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Community structural predictors of spatially aggregated motor vehicle theft rates: Do they replicate?

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Abstract

Community-level motor vehicle theft (MVT) is not spatially random but is influenced by the structural composition of the community. Work to date did not provide a clear picture of the structural correlates of community-level MVT rates for two reasons. Cross-sectional studies had been limited to a single point in time (one wave design). In addition, studies had not adequately controlled for MVT rates in adjoining communities (spatially autocorrelated rates). The current study addressed these limitations. Drawing on structural correlates highlighted by factorial ecology and past work on motor vehicle theft, it anticipated cross-sectional connections between status, stability, age composition, and racial heterogeneity. It sought to learn if these connections persisted at two points in time spanning a decade. Census block group data from a midwestern city were merged with geocoded vehicle theft data, and a comprehensive spatial lag variable was constructed (Land & Deane, 1992). At both points in time, communities with higher MVT rates had lower socioeconomic status, and were surrounded by other communities with higher MVT rates. Community processes driving the connection between status and vehicle theft were suggested. The strong spatial dependency of MVT rates suggests attributes, events, or longer-term trends located in a section of a city may be affecting the communities located there. Issues for prevention were addressed.

Introduction

Motor vehicle theft (MVT) is widespread, costly, and historically under-researched. This work focused on clarifying the community structural characteristics of high MVT rate communities. The question addressed was: What are the demographic characteristics of these locations? In addition, it considered spatial autocorrelation. Doing so recast the question into: What are the demographic characteristics of high MVT rate communities after taking into account the amount of MVT in surrounding communities?

Much of the research that exists suggests MVT is a socially and geographically unique property crime with an uneven distribution throughout the social landscape. For example, Rengert (1997) found MVT hot spots concentrated in very specific areas of the urban landscape of Philadelphia including entertainment districts and school zones with notable temporal shifts throughout the day. Henry and Bryan (2000) found elevated MVT densities in the business district as well as retail, recreational, and suburban areas throughout Adelaide, Australia. Given geographical patterns, and structural correlates that may be somewhat unique, this raises a broader question: are structural correlates of MVT different than structural correlates for other crime types?

Most of the past work on community MVT rates has used single-wave, cross-sectional designs. Thus, little is

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known about the replicability of structural predictors over time. Additionally, existing studies of community MVT rates have generally neglected the spatial relationship that exists throughout the community. Communities with high MVT rates are likely to be near communities also having high MVT rates. Studies either have neglected this issue of spatial autocorrelation, or used inadequate spatial controls by neglecting entire portions of a study area. This study addressed both of these shortcomings.

This work employed the census block group as the unit of analysis serving as a proxy measure of community. Residential settlement patterns throughout the social landscape result in relatively homogeneous communities at the block group level making it an appropriate level of aggregation for investigating ecological impacts on crime.[1] Though not a precise measure of community given the fluidity of community boundaries, it is a suitable alternative. Past work suggests that large units of measurement (e.g., census tracts) obscure social processes while small units (e.g., census face blocks) are susceptible to a large number of locations with no events (e.g., MVT).

Between 1960 and 2004, approximately 60 million vehicles were stolen in the United States (Federal Bureau of Investigation, 2001, 2002, 2003, 2004). The 2003 Uniform Crime Report (UCR) indicated that MVT incidents rose by 10 percent from 1.15 million in 1999 to more than 1.26 million in 2003. Not surprisingly, the consequent monetary costs of this crime also rose, from 8.4 billion dollars in 2002 to more than 8.6 billion dollars in 2003, more than double the 3.3 billion dollars of estimated losses from burglary (Copes, 2003). MVT is the most expensive property crime in the United States with most direct costs passed on to vehicle owners through high insurance premiums.

The indirect monetary and social costs of MVT are similarly substantial. Indirect costs such as the investigation of MVT by law enforcement, prosecution and adjudication of offenders, and lost worker productivity, all take a financial toll (Clarke & Harris, 1992; Field, 1993). According to the Bureau of Justice Statistics for 2004, most victims of MVT lost between one and five days of work with as many as 8 percent of Whites and 11 percent of African–Americans losing between six and ten days of work. A review of 2004 Bureau of Justice Statistics revealed a national motor vehicle theft victim profile as a Black male between the ages of twenty and thirty-four, renting their residence in an urban environment, with their vehicle stolen from a parking lot or garage near their home between the hours of midnight and 6 a.m. (Bureau of Justice Statistics, 2006). The social costs of MVT to communities are not expressible in dollar amounts, but are experienced through diminished quality of life due to compromised public safety. In sum, MVT, while costly, is not simply a monetary problem and vehicle owners are clearly not the only victims.

Vehicle theft, which occurs nearly one hundred times more frequently than homicide each year, has been addressed far less frequently in the literature. Understandably, MVT's crime severity is one reason for this disparity. The intention here is not to suggest that MVT is more serious than homicide, but rather that MVT's frequent occurrence and rising costs warrant more attention than has traditionally been received.

Given what is known about the economic and social toll that MVT imposes, and the high concordance between actual thefts and reported thefts (Karmen, 2004; Maxfield & Clarke, 2004), one might expect to find an abundant body of empirical research addressing the topic though this is not the case. There has been recent research on carjacking (Jacobs, Topalli, & Wright, 2003; Klaus, 1999; Topalli & Wright, 2004). The Bureau of Justice Statistics reported that between 1992 and 1996, there were approximately 49,000 reported carjackings with just over half of them successful. Victims were alone in their vehicles in approximately 92 percent of carjackings, and in 72 percent of carjackings the offender brandishing a firearm (Klaus, 1999). Additional efforts have explored offender decision-making processes (Cherbonneau & Copes, 2005; Copes, 2003), and there is an edited volume on *Understanding and Preventing Car Theft* (Maxfield & Clarke, 2004). Very few studies had come to light on the community structural covariates of MVT rates (see Copes, 1999; Rice & Smith, 2002). No studies had come to light looking at structural covariates using multiple waves of data.

