The model explains 20.2 percent of the variance in the relative risks of residential burglary. According to the Shapiro-Wilks test (Shapiro and Wilks 1965), the model produces a normal distribution of residuals. The values of the variance inflation factor (VIF) indicate that there is no evidence of problematic

Table 2 *The Results of the Akaike Information Criterion (AIC) Procedure for Selecting the Independent Variables*

Variables included in the regression models	***AIC***
$\mathbf{x_2}, \mathbf{x_7}$	5050.1
$\mathbf{x_2}, \mathbf{x_5}, \mathbf{x_7}$	5038.1
$\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_5}, \mathbf{x_7}$	5035.7
$\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}$	5031.1*
$\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}, x_9$	5034.3
$\mathbf{x_1}, \mathbf{x_2}, x_4, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}, x_9$	5042.0
$\mathbf{x_1}, \mathbf{x_2}, x_4, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}, x_9, x_{10}$	5042.8
$\mathbf{x_1}, \mathbf{x_2}, x_4, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}, x_9, x_{10}, x_{11}$	5044.3
$\mathbf{x_1}, \mathbf{x_2}, x_4, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}, x_9, x_{10}, x_{11}, x_{12}$	5047.8
$\mathbf{x_1}, \mathbf{x_2}, x_3, x_4, \mathbf{x_5}, \mathbf{x_7}, \mathbf{x_8}, x_9, x_{10}, x_{11}, x_{12}$	5056.8
$\mathbf{x_1}, \mathbf{x_2}, x_3, x_4, \mathbf{x_5}, x_6, \mathbf{x_7}, \mathbf{x_8}, x_9, x_{10}, x_{11}, x_{12}$	5062.7

Note: Variables in bold are significant at the 5 percent level.
**minimum AIC value.*

Table 3 *Global Multiple Regression Model for Relative Risks of Residential Burglary in London, Ontario*

Independent variables	Coefficients Value	Std. Error	*t* value	Significance Pr(>|t|)	Variance inflation factor (VIF)
(Intercept)	44.033	16.803	2.620	0.009	
x_1	1.252	0.542	2.312	0.021	1.050
x_2	−2.674	0.612	−4.368	0.000	1.113
x_5	1.400	0.487	2.872	0.004	1.189
x_7	1.067	0.159	6.680	0.000	2.800
x_8	0.358	0.174	2.050	0.041	2.971

Note: $R^2 = 0.202$; Shapiro-Wilks normality test on residuals: 0.951, prob. 0.000; Moran's I on residuals: 0.438, prob. 0.001.

levels of multicollinearity (see, e.g., Miller 1990; Insightful Corporation 2001).

All the regression coefficients are statistically significant at the 5 percent level (see Table 3). The relative risk ratios are positively related to the percentage of population with less than a grade nine education (x_1) (see, e.g., Ehrlich 1975; Pratt 2001), unemployment rate (x_5) (see Kohfeld and Sprague 1988; Evans 1989), and the percentage of rented dwellings (x_8) (Bottoms and Wiles 1988; Bernasco and Luykx 2003). On the other hand, there is a negative relationship between the average value of a dwelling (x_2) and the relative risk; that is, the lower the value of a dwelling, the higher the risk of residential burglary. This finding is consistent with results obtained by Sampson and Wooldredge (1987), Evans (1989), Kennedy and Forde (1990), and Bursik and Grasmick (1993). Finally, the positive relationship between the percentage of multifamily houses and the relative risks does not provide direct evidence for an association between economic deprivation and high risk of residential burglary (see Sampson and Groves 1989; Pratt 2001; Ceccato, Haining, and Signoretta 2002). This is because high proportions of multifamily housing can be found in both relatively disadvantaged neighborhoods as well as in more affluent areas of the city (Malczewski, Poetz, and Ianuzzi 2004).

