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Eric L. Piza
CUNY John Jay College

Shun Feng
CUNY John Jay College

Leslie Kennedy
Rutgers University - Newark

Joel Caplan
Rutgers University - Newark

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Place-based correlates of Motor Vehicle Theft and Recovery: Measuring spatial influence across neighbourhood context

Eric Piza
John Jay College of Criminal Justice, USA

Shun Feng
John Jay College of Criminal Justice, USA

Leslie Kennedy
Rutgers University, USA

Joel Caplan
Rutgers University, USA

Abstract
Social scientists have long shown great interest in the spatial correlates of crime patterns. A subset of the literature has focused on how micro-level spatial factors influence the formation of crime hot spots. At the same time, tangential research has highlighted how neighbourhood disadvantage influences crime occurrence. The current study focuses on the intersection of these perspectives through a spatial analysis of Motor Vehicle Theft (MVT) and Motor Vehicle Recovery (MVR) in Colorado Springs, CO. We begin by conducting a Risk Terrain Modelling analysis to identify spatial risk factors significantly related to MVT and MVR occurrence. We then test whether the spatial influences of the criminogenic risk factors differ across traditional measures of neighbourhood disadvantage. Findings suggest that while a citywide effect is evident for multiple risk factors, their spatial influence on crime significantly varies across neighbourhood contexts.

Keywords
environmental criminology, Motor Vehicle Recovery, Motor Vehicle Theft, Risk Terrain Modelling, social disorganisation

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Corresponding author:
Eric Piza, John Jay College of Criminal Justice, 524 W 59th St, Haaran Hall, Room 636.15, New York City, NY 10019, USA.
Email: epiza@jjay.cuny.edu

Introduction

Social scientists have long exhibited great interest in the geography of crime, with the exploration of crime concentration dating back hundreds of years (Weisburd et al., 2009). With the emergence of Geographic Information Systems (GIS), the spatial analysis of crime has greatly accelerated. In explaining crime concentrations, contemporary research has empirically tested the influence of potentially criminogenic environmental features on a number of crime types, including assault (Grubesic et al., 2012; Kennedy et al., 2015), robbery (Bernasco and Block, 2011; Drawve, 2016), shootings (Caplan et al., 2011; Kennedy et al., 2011), and burglary (Caplan et al., 2015; Groff and La Vigne, 2001; Moreto et al., 2014). Tangential to the crime-and-place literature, considerable research has measured the effect of neighbourhood-level factors on crime, particularly violence (Kubrin and Herting, 2003; Morenoff et al., 2001; Sampson and Groves, 1989; Sutherland et al., 2013). Explanatory variables are typically derived from data collected by census bureaus, which measure levels of neighbourhood disadvantage.

To date, Motor Vehicle Crime has been largely absent from the geospatial literature. The current study seeks to help fill this void through an analysis of Motor Vehicle Theft (MVT) and Motor Vehicle Recovery (MVR) in Colorado Springs, CO. We begin by empirically testing the effect of various spatial features on the occurrence of MVT and MVR. We then test whether the influence of the significant risk factors differs across traditional measures of neighbourhood disadvantage. Seven spatial risk factors were significantly associated with MVT while ten were associated with MVR. Subsequent models found that the spatial influence of each risk factor differed according to levels of neighbourhood disadvantage, as measured across six variables. The findings suggest that future research should continue to measure the interaction effects of micro-level environmental risk factors and neighbourhood characteristics on crime patterns.

Review of relevant literature

Motor vehicle theft and recovery

MVT is one of the most commonly occurring crimes in the USA, with 689,527 reported incidents nationwide in 2014 (FBI, 2015). The literature recognises two general types of MVT: (1) those committed for non-monetary purposes, such as joyriding and transportation, and (2) those committed for profit-driven purposes, such as resale, export or dismantling for spare parts (Clarke and Harris, 1992; Roberts and Block, 2012). A key difference between these typologies concerns the procedural nature of the crime. In thefts for profit, offenders benefit directly from the materialistic value of the vehicle, specifically through export or resale of the vehicle, or selling parts on the black market. Such incidents are more likely to be permanent thefts, with the stolen vehicle not being recovered. On the contrary, in thefts involving non-monetary motivations (e.g. transportation and/or joyriding) benefits are largely unrelated to the materialistic value of the vehicle. Stolen vehicles are more likely to be recovered in such instances because these offenders are more likely to abandon the vehicle than offenders motivated by profit.

Considered from a script analysis perspective (Cornish, 1994), the site of the vehicle recovery represents the final step of the MVT. The offender, after receiving the desired benefits, abandons the vehicle. For researchers, stolen vehicle recovery presents additional opportunities to analyse offender behaviour and decision-making. In terms of geospatial analysis, this provides the opportunity to measure the spatial correlates of stolen vehicle recovery sites and whether they differ from those of the theft site. Despite such policy implications, analyses of MVR have been largely absent from the literature (noteworthy exceptions are discussed subsequently).