Structural covariates refer to the fundamental demographic fabric of neighborhoods or communities: status, stability, and racial heterogeneity. Given the potential offender pool for MVT and reflecting on MVT arrests, presence of young males may be relevant as well. The relevance of these features is supported both by findings from the limited MVT literature (Copes, 1999; Rice & Smith, 2002), from the communities and crime literature (Bursik, 1986; Sampson & Grove, 1989), and a long tradition of factorial ecology (Berry & Kasarda, 1977; Hunter, 1971, 1974; Shevky & Bell, 1955). By seeing if structural correlates replicate at two points in time, the possibility of a "common set of spatial ecological conditions favorable to deviant behavior [MVT]" (Ley & Cybriwsky, 1974, p. 127) was addressed. The influence of MVT rates in nearby communities was fully and appropriately modeled (Land & Deane, 1992), as had not been done in earlier works. Doing so ensured that the structure-MVT connections witnessed were not influenced by what was happening in nearby communities.

Literature review

Turning to past literature on structural correlates of MVT, socioeconomic status (SES), often considered a sturdy correlate of community crime rates (Bursik & Grasmick, 1993), links to MVT. Copes (1999) and Hope and Hough (1988) found that areas of lower status tended to have more MVT. A review of the literature by Miethe and McCorkle (2001) uncovered a status correlate, unemployment, related to higher MVT rates. The causal influence of status has been linked to mechanisms of informal social control, suggesting that households in low status communities have fewer resources to fend off the invading criminal elements and have more spatially restricted domains of control extending out from the home (Taylor, 1988). Given past work, MVT and SES were expected to have an inverse relationship.

The literature reviewed by Miethe and McCorkle (2001) found increased MVT associated with residential instability. For example, MVT rates were higher in areas with higher population mobility, and more single-parent families. By way of explanation using the systemic model, residents in less stable census block groups are probably less attached to their locale and may be less willing to collaborate with neighbors on collective crime prevention efforts (Bursik & Grasmick, 1993; Kasarda & Janowitz, 1974). Given past work and the presumed dynamics, higher MVT rates were expected in areas of greater instability.

Turning to racial heterogeneity, Clarke and Harris (1992) found vehicle theft rates to be greater in areas characterized by increased racial and ethnic diversity. Research by Davison (1995), however, found MVT was less likely in heterogeneous communities but more likely in predominantly African–American communities. Existing research suggests that many offending and victimization rates are correlated with ethnic and racial heterogeneity (Bursik & Grasmick, 1993; Sampson & Grove, 1989; Warner & Pierce, 1993). Shaw and McKay (1942) and Bursik and Grasmick (1993) suggested that this outcome was the result of a lack of cohesiveness and consensus in the community. According to Kornhauser (1978), heterogeneous communities are not able to develop solidarity or group level consensus due to the difficulty of integrating diverse subcultural values and norms. More simply, perhaps it is just harder to recognize who "belongs" in more racially heterogeneous communities. Given past work, MVT rates were expected to be higher in racially heterogeneous communities.

Both official statistics and victimization surveys revealed that young people are involved and arrested in disproportionate numbers to their representation in the population. For example, according to Uniform Crime Report data for 2001, youth under eighteen years of age accounted for 26 percent of the population yet represented 28 percent of all index crimes. More specifically, youth under eighteen years of age represented 39 percent of all index property crimes (Federal Bureau of Investigation, 2002). This appeared to be true for MVT as well with young males, particularly those in their teens and early twenties (McCaghy, Giordano, & Henson, 1977; Saville & Murdie, 1988), the age group most frequently arrested for MVT. "The U.S. Department of Justice (1996) indicated that people under 18 years of age accounted for 42 percent of those arrested for auto theft, and people under age 21 accounted for 59 percent of arrests" (Rice & Smith, 2002, p. 317). Vehicle theft rates were expected to link positively to the percent of young males in the population.

Spatial patterning and motor vehicle theft

Factors beyond a community's boundaries may influence that community's crime rate. Potential offenders may have search spaces or routine travel patterns spanning several neighborhoods. There may also be physical, social, target, or service similarities across several communities in a section of a city that elevate or depress certain types of crime risks. Violent (Taylor & Covington, 1988) and property (Ratcliffe & McCullagh, 1999) crime rates are spatially patterned with high rate communities often surrounded by other high rate communities. It seems reasonable to expect communities with high MVT rates may be surrounded by other communities with high rates as well. Previous work on community correlates such as that reviewed above, and other works linking location to type of vehicle theft (Plouffe & Sampson, 2004), potential offender densities (Copes, 1999), land use mixes (Hollinger & Dabney, 1999; Roncek & Faggiani, 1985), and other work on structural correlates (Mayhew, 1990; Messner & Blau, 1987; Miethe & McCorkle, 2001) at varying levels of aggregation strongly suggest such a possibility.

It is not known at this time what specific factors might make a cluster of adjoining communities similarly vulnerable or resistant to MVT, aside from the general classes of factors mentioned above. All that is being suggested at this juncture is that MVT rates may be spatially autocorrelated at the community level, as are many other community crime rates. If MVT is spatially autocorrelated, it is crucial to fully control for the autocorrelation if one seeks to isolate the connections existing within communities.

As has been noted above, many of the structural correlates of MVT are similar to the structural correlates seen for other types of offending and victimization rates. This conclusion may be premature, however, because previous MVT studies either had neglected to control for spatial autocorrelation, or had done so inadequately, as will be explained below. If the controls for spatial autocorrelation are inadequate, estimates of within-community effects may be over extended, suggesting within-community factors are more important than they really are.

Only one known study of MVT at an extremely small but completely legitimate community level controlled for spatial autocorrelation. Rice and Smith (2002) analyzed all MVT in one southeastern city, using street blocks as the unit of aggregation. Their study represented one of the most comprehensive studies to date linking community social structure and land use with MVT. Adding a variable controlling for the spatial autocorrelation of MVT rates had little impact on other predictors in the model, but was itself significant. This finding suggested that "… auto theft on a face block was in fact related not only to the characteristics of the face block… but also to the characteristics of the closely adjacent face blocks" (Rice & Smith, 2002, p. 326).

The Rice and Smith (2002) study, however, might not have adequately controlled for the spatial autocorrelation of MVT. First, only three-quarters of the street blocks in the city were analyzed with little explanation as to why a portion of city blocks were excluded.[2] So their analysis did not cover the entire city. Second, their spatial lag variable, although cross-referenced to articles on comprehensive spatially lagged variables, was not as comprehensive as recommended by those very articles. Some adjoining blocks were ignored, and simplifying assumptions were made about between-block distances. For example, Rice and Smith (2002) only took into account MVTs along the vector a street was running, ignoring MVTs on parallel streets. Further, they used a standardized block distance which then assumed that all blocks were the same length, rather than using the centroid of each adjoining block.[3]

Since their spatial lag variable was not operationalized in line with the suggested guidelines (Land & Deane, 1992), and was constrained by extensive missing data, their control for spatial autocorrelation *may* have seriously *underestimated* the impact of nearby MVT. If exogenous or nearby impacts were underestimated, endogenous, within-community impacts *may* have been *overestimated*. A final comment is that the researchers entered the spatially lagged variable last in the analysis. Thus, the reader did not learn how much MVT within a community can simply be explained by nearby MVT. Although it is not a criticism per se, this would seem to be important information both theoretically and practically.