Since the global multiple regression model explains only 20.2 percent of the variance in the relative risks of residential burglary, it is clear that there are many other factors influencing the risks unaccounted for in the model. In part, this can be attributed to the fact that the estimated parameters represent global averages of processes that might exhibit a substantial degree of spatial variation (Fotheringham, Charlton, and Brunsdon 2002). Thus, some of the unexplained variance may be associated with the assumption of spatial stationarity behind the global regression model (see Note 2). It is reasonable to argue that the results of the global multiple regression hide local variations in the relationships of risks for residential burglary and the contextual variables. For example, some empirical research suggests that crime increases when two neighborhoods of different socioeconomic status are located next to one another (e.g., Evans 1989; Bursik and Grasmick 1993). The global regression, however, does not distinguish between an affluent area surrounded by other wealthy neighborhoods and one that is surrounded by lower-socioeconomic-status neighborhoods. This is because conventional regression is an implicitly stationary model of the relationships between the risks of residential burglary and contextual variables. The parameters of the model are constants across the study area. However, if the relationships between the contextual characteristics and the relative risks of residential burglary are spatially nonstationary, then the global multiple regression model is a misspecification of the actual relationships (see Fotheringham, Charlton, and Brunsdon 2002).

One way of detecting the problem of misspecification of relationships described by the global model is to use the Moran's *I* statistic (see, e.g., Bailey and Gatrell 1995; Fotheringham, Charlton, and Brunsdon 2002; Haining 2003). This statistic can be used to verify that the residuals from the global model are randomly distributed. The residuals from the global regression model exhibit statistically significant positive autocorrelation (Moran's *I* statistic = 0.438; see Table 3). The spatial distribution of the residuals suggests that there are local variations (spatial nonstationarity) in the relationship between the relative risk rates of residential burglaries and the contextual characteristics. One possible approach for analyzing the local variations is to employ the geographically weighted regression (GWR) (see Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Charlton, and Brunsdon 2002).[3]

Geographically Weighted Regression

We use the GWR 2.1 software (Fotheringham, Charlton, and Brunsdon 2002) and ArcView GIS 3.2 (ESRI 1996) for calibrating the GWR model and visualization of the results. The parameter estimation at any of the EA's centroid points (or regression points) depends not only on the input data but also on the kernel chosen and the bandwidth of that kernel. In this study, a continuous weighting function of Gaussian form is selected as the kernel.[4] The bandwidth is optimized as a part of the GWR calibration using the AIC method (see Akaike 1981; Fotheringham, Charlton, and Brunsdon 2002). A Monte Carlo method (Hope 1968) is applied to carry out tests for the following hypotheses: (1) whether the data may be described by a GWR model rather than a nonstationary one, and (2) whether individual regression coefficients are stable over geographic space (see Fotheringham, Charlton, and Brunsdon 2002).

The results suggest that the GWR model is an improvement on the global regression model at the 0.01 level of significance (see the F test in Table 4). The AIC value is reduced from 5,031 for the global regression model (see Table 2) to 4,942 for the GWR model. The R^2 value of 0.59 indicates a reasonably high explanatory performance of the GWR model. As expected, the calibration of the GWR models alleviates the problem of spatially autocorrected error terms. Specifically, it results in reduction of the Moran's I value on residuals from 0.438 (for the global model) to 0.085 (for the GWR model).[5]

The Monte Carlo test on the local estimates for the optimal bandwidth of approximately 2.4 km suggests that there is significant spatial variation in the local parameter estimates for the x_2 and x_7 variables (the average value of dwellings and the percentage of multifamily dwellings, respectively) (see Table 5). The spatial variation in the remaining variables is statistically insignificant (i.e., there is a reasonably high probability that the variation occurred by chance). Interestingly, the optimal bandwidth value fits nicely into empirical studies on the spatial offender-target relationships. For example, Evans (1989) found that almost 50 percent of the burglaries were committed within 0.8 km of the offender's home and that only 14 percent of burglars travel more than 5 km. According to Baldwin and Bottoms (1976), 75 percent of burglars committed their offences within about 3.2 km of the offender's home. Rhodes and Conly's (1981) data on the distance frequency of burglary trips showed that 55 percent of offences were committed within approximately 2.4 km of the offender's home and that the average journey to burgle was about 2.6 km. Costello and Wiles (2001) found that the average journey from home to place of offence for residential burglary was about 3.0 km. Reflecting the empirical evidence, we selected a bandwidth range between 1 and 5 km to analyze the sensitivity of the GWR results to variations in the spatial scale (see Table 5). Notice that the spatial variability in the relationships between the risks of residential burglary and the x_2 and x_7 variables are significant at the spatial scale associated with bandwidths less than 2.4 km (Table 5). This finding suggests that the processes underlying the relationships between the risks of residential burglary and the contextual characteristics operate at a local (neighborhood) scale. It highlights the tendency of burglars to commit offences in their neighborhoods (T. S. Smith 1976; Herbert and Hyde 1985; Evans 1989;