Crime generators, crime attractors and neighbourhood disadvantage

The geospatial analysis of crime is rooted in Environmental Criminology, a perspective comprised of three theories with common interests in the situational aspects of crime: Routine Activities (Cohen and Felson, 1979), Rational Choice (Cornish and Clarke, 1986) and Crime Pattern Theory (Brantingham and Brantingham, 1993). Routine Activities Theory considers crime as the outcome of the spatial and temporal convergence of a likely offender and a suitable target in the absence of a capable guardian. Behaviour patterns of the population determine where and when these criminogenic elements are most likely to converge. Rational Choice Theory considers crime as the outcome of an appraisal process in which the potential offender considers the risks and rewards inherent in a given crime opportunity. While such decisions typically occur in a state of bounded rationality constrained by limited time and information, the offender nonetheless ponders the situation at hand (Clarke and Cornish, 1985). Crime Pattern Theory is typically credited with connecting the tenets of Routine Activities and Rational Choice, explicitly operationalising them to space (Andresen, 2014: 8). Crime Pattern Theory considers daily behaviour patterns as involving three types of activity spaces: nodes (places where people spend extended amount of time, such as home, work and places of recreation), paths (travel routes between nodes) and edges (boundaries between different areas) (Brantingham and Brantingham, 1993: 5). Activity spaces can be made criminogenic by the presence of crime generators and crime attractors, features of the environment that cause crime through the attraction of large numbers of people and/or criminal opportunities that are well known to offenders (Clarke and Eck, 2005: 17).

Caplan (2011) refers to the manner that environmental features influence human behaviour as spatial influence. Caplan (2011) argues that the distribution of certain features across space can influence the attraction of criminogenic elements in a manner that forms and sustains crime patterns. In particular, spatial influence of criminogenic features can be operationalised as distance from individual features or density of multiple features (Caplan, 2011: 63). The notion of operationalisation is key, because prior research suggests that different criminogenic features exert different types of influence on crime. Research in Philadelphia, for example, found that violence is highly clustered within 85 feet of bars then dissipates rapidly (Ratcliffe, 2012), while the effect of schools, halfway houses, and drug treatment centres varies substantially by distance and crime type (Groff and Lockwood, 2014).

Tangential to research on Environmental Criminology, an extensive literature has measured the effect of neighbourhood-level characteristics on crime and victimisation. This literature is largely rooted in the Social Disorganisation theory (Sampson and Groves, 1989; Shaw and McKay, 1942). The core concepts of Social Disorganisation relate to the inability of a neighbourhood to regulate the conduct of its members and a general breakdown in normative consensus (Berg et al., 2012: 413). As per this perspective, Social Disorganisation disrupts the social order to an extent that weakens collective efficacy, defined as the 'willingness [of residents] to intervene for the common good' (Sampson et al., 1997: 919). Measures of Social Disorganisation are typically derived from data collected by census bureaus and has included factors such as poverty, racial heterogeneity, geographic mobility, educational attainment, population density and the young male population.

Poverty is largely considered the most important aspect of Social Disorganisation in terms of crime, given its association with social disinvestment and lack of community organisation (Pratt and Cullen, 2005; Rice and Smith, 2002: 316). Racial heterogeneity refers to the probability of members of different ethnicities living in the same neighbourhood, with high probabilities suggesting the co-existence of conflicting and competing values regarding the appropriateness of illicit conduct (Berg et al., 2012: 412). Geographic mobility refers to population turnover, with residents frequently moving to or from a neighbourhood preventing the formation of shared values (Bruce et al., 1998). Educational attainment is a key component of Shaw and McKay's (1942) concept of neighbourhood status, with neighbourhoods defined by lower levels of education considered an indicator of neighbourhood deprivation (Chainey, 2008). Population density may generate crime by reducing anonymity amongst residents in a manner that interferes with social control while simultaneously offering increased opportunities for offending (Osgood and Chambers, 2000; Sampson, 1983). Lastly, the percentage of the population comprised of young males has been associated with high crime levels. From a Social Disorganisation perspective, this observation has been linked to male juveniles reporting being drawn into crime by other criminally active adolescent males (Kubrin and Herting, 2003; Lilly et al., 2011: 45).

While there is a tendency within the literature to consider Environmental Criminology and Social Disorganisation as competing conceptual frameworks (Braga and Clarke, 2014; Weisburd et al., 2015), the perspectives can have joint utility for crime analysis. In particular, observations from crime-and-place research suggest that understanding community-level context may help explain some of the more nuanced research findings. While specific environmental features have consistently demonstrated city-wide effects on crime, research has demonstrated that crime distribution across a given facility type can be classified according to the J-curve (Eck et al., 2007) or the 80–20 rule (Clarke and Eck, 2005: 18), crime analysis principles demonstrating that a small proportion of individual facilities account for a large proportion of crime experienced by the whole group. For example, 10% of gas stations in Austin, TX accounted for more than 50% of calls for service in 1998–1999 while 5% of retail stores in Danvers, MA accounted for 50% of reported shopliftings from 1 October 2003 through 30 September 2004 (Clarke and Eck, 2005: 28). In explaining why spatial vulnerability (i.e. the presence of criminogenic features) does not automatically lead to crime, Kennedy et al. (2015) discussed the importance of 'exposure' in crime generation. As explained by Kennedy et al. (2015: 5) 'if crime occurred at the place before and if the place is spatially vulnerable, then the likelihood that crime will occur in the future increases'. This concept of 'exposure' could easily be extended to include principles of Social Disorganisation. Just as exposure to a nearby hot spot can aggravate a feature's spatial influence, a feature can be more or less criminogenic depending upon the characteristics of the surrounding neighbourhood. Thus, studying the interaction effects of micro-level spatial risk factors and neighbourhood disadvantage may provide valuable insights.