In short, to date there had been only one community-level study of MVT which attempted to control for how much MVT was happening nearby. The indicator used, however, might have been inadequate, for the reasons noted above. An adequate control variable for nearby crime rates will use an inverse distance weighted density potential model taking into account all community crime rates in the entire jurisdiction (Land & Deane, 1992). It also will employ a two-stage technique to ensure that error components in the spatial lag variable are not connecting to error components in the outcome. The variable used here to control for spatial autocorrelation followed these recommendations.

This study provided a more precise estimate of how much community MVT rates were influenced by nearby MVT rates. Further, having done so for the first time, it generated more precise estimates of how much community MVT rates were influenced by community structure, and which features of the community itself were relevant. It has been suggested that the estimates provided in previous studies, even those attempting to control for nearby crime rates, have been inadequate. Additionally, this study determined if the structural correlates of MVT rates, in one city, were the same from one decade to the next, despite dramatically changing MVT rates.

Finally, and more specifically, the study examined independent and persistent demographic dimensions of community structure (Hunter, 1971; Shevky & Bell, 1955) which had proven important in prior ecological work on structural correlates of MVT: status, stability, racial heterogeneity, and proportion of youthful male population. Whether and how these structural correlates prove important has implications for the broader theoretical question of just how "different" MVT rates are from other types of community crime rates.

Model

This research explored impacts of antecedent structural predictors and adjoining rates of community MVT. The structural predictors used have been highlighted both by factorial ecology and the scant community MVT rate literature. Lower SES, less stability, and more racial heterogeneity may each be linked to weaker or more spatially restricted informal, resident-based control processes including surveillance, and thus, to elevated MVT rates.

If the work finds ecological correlates of MVT rates that replicate a decade later, it would suggest MVT rates link cross-sectionally and consistently to fundamental features of community structure. On the other hand, if the community correlates of MVT vary over time this could suggest that MVT is more dynamic and adaptable necessitating alternative theoretical explanations such as opportunity theory (Miethe & Meier, 1990).

Identifying a prevailing theoretical perspective would inform future policy and prevention initiatives. It could be that depending on the spatial patterning observed, adjustments to the "cone of resolution" are needed. The cone of resolution refers to the organization of knowledge about complex spatial processes in relation to different levels of analysis (Brantingham & Brantingham, 1976; Harries, 1974; Taylor, 1997). If the results show that communities are affected by the MVT rates in adjoining communities, it may be important to start thinking about what processes are taking place in different sectors of a medium-size city.

Data and methodology

Motor vehicle theft data

The MVT incident report data for January 1, 1990 through December 31, 2001 (n = 10,439 MVTs) were provided by a medium-size midwestern city (population > 100,000) police department.[4] The data consisted of "official" MVT incident level information including the address identifier for the location from which the vehicle was stolen. The period of twelve years was chosen because it corresponded to the two most recent decennial United States Census Bureau surveys (1990 and 2000) and allowed for thorough analysis of MVT over the decade.

Decennial census 1990 and 2000 demographic data

Decennial census data showed that the study area experienced both structural stability and structural change over the decade. As Table 1 shows, several city-wide demographics held relatively constant from 1990 to 2000 with increases or decreases of less than 5 percent, for example: population (down .005 percent), individuals living in poverty (down .02 percent), males in the population between the ages of fourteen and seventeen (up 1.5 percent), and the number of vehicles available in the population (up 3 percent).

Other community demographics experienced more dramatic increases and decreases over the decade, for example: median owner occupied property value (up 64 percent), median income (up 24 percent), percent of Black residents in the population (up 18 percent), percent of White residents in the population (down 11 percent), percent of residents in the labor force sixteen years and older who are unemployed (up 7 percent), and percent of the population living in a different house five years prior (down 8.5 percent).

Unit of analysis

The level of spatial aggregation plays an important role in understanding MVT. Areal units used in studies

Table 1
1990 and 2000 census demographic variables and changes over a decade

Predictor	1990	2000	Increase/decrease
Total population	113,504	112,936	−568 (−.005)
Median household income	$29,363	$36,397	$7,034 (24%)
Median property value owner occupied	$51,114	$84,000	$32,886 (64%)
Total number of persons living below poverty level	20,258 (18%)	20,220 (19%)	−38 (−.02%)
Housing units occupied by renters	19,291 (40%)	18,091 (37%)	−1,200 (−6.2%)
Single person housing units	31,768 (66%)	33,370 (68%)	1,602 (5%)
Population living in different house five years prior	59,373 (52%)	54,373 (48%)	−5,000 (−8.4%)
Percent of multiple unit housing	15,632 (32%)	15,166 (31%)	−466 (−3%)
Percent of owner occupied housing units	25,625 (53%)	26,996 (60%)	1,371 (5.4%)
Percent of population unemployed sixteen years old and older	3,711 (4.2%)	3,982 (4.6%)	271 (7%)
Percent Black alone in the population	23,469 (21%)	27,601 (24%)	4,132 (18%)
Percent White alone in the population	87,478 (77%)	78,111 (69%)	−9,367 (−11%)
Percent of males in the population	53,444 (47%)	53,267 (47%)	−177 (−.003%)
Males age fourteen to seventeen	3,179 (6%)	3,226 (6%)	47 (1.5%)
Males age eighteen to twenty-four	6,828 (13%)	6,353 (12%)	−475 (−7%)
Vehicles available	66,308	68,161	1,853 (3%)

of MVT have ranged from countries (Webb, 1994) and cities (Krimmel & Mele, 1998) to the census tract (Copes, 1999) and face block (Rice & Smith, 2002).

The unit of analysis chosen for this study was the census block group (n = 90).[5] The block group unit was appropriate here given the ecological model used. People often choose to be close to those most similar to themselves across a variety of community structural dimensions including: income, age, education, ethnicity, family structure, and housing (Nelson & Wake, 2005).