Table 4 *Analysis of Variance (ANOVA) Table for Geographically Weighted Regression (GWR)*

Source	*SS*	*df*	*MS*	*F*
OLS Residuals	2442307.0	7.00		
GWR Improvement	966039.4	60.58	15945.95	
GWR Residuals	1476267.7	396.42	3724.02	4.2819

Note: OLS = ordinary least squares; SS = sum of squares; MS = mean sum of squares; R^2 = 0.590.

Table 5 *The Results of the Monte Carlo Significance Test (the p-values) for Spatial Variability of the Geographically Weighted Regression (GWR) Parameters and Selected Bandwidths*

Parameter	Bandwidth (in meters)					
	1000	2000	2392*	3000	4000	5000
(Intercept)	0.87	0.47	0.25	0.30	0.33	0.42
x_1	0.36	0.51	0.98	0.99	0.97	0.88
$\mathbf{x_2}$	**0.00**	**0.02**	**0.03**	0.19	0.47	0.55
x_5	0.87	0.39	0.19	0.20	0.21	0.26
$\mathbf{x_7}$	0.23	**0.05**	**0.04**	0.12	0.15	0.21
x_8	0.97	0.82	0.80	0.73	0.57	0.55

Note: Variables in bold are significant at the 5 percent level.
**optimal bandwidth.*

Table 6 *Cross-Classification of the Average Dwelling Value (x_2) and the Percentage of Multi-Family Housing (x_7) for London, Ontario by Enumeration Area (EA)*

		x_2			
		$x_2 \leq \bar{x}_2$		$x_2 > \bar{x}_2$	
		Type of EA	**RR_i**	**Type of EA**	**RR_i**
x_7	$x_7 \leq \bar{x}_7$	A	119.94	B	76.98
	$x_7 > \bar{x}_7$	C	112.37	D	73.70

Note: $\bar{x}_2$ and $\bar{x}_7$ are the average values of the x_2 and x_7 variables for all EAs; RR_i is the relative risk of residential burglary (see Note 1).

Bowers and Hirschfield 1999; Wiles and Costello 2000).

GWR produces a set of local parameter estimates for each EA. Here we limit our discussion to the *t*-values associated with the two statistically significant variables: x_2 (the average dwelling value) and x_7 (the percentage of multifamily housing). Before analyzing the spatial distribution of the *t*-values for x_2 and x_7, it is useful to examine a cross-classification of the two variables by EA (see Table 6). Four types of EAs can be identified according to the average values of x_2 and x_7. Type A occurs where x_2 and x_7 take values below the average for the study area. EAs characterized by the x_2 value below the average and the x_7 value above the average fall into the Type B area, while the reverse cross-classification results in Type C. Finally, the Type D areas have both the x_2 and x_7 values above the average. The spatial pattern of the four types of EAs shows the east–west division (Malczewski, Poetz, and Ianuzzi 2004). The west part of the city contains more-affluent areas—the B and D neighborhoods with above-average dwelling values—while the Type A and C areas are predominantly located in the less-affluent east portion of the city. The relative risks of residential burglary in the A and C areas are considerably higher than in the Type B and D neighborhoods (see Table 6). It is against this background that the spatial pattern of the *t*-values associated with the two statistically significant variables can be analyzed in the context of the hypotheses put forward in the Introduction.