Geospatial analysis of motor vehicle crime

While numerous scholars have described MVT (and, by extension, MVR) as one of the least developed topics in criminology (Maxfield, 2004, Walsh and Taylor, 2007) a body of knowledge on the environmental correlates of MVT has begun to emerge. Levy and Tartaro (2010) tested the influence of activity nodes (comprised of ATMs, payphones, gas stations, bars, bus stops and schools) on single- and repeat-victimisation MVT locations in Atlantic City, NJ. They found that repeat MVT locations were more likely to be near activity nodes than single theft sites. Lu (2006) found that MVT locations in Buffalo, NY were associated with multi-family residences and commercial locations with parking lots. Additional studies have included measures of Social Disorganisation along with environmental features in the study of MVT. Lockwood (2012) found that neighbourhood disadvantage was associated with higher counts of overall MVT as well as MVT 'initiator' events, which are the incidents representing the initial offense in a near-repeat offending pattern. Copes (1999) found that MVT is more likely to occur along longer roads, in neighbourhoods with greater density of roads, and in neighbourhoods with a higher percentage of persons living below the poverty line in Lafayette, LA. Walsh and Taylor (2007) found MVT in a Midwestern US city to be most common in neighbourhoods with low socio-economic status that were surrounded by other neighbourhoods with high MVT rates. Suresh and Tewksbury (2013) analysed MVT and MVR in Louisville, KY from a Social Disorganisation perspective, finding that concentrations of both MVT and MVR were significantly related to high levels of poverty, unemployment and vacant housing as well as church parking lots in socially disadvantaged neighbourhoods.

The analysis of Rice and Smith (2002) is perhaps the best example of the integration of Environmental Criminology and Social Disorganisation perspectives in the study of MVT. In addition to including both Environmental Criminology (specifically Routine Activities) and Social Disorganisation variables in the analysis, Rice and Smith (2002) conducted a follow-up model with 13 interaction terms between the different types of variables. As argued by Rice and Smith (2002: 322), 'social disorganization attributes should interact with the opportunity variables included in the routine activity operationalization' to produce a differential effect on crime than either generates independently. The interaction model findings were supportive of this hypothesis, with the model explaining a larger percentage of the variance than the competing models and certain interaction types generating circumstances conducive to MVT.

Summary and scope of the current study

The frequency of research on Motor Vehicle Crime is not commensurate with the level of hardship it inflicts upon society, particularly within urban centres of the USA (Maxfield, 2004). With that said, a body of knowledge has begun to develop that analyses the influence of environmental features and neighbourhood factors on the occurrence of MVT and, less frequently, MVR. While this is a welcome development, additional research is needed to build upon the scope of these studies. For one, outside of Suresh and Tewksbury (2013), MVR has not been subjected to geospatial analysis. This is a key gap in the literature, as understanding spatial risk factors of MVR hot spots can generate practical benefits in the study and prevention of MVT. In addition, there is a need to better understand heterogeneity of spatial influence across the landscape. In exploring such issues, it is helpful to understand how risk factors interact with neighbourhood-level factors to influence the nature of crime patterns. Outside of Rice and Smith (2002), we are unaware of such an approach being incorporated in the study of MVT, and are aware of no study that applied such an approach in the study of MVR.

The current study seeks to address the aforementioned gaps in the literature through a geospatial analysis of MVT and MVR incidents in Colorado Springs, CO occurring from 1 November 2012 to 31 October 2013. The analysis involved two distinct steps. First, using Risk Terrain Modelling (RTM), environmental risk factors and their associated spatial influences were identified for both MVT and MVR. We then tested whether the spatial influence of the significant risk factors differed across traditional measures of neighbourhood disadvantage. Interaction terms included in a regression model identified the neighbourhood contexts that aggravated, mitigated or neutralised risk factor influence.

Methodology

Study setting

Colorado Springs is the second largest city in Colorado, with an estimated 2014 population of 445,830. Colorado Springs is a largely middle class city, with a median household income of US$53,962 and poverty level of 13.7%, reflective of the economic condition of Colorado as a whole (median income of US$58,433 and poverty rate of 13.2%). Approximately 79% of residents are White with Blacks accounting for 6.3% of the population. A total of 16.1% of residents identify themselves as Hispanic or Latino (US Census Bureau, 2015). Colorado Springs reported 2673 MVT incidents during the study period, which translates to an MVT rate of 599.55 per 100,000 residents. This rate is above the national average MVT rate of 420.90 per 100,000 for cities with populations greater than 250,000 as per Uniform Crime Report figures (FBI, 2015). Within Colorado, the MVT rate for Colorado Springs is the second highest in the state, behind only Denver (FBI, 2015). The Colorado Springs Police Department has been recognised as a national leader of Problem-Oriented Policing in the USA (Maguire et al., 2015), with a long history of commitment to research and evaluation. In this vein, the Colorado Springs Police Department partnered with the authors for the purpose of analysing the spatial distribution and spatial correlates of MVT and MVR.

Data sources

GIS layers of MVT and MVR incidents were provided by the Colorado Springs Police Department's Crime Analysis Unit. Data were provided as GIS shapefiles for use in the ArcGIS 10.3 software. Of the 2673 MVT incidents reported during the study period, 950 were temporary thefts with the stolen vehicle recovered later in time, corresponding to a recovery rate of 36%. This recovery rate is below the national average of 43.2%, based upon the most recently available figures (BJS, 2011).[1] These 950 temporary MVTs were included in the final analysis. A total of 947 (99.7%) and 939 (98.8%) MVT and MVR locations, respectively, were successfully geocoded. Figure 1 displays the spatial distribution of MVT and MVR incidents. Visual inspection of kernel density maps suggests that MVT and MVR hot spots overlap in Colorado Springs, however there are clear distinctions between MVT and MVR sites. Specifically, MVT and MVR densities are only weakly correlated, according to both Pearson's (-0.26, $p < 0.001$) and Spearman's rho (-0.22, $p < 0.001$) statistics. Disaggregate statistics suggest that motor vehicle thieves travelled significant distances before abandoning the vehicle. MVR locations were an average distance of 4.14 miles from the