Changes in census boundaries over time, a problem commonly referred to as the modifiable area unit problem (MAUP) (Openshaw, 1984; Ratcliffe & McCullagh, 1999), were addressed using a commercial data product from Geolytics to normalize the 1990 block group boundaries to match the 2000 boundaries.[6]

Dependent variable

Motor vehicle thefts were geocoded with a 95 percent hit rate or better, well exceeding Ratcliffe's (2004) suggested minimum threshold of 85 percent. Counts of MVT were aggregated to census block groups. The average count of MVTs for the years 1990 and 1991 was used for the beginning of the decade (Time 1), 2000 and 2001 for the end of the decade (Time 2). Rates were computed using the number of vehicles registered in the block group multiplied by 1,000 and natural base logged after adding one to each count to reduce skewness.[7, 8]

Sociodemographic structural predictors

Factorial ecology has shown that the three demographic dimensions studied here (status, stability, and race) have emerged as primary elements of community demographic fabric across many American communities in many American cities over several decades (Hunter, 1971; Shevky & Bell, 1955; Shevky & Williams, 1949). No work to date had empirically shown that *net* of these three primary dimensions, other ecological demographic components contribute additionally to studying community demographic structure. Thus, additional dimensions probably would not be independent of these three core dimensions already represented.

A complete list of the descriptive statistics for each community structure variable used to create the predictor indexes, as well as the actual indexes for Time 1 and Time 2 can be reviewed in Tables 2 and 3.

SES

A socioeconomic status index was created. For each block group, the z-scores for median property value logged, median income logged, and an inverted measure of the percent of people living below the poverty line, created by multiplying the number by-1, were summed. The Time 1 (1990) Cronbach's alpha for the computed three-item index was .896 and the Time 2 alpha value was .888. Due to multicollinearity issues between SES and the spatial autocorrelation variable, the two were separated. Spatial autocorrelation was used to predict SES, and the resulting residual SES was saved. This portion of the SES predictor did not correlate with the spatial autocorrelation variable and was entered into the Time 1 and Time 2 models as the "new" residualised SES predictor. This approach means that spatially adjacent MVT rates were fully controlled, and that the only portion of SES used in the model was that segment independent of nearby MVT rates.

Table 2
1990 descriptives of all census predictors before indexing SES and instability

Predictors	N	Min.	Max.	Mean	S.D.
Total population 1990	90	399	5,551	1367.97	882.64
Median household income logged	90	8.52	11.36	10.06	.55
Median property value logged	88	9.36	12.02	10.61	.55
Percent of the population w/income below poverty level (x − 1)	90	93	0	20	19
Percent of housing units occupied by renters	90	4	100	42	21
Percent of one-person housing units	90	1	71	30	12
Multiple unit housing as a percent of total housing units	90	0	98	28	24
Percent of population living in a different house five years prior	90	21	84	51	11
Percent of males in the population age fourteen to seventeen	90	0	8	2.76	1.8
Percent of males in the population age eighteen to twenty-four	90	1	43	5.92	6.89
Heterogeneity	90	0	.25	.11	.08
Spatial autocorrelation	90	−1454.95	15068.91	10394.65	3180.65
Contiguous boundary	90	0	1	.12	.329
Straddle boundary	90	0	1	.14	.354
SES index	90	−6.64	5.97	−.0000002	2.73
Instability index	90	−4.50	5.36	.0000007	1.79

Table 3
2000 descriptives of all census predictors before indexing SES and instability

Predictors	N	Min.	Max.	Mean	S.D.
Total population	90	4	6,164	1366.66	1006.73
Median household income logged	90	8.81	11.56	10.36	.52
Median property value logged	88	9.84	12.26	11.10	.56
Percent of the population w/income below poverty level (x − 1)	90	62	0	21.53	18
Percent of housing units occupied by renters	90	2	100	37	20
Percent of one person housing units	90	0	72	31	11
Multiple unit housing as a percent of total housing units	90	0	100	26	25
Percent of population living in a different house five years prior	90	0	85	48	14
Percent of males in the population age fourteen to seventeen	90	0	8	3	2
Percent of males in the population age eighteen to twenty-four	90	0	39	5	6
Heterogeneity	90	0	.25	.12	.08
Spatial autocorrelation	90	7471.7	53871.42	31449.30	12279.25
Contiguous boundary	90	0	1	.12	.329
Straddle boundary	90	0	1	.14	.354
SES index	90	−5.52	5.33	.00020	2.69
Instability index	90	−4.87	10.25	.0000004	3.06

Stability

Z-scores for percent of housing units occupied by renters, percent of housing units occupied by one person, percent of multiple housing units, and percent of people age five and older not residing in the same house five years prior were summed. The Time 1 (1990) Cronbach's alpha for the four-item stability index was .841 and the Time 2 (2000) alpha value was .762.

Racial heterogeneity

Following other researchers (Miethe & McDowall, 1993; Rice & Smith, 2002) racial heterogeneity was measured by the ratio of White to Black persons in each block group's population (White/total population) × (Black/total population).[9] An African–American predictor was substituted for heterogeneity, but resulted in too much multicollinearity.

Age structure

As a measure of motivated offenders, the percent of persons in each block group aged fourteen through seventeen and the percent aged eighteen through twenty-four were also entered.

Population

Total population was also entered into several models as a control. At this point it was not clear if this variable reflected the number of available guardians or the number of proximate potential offenders, or possibly a little of both. The correlation between total population and number of registered vehicles, however, was very high: .926 in 1990 and .935 in 2000 (p's < .01). With population entered, tolerance and variance inflation factors (VIF) exceeded recommended thresholds, indicating a multicollinearity problem. As a result, analyses were run with and without population entered as a variable. Tables 6 and 7 show that neither the R^2 change nor the significant predictors were substantially influenced.

Spatial autocorrelation

Following a two-stage least squares procedure (Land & Deane, 1992) an instrumental variable was created.[10]

Spatial boundaries

Two dummy variables were created. The first represented census block groups within the city boundary limits which touched the city boundaries (contiguous boundary). This variable controlled for edge effects. The second represented census block groups whose boundaries extended outside the city limits boundary (straddle boundary). Since only part of these block groups fell within the city, the total number of MVTs in these locations was not known.

Correlation coefficients for each of the Time 1 and Time 2 predictors and the logged motor vehicle theft outcome variable can be reviewed in Tables 4 and 5.