The spatial patterns of the two parameters are shown in Figures 3 and 4. Higher values (either positive or negative) indicate that the explanatory variable has a greater influence in that area, whereas lower values indicate that the predictor variable is less influential in that area. As noted, the global relationship between the average dwelling value and risk of burglary is significantly negative, with a *t*-value of -4.368 (Table 3), suggesting that the more affluent the area, the lower the relative risk of residential burglary. However, the GWR results show that the contribution of the variable x_2 in the regression equation has changed over the study region, including sign change from negative to positive (see Figure 3). This signals that the relationship is more complex than is suggested by the global regression results. In fact, there are relatively small areas of the city where significantly inverse relationships between the relative risks of burglary and the average dwelling values exist. These areas are located in the southwest and northeast sectors of the city. Within these areas, the inverse relationships are significant at the 1 percent level (that is, the *t*-value ≤ -2.58). They are connected by a belt of EAs where the inverse relationships are significant at the 5 percent level ($-2.58 \leq t \leq -1.96$). It is important to note that the neighborhoods with significantly negative relationships between RR_i and x_2 are primarily located in relatively deprived areas, especially in the northeast sector of the city (the A and C neighborhoods; see Table 6). Thus, the finding seems to provide support to the *area deprivation hypothesis*, suggesting that the relatively deprived communities tend to have more residential burglaries than relatively affluent neighborhoods (see Sampson and Wooldredge 1987; Kennedy and Forde 1990; Miethe and Meier 1994).

There are two pockets showing a significantly positive relationship between victimizations and average dwelling values in the southeast and northwest sectors of city (see Figure 3). These are very different areas as far as their socioeconomic status is concerned. The former contains relatively deprived neighborhoods (the Type A and C neighborhoods with a high proportion of immigrants and low-income groups). An important feature of the northwest area is its location in the vicinity of the UWO campus. The communities located in the northwest sector of the city fall into the Type B and D areas (see Table 6). They typically contain a high proportion of university students and are characterized by high residential mobility and a large proportion of rental dwellings. Thus, the spatial pattern of the significantly positive

Figure 3 *Geographically weighted regression: the t-values for x_2 (the average value of dwelling).*

relationships between RR_i and x_2 is consistent with the *area variability hypothesis* (Ceccato, Haining, and Signoretta 2002; Herbert 2002). It is argued that social organization and informal social control are especially vulnerable in neighborhoods with overrepresentations of young people and transient populations (Henson and Stone 1999). On the other hand, this finding seems to support the *routine activities hypothesis* (Cohen and Felson 1979; Koening and Linden 2004), which postulates that neighborhoods with high proportions of rental housing and student population provide the quintessential environment for the convergence of three elements: motivated offenders, suitable targets, and the absence of capable guardians (Henson and Stone 1999). Thus, the finding suggests that routine activities and area variability (social disorganization) provide complementary insights into the target/offender/absence-of-capable-guardian convergence (Bursik and Grasmick 1993; Hancock 2001).

The global relationship between the relative risks of residential burglary and the percentage of multifamily housing is significantly positive with a t-value of 6.680 (see Table 3). Figure 4 shows that most of the local parameters are also positive. In general, the influence of multifamily housing on victimizations is strongest in the core of the city and tends to decline with distance from the city center. The relationships in the core of the city and adjacent neighborhoods are significant at the 5 percent and 1 percent levels according to the Bonferroni-adjusted critical t-values of 4.35 and 4.69, respectively (see, e.g., Fotheringham, Charlton, and Brunsdon 2002). On the other hand, the peripheral neighborhoods tend to be characterized by statistically insignificant relationships between RR_i and x_7. To this end, it is important to notice that the core of the city and adjacent areas are characterized by lower housing standards as compared with the quality of housing in the peripheral neighborhoods (Malczewski and

Figure 4 *Geographically weighted regression: the t-values for x_7 (the percentage of multifamily housing).*

Rinner 2005). This observation suggests that the spatial pattern of the t estimates for x_7 is, to some degree, a function of housing quality. Furthermore, the peripheral neighborhoods are more affluent and better organized, with a stronger sense of community identity, as indicated by higher participation in neighborhood watch programs (NWL 2004). The results suggest that an increase in the proportion of the population living in multifamily housing has a considerably greater impact on the increase of victimization in the more economically disadvantaged neighborhoods of the core of the city and adjacent areas than in the more affluent peripheral communities (especially those located in the northwest and southwest sectors of the city). Thus, the pattern of the relationship between RR_i and x_7 seems to support both the *area affluent* and the *local social control* hypotheses, suggesting that more affluent, ordered, well-organized neighborhoods experience less crime (see, e.g., Bursik and Grasmick 1993; Ceccato, Haining, and Signoretta 2002; Herbert 2002).