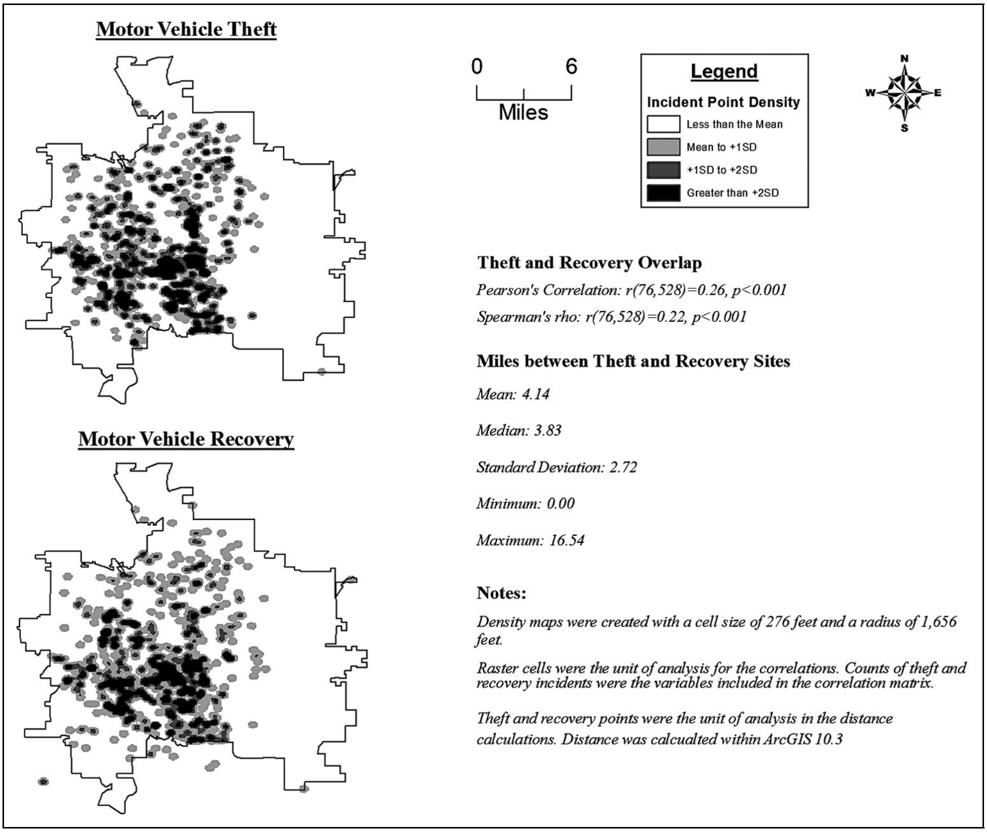

Figure 1. Motor Vehicle Theft and Recovery concentration.

location of theft, with a median of 3.83 miles and a standard deviation of 2.72 miles. This suggests that, at the incident level, the locations of MVT and MVR are distinct from one another. In other words, stolen vehicles were typically recovered far from where they were stolen.

The RTM analysis included 19 environmental risk factors: bars, bowling centres, commercial zoning, convenience stores, disorder-related calls for service,[2] foreclosed properties, hotels and motels, multi-family housing complexes, parks, sit-down restaurants, gas stations with convenience stores,[3] schools, liquor stores, malls, night clubs, parking stations and garages, retail shops, takeout restaurants and variety stores. Ten risk factors were provided by the Colorado Springs Police Department[4] as GIS shapefiles, the same format as the MVT and MVR data. The remaining data were obtained from InfoGroup (www.infogroup.com) a leading provider of residential and commercial information for reference, research and marketing purposes.[5] The InfoGroup data were provided in spreadsheet format with X/Y coordinates provided for each case. Researchers used the X/Y coordinates to manually geocode the data, with the projection set to match the data provided by the Colorado Springs Police Department (Colorado State Plane, NAD 1983). Prior research has identified many of these risk factors as criminogenic, in terms of overall street-level crime occurrence and/or MVT. Other risk factors were included at the recommendation of Colorado Springs Police Department personnel, based upon their knowledge of local crime conditions. This selection method helps ensure that the factors included in the study are both empirically driven and practically meaningful (see Table 1) (Kennedy et al., 2015).

Lastly, the analysis included neighbourhood-level data collected from the US Census Bureau's American Community Survey 5-year estimates (2009–2013).

Data were collected at the census tract level, which prior research has consistently used as an operationalisation of neighbourhood (Griffiths and Chavez, 2004; Kubrin and Herting, 2003; Stucky et al., 2016), and are collectively identified as census variables. We included six separate census variables, all of which have been positively associated with crime occurrence in prior research: the percentage of persons below the poverty line (Pratt and Cullen, 2005); racial heterogeneity[6] (Berg et al., 2012); geographic mobility: percentage of persons who lived at a different address the previous year (Bruce et al., 1998); educational attainment: percentage of adults without a high school diploma or equivalent degree (Chainey, 2008); population density: persons per square mile (Osgood and Chambers, 2000; Sampson, 1983); and the young male population: percentage of persons that are male between the ages of 15 and 24 (Kubrin and Herting, 2003). Data were joined to a GIS layer of census tracts in El Paso county, which encompasses Colorado Springs, for the analysis ($N = 130$).