Additional specification

For each decade, two series of OLS regression models were computed. The first model series used the variables as described above. The second converted all predictors, except the two dummy boundary variables, into population weighted percentiles (pwp). This alternative ordering is appropriate in ecological analyses because it captures each census block group's position, relative to all the other block groups in the city, on each

Table 4
Correlation matrix of time 1 (1990/91) predictors of logged motor vehicle theft rates

	1	2	3	4	5	6	7	8	9	10	11
1	1										
2	−.297**	1									
3	−.825**	.376**	1								
4	.543**	.019	−.491**	1							
5	.355	−.143	−.596	.282**	1						
6	.127	.036	.132	−.068	.037	1					
7	.123	−.047	.008	.359**	−.086	−.290**	1				
8	−.145	−.034	.139	−.142	.141	.013	−.149	1			
9	−.322	.405**	.272**	−.128	−.147	.109	−.111	−.153	1		
10	.646**	−.466**	−.676**	.440**	.495**	−.129	.327**	−.258*	−.546**	1	
11	.727**	−.205	−.753**	.356**	.496**	.321**	−.062	−.125	−.202	.502**	1

Note: N = 90.
* Correlation is significant at the .05 level.
** Correlation is significant at the .01 level.
1 = 1990/91 logged MVT rate w/registered vehicles as the denominator (outcome).
2 = population.
3 = SES index.
4 = instability index.
5 = racial heterogeneity.
6 = percent of males in the population age fourteen to seventeen.
7 = percent of males in the population age eighteen to twenty-four.
8 = contiguous boundary (control).
9 = straddle boundary (control).
10 = spatial autocorrelation (control).
11 = African American.

Table 5
Correlation matrix of time 2 (2000/01) predictors of logged motor vehicle theft rates

	1	2	3	4	5	6	7	8	9	10	11
1	1										
2	−.416**	1									
3	−.859**	.416**	1								
4	.340**	−.038	−.376**	1							
5	.553**	−.195	−.626**	.265*	1						
6	.107	.045	−.125	−.307**	.214*	1					
7	.095	.018	−.054	−.239*	−.056	−.236*	1				
8	−.130	−.071	.169	−.063	−.165	−.093	−.134	1			
9	−.401*	.531**	.242*	−.165	−.148	.020	−.132	−.153	1		
10	.810**	−.501**	−.764**	.237*	.536**	.042	.259*	−.197	−.480**	1	
11	.777**	−.316**	−.807**	.294**	.524**	.139	−.161	−.180	−.231*	.662**	1

Note: N = 90.
* Correlation is significant at the .05 level.
** Correlation is significant at the .01 level.
*** Correlation is significant at the .001 level.
1 = 2000/01 logged MVT rate w/registered vehicles as the denominator (outcome).
2 = population.
3 = SES index.
4 = instability index.
5 = racial heterogeneity.
6 = percent of males in the population age fourteen to seventeen.
7 = percent of males in the population age eighteen to twenty-four.
8 = contiguous boundary (control).
9 = straddle boundary (control).
10 = spatial autocorrelation (control).
11 = African American.

variable (Bursik, 1986). These nonlinear transformations put each block group's score in the context of all other block groups and have been employed in ecological analyses of status (e.g., Bursik, 1986; Choldin, Hanson, & Bohrer, 1980), and crime and delinquency (e.g., Bursik, 1986; Taylor & Covington, 1988). Population weighting the percentile scores recognizes that different block groups have different sized populations. Each block group's position on a variable in its population weighted percentile form indicates what fraction of the city's total population scores at or below that block group's score.[11]

Results

Separate regressions were initiated for each wave of data. For each wave, there was a regression with untransformed variables, and a regression with variables transformed to population weighted percentiles. The small sizes of the coefficients in all of the models were just due to the metric of the dependent variable after logging to reduce skewness. The OLS regression analyses are presented in Table 6 (Time 1) and Table 7 (Time 2). The last two columns in each table show results when all predictors were population weighted percentiles.

The MVT rates were powerfully influenced by the rates in nearby communities, and more so by the end of the decade. Around 1990, almost 42 percent of logged MVT rates were explained by the surrounding rates (Table 6, Model A). A decade later (Table 7, Time 2, Model A), surrounding rates explained 65.6 percent of the outcome, a marked increase from a decade earlier. By the end of the decade, each community was more influenced by the rate of MVT in other nearby communities than they were at the beginning. Whether this is due to target, enforcement, offender, or land use changes is not known. This issue will be further addressed in the discussion section.

The second sequence of analyses (Model B) consisted of Time 1 and Time 2 models with all structural predictors and controls other than SES and population. Both variables were temporarily removed due to multicollinearity concerns. SES was highly correlated with spatial autocorrelation, and population correlated with registered vehicles, the denominator in the MVT rate outcome. The structural predictors included in the model explained 56.3 percent of the variance in the Time 1 logged MVT rate (Table 6, Time 1, Model B), a 15.3 percent increase over the model with just the spatial autocorrelation variable. At the end of the decade (Table 7, Time 2, Model B), all these variables explained 71.6 percent of the variance, an increase of 6 percent compared to the model with just the spatial autocorrelation predictor.

All of the significant predictors in the models were in the direction expected. As predicted, instability elevated

Table 6
OLS cross-sectional models for 1990/91, time 1, logged motor vehicle theft rates without and with population weighting

Variable	Model A	Model B	Model C	Model D	Model E	Model F
					ppw	*ppw*
	B	*B*	*B*	*B*	*B*	*B*
Population	–	–	–	.00006	−.000025	.000017
Residual SES	–	–	−.303***	−.309***	–	−.660***
Instability	–	.225***	.077	.067	.228**	.119
Heterogeneity	–	−.832	−2.804**	−2.911**	.001	−.001
Males fourteen to seventeen	–	.114***	.050	.049	.001	.001
Males eighteen to twenty-four	–	−.024	.005	.005	.0003	.0003
Contiguous boundary	–	.100	−.033	−.016	.034	.0004
Straddle boundary	–	.036	−.225	−.245	−.022	.0001
Spatial auto-correlation	.000020***	.00019***	.00020***	.000021***	.000041***	.000051***
R^2	.417	.563	.761	.762	.523	.657

Note: N = 90.
* Significant at the .05 level.
** Significant at the .01 level.
*** Significant at the .001 level.
Model A = time 1 OLS regression analysis with only spatial autocorrelation (control).
Model B = time 1 OLS regression analysis with all variables less SES and population.
Model C = time 1 OLS regression analysis including residualised SES less population.
Model D = time 1 OLS regression analysis including all predictors and controls.
Model E ppw = time 1 population weighted OLS regression analysis with all variables less SES.
Model F ppw = time 1 population weighted OLS regression analysis with all variables including residualised SES.