Conclusions

This article has presented an exploratory analysis of the spatial pattern of relative risks of residential burglary and its relationships with contextual socioeconomic characteristics of neighborhoods in London, Ontario. These relationships have been examined using conventional (global) multiple regression and GWR. Given the limitations of the global regression modeling to analysis spatial nonstationarity, we have focused on GWR as a tool for examining spatially varying relationships.

The GWR results have shown that there are significant spatial variations in the relationships between the relative risks of residential burglaries and the average value of dwellings and the percentage of multifamily housing. Interestingly, the two statistically significant variables in the GWR model point to the importance of target selection factors. The GWR results suggest that target selection involves different processes in different parts of the city. It is reasonable to argue that the pattern of residential burglary in London, Ontario, is a product of three different behavioral scenarios: (1) the target attractiveness scenario in relatively affluent communities in the peripheral neighborhoods of the city (especially those communities located in the northwest sector of the city), (2) the opportunistic activity scenario in relatively deprived areas in the core of the city and adjacent communities (especially, those located in the southwest sector of the city), and (3) a combination of the target attractiveness/opportunity scenarios in the neighborhoods adjacent to the UWO campus (see Ceccato, Haining, and Signoretta 2002).

The GWR results are potentially useful in targeting priority areas for crime prevention and for informing local planning and policy development. They suggest that preventive policies should be informed by an understanding of crime's contextual factors. In particular, these factors should be examined locally, and different policies aimed at preventing and reducing crime should be applied in different neighborhoods of the city (Brantingham 1989; Bowers and Hirschfield 1999; Harries 1999). For example, different prevention policies could be recommended for the high-burglary neighborhoods adjacent to the UWO campus and the deprived communities in the east part of the city. A policy designed to increase public participation in neighborhood watch and related programs (such as citizen patrols and some type of property marking) may be sufficient to reduce victimizations in the neighborhoods located near the UWO campus (see, e.g., Brantingham 1989). However, the same approach is unlikely to be effective in the economically deprived neighborhoods of the east end of the city. In this case, regeneration initiatives and antipoverty programs (Hancock 2001) aimed at reallocation of resources and properly locating high-crime neighborhoods within the wider social structure should be considered as tools for preventing and reducing crime (Bursik and Grasmick 1993).

These results must be considered in light of certain limitations of the analysis. Limitations of the GWR approach have been discussed by Brunsdon, Fotheringham, and Charlton 1996, Leung, Mei, and Zhang (2000a, b), Fotheringham, Charlton, and Brunsdon (2002), and Páez, Uchida, and Miyamoto (2002a, b) and will not be repeated here (see also Note 3). In the Data section, we noted some limitations in terms of data quality and comprehensiveness of the burglary data set. Furthermore, the census data *do not* refer to the locations where burglaries occurred. Actually, the data describe the characteristics of the victim's EAs (neighborhoods). Since the results are based on victimization data (the locations of burglary incidents), some of the conclusions derived from this analysis are based on the premise that high-crime neighborhoods and neighborhoods with high numbers of resident offenders are the same. Although there is empirical evidence to show that burglars tend to commit offences in their neighborhoods (e.g., T. S. Smith 1976; Herbert and Hyde 1985; Ceccato, Haining, and Signoretta 2002), this issue requires further examination that would involve data on the actual location of offenders in the study area. ■

Notes

[1] The relative risk (RR_i) ratio is defined as follows (Bailey and Gatrell 1995): $RR_i = 100(o_i/e_i)$, where $e_i = p_i(\Sigma o_i/\Sigma p_i)$ is the expected number of burglaries in the i-th EA in 1998–2001, o_i is the observed number of residential burglaries in the i-th EA in 1998–2001, and p_i is the "population at risk" (the number of dwellings) in the i-th EA in 1999. If the RR_i values are less than 100, then EA is characterized by relatively low risk (that is, the risk is less than expected for the study area). The RR_i values greater than 100 indicate that the risk is greater than expected.