Analytical strategy

In conducting Risk Terrain Modelling, we used the RTMDx Utility developed by the Rutgers Center on Public Security (Caplan and Kennedy, 2013). RTMDx uses a precise set of statistical tests to (1) choose the appropriate operationalisation of each risk factor; (2) determine the appropriate model type (Poisson or negative binomial); and (3) determine the relative importance of risk factors in influencing crime outcomes (Heffner, 2013). For the analysis, Colorado Springs was modelled as a set of contiguous grids of equally sized 276 ft $\times$ 276 ft. cells ($N = 76{,}528$), representing approximately one-half of the average block length in the city, as measured within ArcGIS. RTMDx tests risk factor influence through a penalised regression model with crime counts (in this case, MVT or MVR) as the dependent variable. Various operationalisations of the aforementioned risk factors are independent variables, with RTMDx measuring whether each raster cell is within a certain distance of the risk factor (i.e. proximity) or in an area of high concentration of the risk factor (i.e. density). Each risk factor was tested at three distances: 1 block (552 ft), 2 blocks (1104 ft) and 3 blocks (1656 ft). Through this method, the 19 risk factors generated 84 independent variables that were tested for significance.

Incorporating 84 covariates in a single model may present problems with multiple comparisons, in that we may detect spurious correlation simply because of the number of variables tested. The penalised regression method used by RTMDx alleviates potential problems with spurious correlation owing to multiple comparisons by reducing the large set of variables to a smaller set of variables with non-zero coefficients. This is accomplished through an elastic net method that forms five stratified folds from the raster cells, balancing crime counts between the folds. This balancing process is done to ensure that there is some variance across the folds to aid in the numeric stability of the modeling process. For each covariate, RTMDx then builds five simultaneous models for each fold to rigorously test the influence of each independent variable on the

Table 1. Risk factor conceptualisation and justification.

Risk factor	Justification	Example source(s)
Bars	Research has frequently found bars to generate street-level crime. Motor vehicles are likely to be parked near bars (and restaurants) in the evening hours, creating opportunities for MVT	Levy and Tartaro (2010); Rice and Smith (2002)
Bowling centres	CSPD identified bowling centres as a particular type of entertainment venue that may generate opportunities for MVT. Environmental criminologists have referred to such crime-generating venues as social crime facilitators	Clarke and Eck (2005)
Commercial zoning	Research has found commercial locations to be at heightened risk of MVT, presumably because of the concentration of automobiles in such areas	Lu (2006)
Convenience stores	Research has found that convenience stores and corner grocery stores generate street-level crime in the surrounding vicinity	Bernasco and Block (2011); Myers (2002)
Gas stations with convenience stores	Research has shown gas stations to be associated with repeat MVT locations. CSPD officials further recommended that we include only gas stations with convenience stores given the unique opportunity structure at such gas stations (see footnote 2)	Levy and Tartaro (2010)
Disorder-related calls for service	Reviews of research find evidence that social disorder stimulates street-level crime, both directly and via its impact on other aspects of community	Skogan (2015)
Foreclosed properties	Foreclosures and general vacant housing have been found to generate the occurrence of crime, including MVT	Katz et al. (2013); Suresh and Tewksbury (2013)
Hotels and motels	Prior research including both routine activity and Social Disorganisation variables has found the presence of a hotel or motel to be the most powerful predictor of MVT	Rice and Smith (2002)
Multi-family housing complexes	Large-scale multi-family dwellings have been associated with lower guardianship and higher criminal activity, including MVT. Victimisation surveys suggest that people residing in single-family structures are less likely to experience MVT than people residing in multi-family structures	Lu (2006); Poyner (2006); Rice and Smith (2002)
Parks	Research has found parks to be related to predatory crime, owing to their typically low levels of guardianship	Groff and McCord (2011)
Sit-down restaurants	Motor vehicles are likely to be parked near restaurants (and bars) during evening hours, creating opportunities for theft	Rice and Smith (2002)
Schools	Research has found that schools increase property crime in the surrounding area	LaGrange (1999); Roncek (2000)
Liquor stores	Research has found the presence of off-premise liquor establishments to be associated with heightened occurrence of predatory crime	Bernasco and Block (2011); Snowden and Pridemore (2013)
Malls	Malls provide heightened levels of risk for MVT owing to the large-scale availability of parking and the fact that patrons leave their vehicles unattended for extended periods of time	Clarke (2002); LaGrange (1999); Lu (2006)

(continued)

Table 1. Continued

Risk factor	Justification	Example source(s)
Night clubs	CSPD officials suggested that nightclubs might exert a similar spatial influence as bars on MVT since both facilities serve alcohol to patrons on-premise	Levy and Tartaro (2010); Rice and Smith (2002)
Parking stations and garages	Parking stations and garages low in access control or supervision have been found to suffer from heightened levels of MVT	Clarke (2002)
Retail shops	Retail business outlets have been shown to generate incidents of predatory crime, and may offer heightened risk for auto theft owing to the presence of parking facilities for customers	Caplan et al. (2011); Lu (2006)
Takeout restaurants	Restaurants serving predominately take-out orders can lead to high levels of foot traffic and low levels of guardianship, which can promote crime	Felson (2002); Kennedy et al. (2011)
Variety stores	CSPD officials suggested that variety stores (e.g. dollar stores or general stores) might exert a similar spatial influence as big box retail shops since both types of establishments largely attract consumers with automobiles	Caplan et al. (2011); Lu (2006)

crime outcome, and identify a set of variables with useful predictive value (i.e. with non-zero coefficients).