MVT rates in both Time 1 (.225) and Time 2 (.088) models. The percent of males in the population between the ages of fourteen and seventeen did likewise (.114), but was significant in the Time 1 model only. Spatial autocorrelation remained significant in both Time 1 (.00019) and Time 2 (.000082). Even after controlling for the basic demographic composition of each community, the MVT rates in nearby locations were still influential.

An F-test of the R^2 change between Models A and B for both periods revealed that the inclusion of the structural predictors, less SES and population, added significant explanatory power ($p < .001$ – 1990; $p < .01$ – 2000). This finding affirmed that ecological structure of the community did matter and significantly affected the MVT rates. At both Time 1 and Time 2, MVT rates were higher in less stable areas and in proximity to other communities with elevated MVT rates.

Adding in residualised SES, however, changed which predictors were significant (Model C). As previously discussed, residualised SES was created in order to have both SES and spatial autocorrelation in the models together and not violate multicollinearity concerns. Residualised SES is simply the portion of SES not predicted by MVT rates in nearby communities. As Tables 6 and 7 show (Model C), adding residualised SES increased explanatory power: from 56 percent to 76 percent around 1990, and from 72 percent to 81 percent around 2000. In all but one case, the significant predictors worked in the direction expected. Areas of higher residualised SES had lower logged MVT rates (Time 1 = −.303 and Time 2 = −.301). This fits with how status correlates with violent crime rates at the community level. Heterogeneity (−2.804) was only significant in the Time 1 model and it was not in the direction expected. Areas with more heterogeneity experienced lower MVT rates. The straddle boundary control (−.510) was only significant in the Time 2 model with lower MVT rates in areas straddling the city boundary. The spatial autocorrelation control remained a significant predictor in both Time 1 (.00021) and Time 2 (.000083).

An F-test the R^2 change for both models revealed that the inclusion of residualised SES increased the explained variance ($p < .001$ – 1990; $p < .01$ – 2000). Even after controlling for nearby MVT rates, and other elements of demographic fabric, community status still had a powerful influence on the outcome, at both points in time.

The fourth series of Time 1 and Time 2 OLS models contained all of the predictors and controls including population (Model D). As Tables 6 and 7 show, the significant predictors in Time 1, Model D, explained 76.2 percent of the variance in logged MVT rates and the Time 2, Model D, significant predictors explained 81 percent of the variance.

Table 7
OLS cross-sectional models for 2000/01, time 2, logged motor vehicle theft rates without and with population weighting

Variable	Model A	Model B	Model C	Model D	Model E	Model F
					ppw	*ppw*
	B	*B*	*B*	*B*	*B*	*B*
Population	–	–	–	.000055	−.000015	.000014
Residual SES	–	–	−.301***	−.306***	–	−.606***
Instability	–	.088**	.009	.006	.001	−.0001
Heterogeneity	–	1.296	−.177	−.231	.001	−.00025
Males fourteen to seventeen	–	7.244	1.923	1.483	.0005	.000015
Males eighteen to twenty-four	–	−2.616	−.313	−.437	−.0002	.0000061
Contiguous boundary	–	.146	.043	.050	.018	.011
Straddle boundary	–	−.027	−.510	−.573*	−.012	−.114*
Spatial auto-correlation	.000088***	.000082***	.000081***	.000083***	.000016***	.000018***
R^2	.656	.716	.809	.810	.696	.785

Note: N = 90.
* Significant at the .05 level.
** Significant at the .01 level.
*** Significant at the .001 level.
Model A = time 2 OLS regression analysis with only spatial autocorrelation (control).
Model B = time 2 OLS regression analysis with all variables less SES and population.
Model C = time 2 OLS regression analysis including residualised SES less population.
Model D = time 2 OLS regression analysis including all predictors and controls.
Model E ppw = time 2 population weighted OLS regression analysis with all variables less SES.
Model F ppw = time 2 population weighted OLS regression analysis with all variables including residualised SES.

Similar to Model C, all but one of the significant predictors were in the direction expected. At both Time 1 and Time 2, logged MVT rates were higher in lower SES communities (Time 1 = −.309 and Time 2 = −.306); and in communities closer to other higher rate communities (Time 1 = .00021 and Time 2 = .000083). Heterogeneity (−2.911) linked to lower rates at Time 1, which was unexpected, but this impact failed to also appear at Time 2. The straddle boundary control (−.573) was again only significant in the Time 2 model with lower MVT rates in areas straddling the city boundary. An F-test of the R^2 change for both models showed that the inclusion of population in the models was not significant in either model, having no notable impact on explained variance in the MVT outcome.

In sum, at both Time 1 to Time 2, MVT rates were higher in lower SES communities, and in communities close to other communities with high MVT rates.

The last two OLS models used the population weighted percentile transformation for all predictors except the contiguous and straddle boundary controls. The population weighted percentiles (pwp) captured relative position as compared to the position of all other communities in the study area. Furthermore, these transformations were theoretically appropriate and allowed for the ranking of community MVT rates relative to each other community in the city, taking each community's population into account. The population weighted regression models contained the same predictors and outcome variable as the non-percentile models.

Models E and F, using all variables in population weighted percentile form for both Times 1 and 2, tell essentially the same story. In model E, at both points in time, only residualised status and adjoining rates were significant, as they were in the untransformed models. As happened in the Time 1 models, when status was added instability became nonsignificant. As happened in the Time 2 Model C, with the transformed variables the MVT rate was lower in communities straddling the city boundary (Model E). The most important point here is that the main results observed in Model C—residualised status and spatial lag driving MVT rates-appeared as well when using a population weighting procedure focusing on how each community was positioned, for each attribute, relative to other communities.

In conclusion then, the results can be simply summed. Nearby MVT rates powerfully drove (no pun intended) community MVT rates. Further, when fully and appropriately controlling for these spatial dynamics, the only other community component significantly driving MVT rates at both points in time was that portion of community status unrelated to nearby MVT rates. Other structural correlates appeared in various models, but they failed to replicate across periods. In addition, the extent to which the communities were influenced by the MVT rates nearby appeared to increase from the beginning to the end of the decade.