[2] The global multiple regression model has the following form: $y_i = \beta_0 + \sum_{k=1}^{n-1} \beta_k x_{ik} + \varepsilon_i$, where y_i represents independent variable at the i-th EA ($i = 1,2,\ldots,m$), which is a function of n parameters β_0 and β_k ($k = 1,2, \ldots, n-1$) and ($n-1$) contextual explanatory variables x_{ik}; the ε_i's are independent normally distributed, unobserved error terms (or residuals) with zero mean and constant variance. The ordinary least squares (OLS) method is typically employed to estimate the parameters (see, e.g., Miller 1990; Selvin 1998). The method is based on a set of assumptions such as normality, homogeneity of variance, and independence of residuals. Spatial autocorrelation (or spatial dependency) and spatial nonstationarity (spatial heterogeneity) are two properties of spatial data that may undermine the

assumptions behind the traditional regression models (see, e.g., Bailey and Gatrell 1995).

[3] The GWR model is an extension of the global multiple regression (see Note 2). It has the following form: $y_i = \beta_{i0} + \sum_{k=1}^{n-1} \beta_{ik}x_{ik} + \varepsilon_i$, where β_{i0} and β_{ik} are the values of the parameters at the i-th location. To calibrate the model, a modified, weighted, least squares approach is used so that the data are weighted according to their proximity to the i-th location. Data from observations closer to i are weighted more heavily than those farther away. Hence, the estimator for the parameters in GWR can be expressed in the matrix format as follows: $\hat{\beta}_i = (X^T W_i X)^{-1} X^T W_i Y$, where W_i is an $m \times m$ matrix (the diagonal elements of the matrix denote the geographical weighting of observed data for the i-th location and off-diagonal elements are zeros) (Fotheringham, Charlton, and Brunsdon 2002). The GWR procedure provides us with all elements and diagnostics of a global regression model including parameter estimates, goodness-of-fit measures, and t-values on a local basis. One advantage of the GWR modeling is that it addresses the problem of spatial nonstationarity directly (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Charlton, and Brunsdon 2002). Also, there is empirical evidence to show that, usually, the residuals obtained from GWR do not exhibit any spatial pattern (see Fotheringham, Charlton, and Brunsdon 2002). The present study is consistent with this finding. Further discussion of the advantages and disadvantages of the GWR modeling can be found in Leung, Mei, and Zhang (2000a, b) and Páez, Uchida, and Miyamoto (2002a, b).

[4] A fixed Gaussian kernel function has the following form: $w_{ij} = \exp\lfloor -(d_{ik}/\alpha)^2 \rfloor$, where α is the bandwidth and d_{ik} is the distance between location i and k. Alternatively, an adoptive bandwidth can be used. In this case, the following bi-squared function can be implemented: $w_{ij} = [1-(d_{ik}/\alpha)^2]^2$, if $d_{ik} \leq \alpha$, and $w_{ij} = 0$, if $d_{ik} > \alpha$ (Fotheringham, Charlton, and Brunsdon 2002). Although the findings reported in this article are based on the implementation of GWR with a fixed kernel, we have also used GWR with an adoptive kernel. The results produced by GWR with the two weighting functions are very similar. For example, the AIC values are: 4942.1 and 4939.8 for optimal fixed and adoptive kernels, respectively. There are only two variables (x_2 and x_7) in the GWR models with optimal fixed and adoptive bandwidths that are statically significant at the 5 percent level. The spatial patterns of the t-values for x_2 and x_7 produced by the GWR model with an optimal fixed kernel (see Figures 3 and 4) are very similar to those obtained for an optimal adoptive kernel.

[5] It is also important to examine casewise diagnostics such as the local R^2 statistics, standardized residuals, and influence statistics. The local R^2 values are in the range from 0.445 to 0.779, indicating that the models calibrated at the regression points (EAs) replicate the data in the vicinity of that point reasonably well. The standardized residuals provide another set of casewise diagnostic measures that can be used to identify unusual cases (EAs). For the GWR model, the values of the standardized residuals range from -2.401 to $+2.769$. More then 95 percent of the standardized residuals are between -2.58 and $+2.58$, indicating that the distribution of residuals is approximately normal. It is also important that we know whether individual cases exert a significant effect on the results. The Cook's distance provides a suitable measure (Fotheringham, Charlton, and Brunsdon 2002). For the GWR model, the maximum value of the Cook's distance is 0.044. This small value of the measure indicates that there are no unusual cases in terms of the dependent or independent variables (see, e.g., Miller 1990).

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