For the current study, RTMDx selected 32 variables as potentially useful in the MVT model and 34 in the MVR model. These variables were then utilised in a bidirectional step-wise regression process to determine the final model type. Following a null model with no model factors, the Utility adds each variable to the null model and re-measures the Bayesian Information Criteria (BIC) score to identify the most parsimonious combination of variables. The BIC score balances how well the model fits the data against the complexity of the model. After each iteration, the model with the lowest BIC score is selected as the new candidate model (the model to surpass). RTMDx repeats the process, adding and removing variables one step at a time, until no variable addition/removal surpasses the previous BIC score. RTMDx repeats this process with two stepwise regression models: one Poisson and one negative binomial. At the end, the Utility chooses the best model with the lowest BIC score. RTMDx also produces a relative risk value that can be interpreted as the weight of the individual risk factor, and therefore may be used for comparison across all risk factors (for more information on the statistical procedure of RTMDx, see Heffner, 2013).

Following the RTM analysis, negative binomial regression models were conducted using Stata 13.0 statistical software to measure whether the spatial influence of the significant risk factors was maintained across neighbourhood contexts.[7] Similar to the RTM analysis, units of analysis were 276 ft × 276 ft raster cells (N = 76,528). For each significant risk factor, a dichotomous variable measured whether each cell fell within the optimal spatial influence (1) or not (0). Additional variables measure the level of neighbourhood disadvantage in the surrounding census tract, according to the six aforementioned census variables. Each

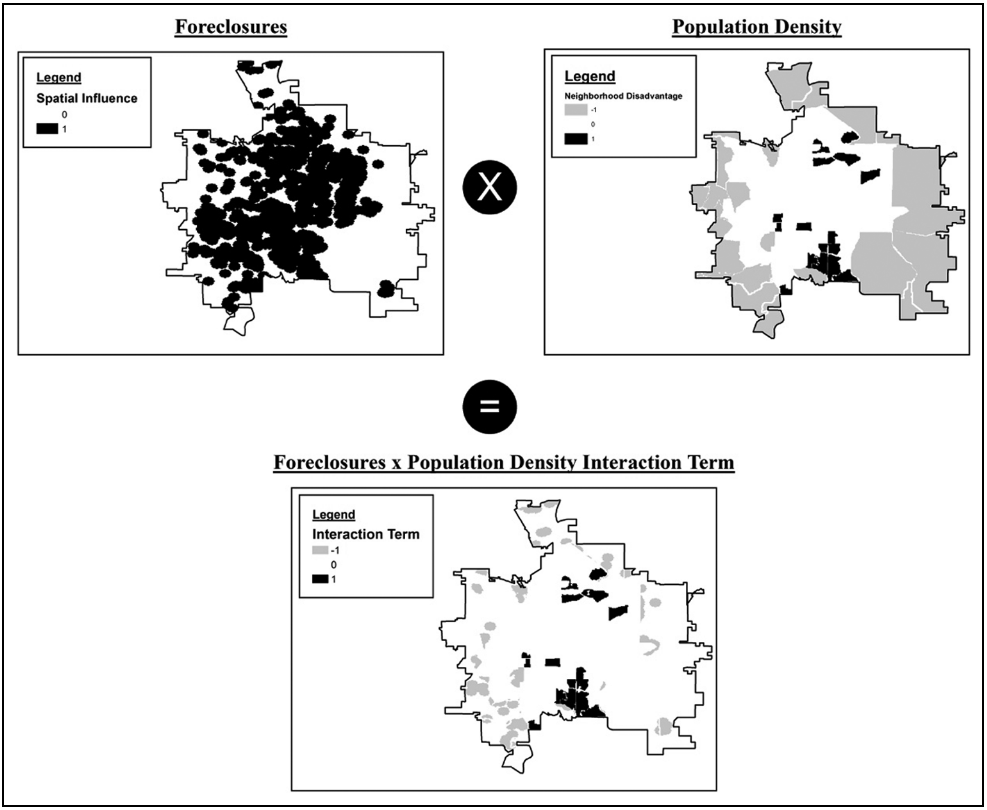

Figure 2. Spatial influence and neighbourhood vulnerability maps.
Note: In each of the maps, grid cells are the unit of analysis.

census variable was re-coded so that the value in each census tract was identified as greater than 1 standard deviation below the mean (-1), between 1 standard deviation below the mean and 1 standard deviation above the mean (0), or greater than 1 standard deviation above the mean (1). We decided to operationalise the census values in this manner to provide standardised measures across variables. Table 2 displays descriptive statistics for the dichotomous RTM and re-coded census variables.

The dichotomous variable for each significant risk factor was multiplied with each re-coded census variable to create six interaction terms: risk factor $\times$ racial heterogeneity, risk factor $\times$ young male population, risk factor $\times$ geographic mobility, risk factor $\times$ no high school, risk factor $\times$ population density, and risk factor $\times$ poverty. Figure 2 provides a visual example of this process. This resulted in 42 interaction terms in the MVT model and 60 interaction terms in the MVR model. For both models, a spatial lag variable was created within the GeoDa spatial analysis software to control for the observed presence of spatial autocorrelation.[8] To measure the presence of multicollinearity, we calculated the variance inflation factor (VIF) and associated tolerance (1/VIF) for each of the exploratory variables (Hamilton, 2013: 203).

Table 2. Descriptive statistics.