Discussion

The current work sought to learn what core elements of community demographic structure linked to MVT rates. Two periods of time, a decade apart, were explored with the potential influences of the MVT rates from nearby areas considered. One of the more noteworthy findings of this research was that community SES and nearby MVT rates were the only two consistently significant ($p < .001$) community structural predictors of MVT rates. After fully and appropriately controlling for nearby MVT rates, these results were different from earlier works which have suggested other structural correlates of MVT rates. For example Copes (1999) found the percent of young males and the percent of multiple housing-units were significant predictor of MVT. Rice and Smith (2002) found that the number of African–Americans were significant predictors of MVT. Gilliam and Damphousse (2000) found residential instability significantly related to MVT.

The relevance of those additional community parameters beyond SES may have emerged because those studies failed to fully control for nearby MVT rates. It is also possible, of course, that those different results in prior studies could be due to different levels of aggregation, different locations, different demographics, and/or data from different times. The current results suggested MVT rates were driven, cross-sectionally, simply by two factors: (1) SES, and (2) how much MVT there was nearby. The strong status finding suggests that low status communities have higher vehicle theft rates. The strong spatial relationship of MVT rates across nearby communities suggests attributes, events, or longer-term trends located in a section of a city may be affecting the communities located there.

Changes introduced between Time 1 and Time 2 included increased target hardening devices such as keyless entry and LOJAC. One might expect these would moderate vehicle thefts. From a routine activities perspective, these decreased target suitability. Nonetheless the rate and incidence of MVT increased over the decade some 200 percent in this city. One might expect that the introduction of "new" vehicles with better security was uneven throughout the study area. Yet, there was still a great deal of predictability in MVT rates based upon community structure. One reviewer suggested, in light of these points, that a routine activities perspective may not be the most helpful when the focus is on MVT rates in the community.

These findings clearly indicate the importance of having researchers think about MVT spatially. The MVT rates nearby explained anywhere from four-tenths to two-thirds of the rates. Stated differently, knowing nothing about a target community other than the MVT rates in all other communities in the city, and how far away each of those were from the target community, explained anywhere from four-tenths to two-thirds of the outcome. Theoretical elaboration taking such spatial patterns into account is needed and has generally been lacking in the existing literature. Are the impacts of what is happening nearby due to offender travel and search patterns, similarity of targets, comparable social, behavioral, or physical features of communities near one another, or enforcement patterns that differ by city sector, or some combination of these? To belabor a perhaps obvious point, since cars move throughout a geographic landscape, this strong concentrated spatial relationship is surprising.

The strong status connection with motor vehicle theft rates brings back the larger theoretical question—do community motor vehicle theft rates "need" a theory different than the ones used to explain community differences in violent crime rates, for example. One of the sturdiest correlates of violence rates is socioeconomic status (Land, McCall, & Cohen, 1990). If it is also the *only* sturdy endogenous structural correlate of community MVT rates, then perhaps vehicle theft theories should concentrate on some of the same intervening processes which have been used to explain violent crime's structural correlates. Collective efficacy theory (Sampson, Raudenbush, & Earls, 1997) or differential patterns of service delivery and/or enforcement (Logan & Molotch, 1987) seem likely possibilities.

This study identified several antecedent demographic community features, and suggested how they might link to various theoretical processes relevant to MVT. The lack of inquiry into specific theoretically relevant behavioral, social, and cognitive community-level processes remains a deficit in the ecological literature. The findings of this study suggest dynamics at the community level, and at the city sector level, may both be relevant to MVT rates.

With regard to policy, one has to be careful making recommendation based upon cross-sectional analyses, but this research does shed light on avenues to pursue towards more informed policy. This research identified two replicating predictors of motor vehicle theft rates: a status correlate and spatially lagged motor vehicle theft rates. So efforts to improve community level SES and focus resources in areas that are in close proximity to other communities with elevated vehicle theft rates through the use of police problem solving and response strategies could aid in apprehending offenders and/or deterring would-be thieves.

Further, given the strong spatial relationship seen here, it does not appear that micro level prevention strategies would necessarily be more effective than generalized patrolling. Patrolling in hot communities may be better than directed patrols focused just on hot spots. Stated differently, and ignoring for the moment temporal variations, time need not be spent on precisely locating high theft locations. At this point, however, intervention directed at processual dynamics is not possible given the lack of knowledge about the social processes facilitating vehicle theft in the community. Simply saying that improving SES conditions will reduce vehicle theft rates offers no specific targeted strategy for success since improving SES, it could be argued, could reduce many crimes.

There were limitations in the study that need to be addressed. First, as was also true in other MVT studies, there were no land use controls. For example, residential, commercial, and mixed-use areas all require a closer look given their role in creating differing opportunity structures. Nonetheless, registered vehicles served as the denominator partially controlling for land use variations, albeit indirectly. Further, block groups, while considered spatially homogeneous, differ in size with large units possibly containing multiple land uses impacting opportunities and outcomes. Official police data were used which may have suffered from coding and data entry errors. Although it was not a limitation per se of the study, the generalizability of the current findings is unknown. This was essentially a case study in a specific midwestern city which may or may not have experienced similar structural shifts as other cities.

Perhaps counter balancing these possible deficits were important strengths of the study. Data were examined at two points in time, clarifying what cross-sectional predictors were significant at both points in time. In short, there was an internal replication. In addition, the two most key results held constant when using both the raw variables and the variables that had been population percentile weighted. This represented another form of internal replication. Further, the spatially lagged variable took into account theft rates in the entire jurisdiction, and used the appropriate inverse distance-weighted two-stage procedure. This was the first study of motor vehicle theft rates at the community level, of which these authors were aware, that fully and appropriately controlled for the spatial autocorrelation of these rates.

Turning now to future research, a logical next step in this vein is to examine the relationship between community structural predictors and motor vehicle theft temporally. In other words, what are the lagged and contemporaneous impacts of social structural predictors on unexpected changes in vehicle theft from T1 to T2? Further, inquiry into the specific dynamic processes driving the relationships observed is an important next step. Micro level data collection would facilitate the study of dynamic social processes driving MVT rates. Additional exploration should also include land use data to study vehicle theft spatial patterning trends as they are influenced by activity space and opportunity. The use of additional data sources such as newly available citywide orthophotography and traditional zoning data will help to identify land use characteristics within the study area and further assist in locating crime attractors and generators within the community. Future research conducted in other comparable cities employing appropriate spatial controls and examination over time should also be conducted to validate the findings from the current study.

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Notes

1. A census block group is a cluster of census blocks containing between 250 and 550 housing units. Block groups, similar to all spatial units of analysis, do suffer from limitations. While they are spatially homogenous, large block groups may have different opportunity structures present throughout given that the composition of land as either residential or commercial or mixed may shift within a large block group.