Variable	Motor Vehicle Theft model					Motor Vehicle Recovery model				
	Continuous measures		Ordinal measures (%)			Continuous measures		Ordinal measures (%)		
	Mean (SD)	Min (Max)	−1	0	1	Mean (SD)	Min (Max)	−1	0	1
***Dependent variable*:**										
Crime incident count	0.12 (0.13)	0 (6)	–	–	–	0.12 (0.14)	0 (7)	–	–	–
***Risk factors*:**										
Disorder calls	–	–	–	69,431 (90.73)	7097 (9.27)	–	–	–	70,105 (91.61)	6423 (8.39)
Foreclosures	–	–	–	39,717 (51.90)	36,811 (48.10)	–	–	–	39,717 (51.90)	36,811 (48.10)
Multi-family housing complexes	–	–	–	40,624 (53.08)	35,904 (46.92)	–	–	–	40,624 (53.08)	35,904 (46.92)
Hotels & motels	–	–	–	75,105 (98.14)	1423 (1.86)	–	–	–	75,105 (98.14)	1423 (1.86)
Sit-down restaurants	–	–	–	54,110 (70.71)	22,418 (29.29)	–	–	–	54,110 (70.71)	22,418 (29.29)
Parks	–	–	–	31,535 (41.21)	44,993 (58.79)	–	–	–	31,535 (41.21)	44,993 (58.79)
Commercial zoning	–	–	–	52,479 (68.57)	24,049 (31.43)	–	–	–	52,479 (68.57)	24,049 (31.43)
Convenience stores	–	–	–	–	–	–	–	–	74,332 (97.13)	2196 (2.87)
Gas stations w/convenience stores	–	–	–	–	–	–	–	–	72,479 (94.71)	4049 (5.29)
Schools	–	–	–	–	–	–	–	–	63,032 (82.36)	13,496 (17.64)
***Socio-demographics*:**										
Racial heterogeneity	0.08 (0.04)	0.00 (0.16)	12,118 (15.83)	57,265 (74.83)	7145 (9.34)	Same as Motor Vehicle Theft Model				
Young male population	13.17 (8.03)	0 (98.53)	0 (0)	69,937 (91.39)	6591 (8.61)	ibid.				

(continued)

Table 2. Continued

Variable	Motor Vehicle Theft model					Motor Vehicle Recovery model				
	Continuous measures		Ordinal measures (%)			Continuous measures		Ordinal measures (%)		
	Mean (SD)	Min (Max)	−1	0	1	Mean (SD)	Min (Max)	−1	0	1
Geographic mobility	17.37 (9.69)	0 (60.11)	6476 (8.46)	60,647 (79.25)	9405 (12.29)	ibid.				
% Adults with no high school diploma	18.13 (9.87)	0 (42.5)	21,363 (27.92)	49,406 (64.56)	5759 (7.53)	ibid.				
Population density	1838.44 (1992.05)	0 (9701.49)	36,947 (48.28)	35,727 (46.68)	3854 (5.04)	ibid.				
% Poverty	6.714 (7.14)	0 (40.60)	5386 (7.04)	65,775 (85.95)	5367 (7.01)	ibid.				

Notes: Unit of analysis: 276 ft × 276 ft cells. $N = 76,528$.

A tolerance lower than 0.1 suggests the presence of significant collinarity with another variable. Tolerance values ranged from 0.15 to 0.98 in the theft model and from 0.14 to 0.98 in the MVR model, showing an absence of multicollinarity.[9]

Findings

Table 3 displays the results of the RTM analysis. For both MVT and MVR, RTMDx identified a negative binomial regression model as the optimal model. Seven risk factors were significantly associated with MVT: disorder calls for service, foreclosures, multi-family housing complexes, hotels and motels, sit-down restaurants, parks and commercial zoning. Ten risk factors were significantly associated with MVR: disorder calls for service, foreclosures, multi-family housing complexes, hotels and motels, convenience stores, commercial zoning, gas stations with convenience stores, parks, sit-down restaurants and schools. There is some clear overlap in the findings, as each of the seven risk factors associated with MVT were also spatially correlated with MVR. However, closer examination of the findings reveals some differences. For one, three risk factors associated with MVR (convenience stores, gas stations with convenience stores and schools) were unrelated to MVT. In addition, while having the highest relative risk value in both models, disorder calls differentially influenced MVT and MVR. MVT occurrence was significantly higher within a 1104 ft (approximately two blocks) density of disorder calls for service while the influence of disorder calls on MVR extended only 552 ft (approximately one block). All other risk factors related to both MVT and MVR exhibited similar spatial influence on both crime types.

Table 4 displays the findings of the MVT negative binomial regression model. For ease

Table 3. Risk factor testing.

Risk Factor	N	Motor Vehicle Theft Op.	S.I.	Coef.	RRV	Motor Vehicle Recovery Op.	S.I.	Coef.	RRV
In the final RTM									
Disorder calls	16,325	Dens.	1104 ft	1.30	3.69	Dens.	552 ft	1.59	4.88
Foreclosures	899	Prox.	1656 ft	0.89	2.46	Prox.	1656 ft	0.75	2.11
Multi-family housing complexes	11,261	Prox.	1656 ft	0.90	2.46	Prox.	1656 ft	0.65	1.92
Hotels & motels	111	Prox.	552 ft	0.64	1.90	Prox.	552 ft	0.63	1.88
Sit-down restaurants	550	Prox.	1656 ft	0.61	1.85	Prox.	1656 ft	0.41	1.50
Parks	14,464	Prox.	1656 ft	0.44	1.55	Prox.	1656 ft	0.48	1.61
Commercial zoning	13,485	Prox.	1656 ft	0.31	1.37	Prox.	1656 ft	0.52	1.68
Convenience stores	77	–	–	–	–	Prox.	552 ft	0.62	1.85
Gas stations w/convenience stores	28	–	–	–	–	Prox.	1656 ft	0.50	1.68
Schools	106	–	–	–	–	Prox.	1656 ft	0.30	1.35
Intercept (rate)	–	–	–	−6.56	–	–	–	−6.48	–
Intercept (overdispersion)	–	–	–	−1.05		–	–	−0.82	–
Tested but not in the final RTM									
Bars	111	–	–	–	–	–	–	–	–
Bowling centres	8	–	–	–	–	–	–	–	–
Liquor stores	93	–	–	–	–	–	–	–	–
Malls	6	–	–	–	–	–	–	–	–
Night clubs	15	–	–	–	–	–	–	–	–
Parking stations & garages	6	–	–	–	–	–	–	–	–
Retail shops	57	–	–	–	–	–	–	–	–
Takeout restaurants	299	–	–	–	–	–	–	–	–
Variety stores	21	–	–	–	–	–	–	–	–