2. They assure the reader that the non-analyzed blocks were similar to the analyzed blocks, but do not explain why a substantial portion of the city was left out.

3. A generalized motor vehicle theft potential variable, following the logic for population density potential models, takes into account *all* other locations: "to calculate the population potential for a set of n location, *each* place is treated successively as the point of reference"(Land & Deane, 1992, p. 227, emphasis added). Rice and Smith failed to do this. Rather, they just took into account the motor vehicle theft occurring ten blocks away from each study block *along* the vector that street was running (Rice & Smith, 2002, p. 325). This ignored motor vehicle thefts occurring on streets running parallel to each study street. In addition, rather than use the exact centroid of each adjoining block to calculate its distance for inverse distance weighting, they used a standardized distance, which is comparable to assuming that all blocks in the city are of the same length. Their footnote 18 made it clear that street blocks were of unequal length. In that footnote, they indicated they did not go the full ten blocks up and down a street if the total distance exceeded a mile.

4. MVTs that were inaccurately reported to state or county-level law enforcement were included in the present data file. MVTs with addresses within city limits were sorted out of a statewide reporting system and referred back to the correct jurisdiction. This process resulted in accurate data for the study area.

5. Block groups are finite enough to allow for meso level data analysis in relatively spatially homogeneous geographic units. Large units are not conducive to the study of meso level community structure obscuring relationships between structure and crime. Small units such as the face block make the calculation of MVT rates difficult (Copes, 1999), and pose challenges arising from an extremely large number of units with zero events and/or an extremely low number of events, thus creating problems for both modeling and rate stability.

6. The "normalizing" function created identical units of analysis over time. Geolytics documentation provides the following national level explanation: 1990 to 2000 block relations were determined from Tiger Files 2000. Eighty-five percent of blocks had a 1:1 relationship, 10 percent had a 2:1, and 5 percent had a greater than 2:1 relationship. Block splits between 1990 and 2000 were weighted by an analysis of the 1990 streets. The assumption is that roads indicate where people reside. The 1990 streets were determined using Tiger Files 1992 which facilitated correspondence between 1990 and 2000 blocks. A weighting value was then used to help split block demographics for those blocks that had been split or merged between the two decennial censuses. The file produced by this process was the 1990 to 2000 Block Weighting File (BWF). From this BWF, the 1990 data could be associated to any 2000 geography (tract, zip code, county, etc.).

7. Skewness for 1990 = −.298 for the logged rate; skewness for 2000 = −.411 for the logged rate.

8. The use of registered vehicles as the denominator controls for opportunity in the availability of vehicles in each census block group (CBG). Two alternative denominators were explored including the total number of households and aggregate population age sixteen and older. The Kendall Tau B correlations between these rates using alternate denominators were as follows:

Time 1, 1990/91 Kendall Tau B correlations for vehicle theft rates with alternative denominators

	MVTHH	MVTRegV	MVT16+
MVTHH	1	.844**	.863**
MVTRegV	.844**	1	.863**
MVT16+	.863**	.863**	1

Time 2, 2000/01 Kendall Tau B correlations for vehicle theft rates with alternative denominators

	MVTHH	MVTRegV	MVT16+
MVTHH	1	.888**	.917**
MVTRegV	.888**	1	.906**
MVT16+	.917**	.906**	1

Notes: ** Correlation is significant at the .01 level; MVTHH = motor vehicle theft rate with CBG households as the denominator; MVTRegV = motor vehicle theft rate with CBG registered vehicles as the denominator; MVT16+ = motor vehicle theft rate with individuals sixteen years of age and older in the CBG as the denominator.

9. It is worth noting that prior to creating the racial heterogeneity index, a race variable (percentage of the population that was Black) was entered into the analysis. The inclusion of this predictor resulted in high multicollinearity as indicated by the Time 1 and Time 2 correlation

matrixes (see Tables 2 and 3), variance inflation factor (VIF), and tolerance statistics generated by SPSS; this was especially true in relation to the heterogeneity predictor suggesting a strong linear dependency. Based upon a series of analyses, the decision was made to use the heterogeneity index rather than the Black variable due to fewer collinearity concerns. Furthermore, the heterogeneity equation captured a better measure of racial composition and integration. Research by Clarke and Harris (1992) and Rice and Smith (2002) found that motor vehicle thefts were higher in heterogeneous environments.

10. A generalized motor vehicle theft potential variable, following the logic for population density potential models, takes into account *all* other locations: "to calculate the population potential for a set of n location, *each* place is treated successively as the point of reference" (Land & Deane, 1992, p. 227, emphasis added). The crime-potential variable measures the cumulative proximity of motor vehicle theft of all the areas surrounding a particular place. The formula for calculating the current crime potential variables according to Land and Deane (1992) is as follows (with minor modification):

$$\mathrm{CP}i = \Sigma(Pj/\mathrm{D}ij); -j \neq i; -i = 1, \ldots, n,$$

where:

CPi = the crime potential for location i (i = the target CBG)
Pj = the number of motor vehicle thefts for CBGj in the environment of CBGi
Dij = is the distance of CBGj from CBGi, and the summation is taken over all locations j other than i.

Next, the MVT potential variables for Time 1 and Time 2 must be "cleaned up" to avoid correlation between the MVT potential variable and the error term. Using a two-stage process (Land & Deane, 1992), instrumental variables that were predictors of the MVT potential variables were identified. For a more thorough explanation of the mechanics employed see Walsh, 2005, pp. 242–244.

11. The motor vehicle theft population weighting percentile score was computed following a formula, with slight modification, previously used by Taylor (1988):

$$[\text{Sum } (i = i - \text{M}) \text{ Household}_i] \text{ Motor Vehicle Theft Percentile}_M = 100 \times [\text{Sum}(j = j - n) \text{ Households}_j]$$

Household$_i$, is the number of households in the ith lowest CBG, Household$_j$ is the total number of households in all CBG in the city,
M = the CBG of interest, and
n = the total number of CBGs examined.

Thus a CBG with the lowest (for example) motor vehicle theft rate in the city would have a vehicle theft percentile score of 0; the CBG with the highest rate would have a score approaching 100. Also, a CBG with a vehicle theft score of 50 is a CBG in which the vehicle theft rate is equal to or greater than the CBG vehicle theft rate experienced by 50 percent of the households in the city's CBGs.

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