Notes: Abbreviations: Op., Operationalisation; Dens, Density; Prox., Proximity; S.I., Spatial influence; Coef., Coefficient; RRV, Relative risk value.
RTMDx only accepts point files as inputs. Multi-family housing complexes, parks and commercial zoning were provided as polygons and converted to polygons prior to the analysis. To conduct the conversion, researchers first converted the perimeter of each polygon to a series of points placed about one half block (i.e. 276 ft) from each other. To convert the interior of the polygon, the vector was first converted to a raster grid with cell size of 276 ft. The raster was then converted to a point file, with each raster cell centroid represented as a single point. The *N* values in Table 1 are the number of points input into RTMDx. The points were created from the following number of polygon features: 459 multi-family housing complexes, 26 commercial zoning areas and 530 parks.

Table 4. Negative binomial regression findings, interaction terms IRR (RSE). Motor Vehicle Thefts.

	Racial heterogeneity	Young male population	Geographic mobility	No High School	Population density	Poverty
Disorder calls	1.37	20.82	0.52	1.89	0.83	1.77
	(0.52)	(15.78)**	(0.13)**	(0.64)	(0.24)	(0.56)
Foreclosures	2.08	0.10	1.67	0.84	0.74	1.28
	(0.56)*	(0.07)**	(0.38)*	(0.19)	(0.10)*	(0.36)
Multi-family housing complexes	0.37	1.57	0.70	0.96	3.59	2.24
	(0.11)**	(0.99)	(0.15)	(0.25)	(0.35)**	(0.55)**
Hotels & motels	0.56	0.01	0.57	6.26	0.31	0.32
	(0.36)	(0.00)**	(0.20)	(2.81)**	(0.17)*	(0.18)*
Sit-down restaurants	1.43	0.58	0.76	0.88	0.53	1.55
	(0.35)	(0.51)	(0.19)	(0.19)	(0.10)**	(0.34)*
Parks	0.83	7.29	0.90	1.92	2.00	0.68
	(0.17)	(5.01)**	(0.17)	(0.35)**	(0.26)**	(0.16)
Commercial zoning	1.22	0.21	0.49	0.87	0.71	0.46
	(0.34)	(0.83)**	(0.11)**	(0.20)	(0.12)*	(0.12)**
Spatial lag	1.22 (0.30)**					
Log =	−4417.84					
Wald X^2 =	7105.87					
Wald d.f. =	43					
N =	76,528					

Notes: Abbreviations: IRR, Incident rate ratio; RSE, Robust standard error. *$p < 0.05$; **$p < 0.01$.

of interpretation, the findings are presented in a matrix with risk factors in rows and census variables as column headings. Cells where a risk factor and census variable intersect represent the interaction term between the two covariates. Findings are presented as Incidence Rate Ratios (IRR), which can be interpreted as the rate at which the dependent variable is observed, with a value of 1 as the baseline. An IRR of 0.90 suggests that, controlling for other independent variables, a 1-unit increase in the variable is associated with a 10% decrease in the rate at which the dependent variable occurs while an IRR of 1.10 suggests a 10% increase in the rate at which the dependent variable occurs (Braga and Bond, 2008: 590).

What is immediately clear from the table is the fact that, despite exhibiting a citywide effect on MVT, the influence of each risk factor was aggravated, mitigated or neutralised across various measures of neighbourhood disadvantage. Disorder calls were particularly criminogenic in neighbourhoods with high young male populations, with MVT counts increasing by 20 times (IRR = 20.82) with each 1-unit increase in the interaction term. Conversely, a negative correlation was observed in the geographic mobility interaction, with MVT counts decreasing by 48% (IRR = 0.52) with each 1-unit increase in the interaction term. Each of the other four disorder calls interaction terms did not achieve statistical significance. Similar variability was observed with each of the other risk factors. For foreclosures, statistically significant, positive effects were observed for the racial heterogeneity (IRR = 2.08) and geographic mobility (IRR = 1.67) interaction terms with statistically significant, negative effects observed in the young male population (IRR = 0.10) and population density (IRR = 0.74) terms. For multi-family housing, positive effects were observed in the population density (IRR = 3.59) and poverty (IRR = 2.24) interaction terms, with increases in the racial heterogeneity term associated with decreased MVT (IRR = 0.37). For hotels & motels, each 1-unit increase in the youth population term was associated with an extremely sizable (i.e. 99%) reduction in MVT (IRR = 0.01), with the poverty (IRR = 0.32) and population density (IRR = 0.31) terms also exhibiting negative relationships. Each 1-unit increase in the no high school interaction term was associated with an over six-fold increase in MVT (IRR= 6 .26). Only two of the sit-down restaurant interaction terms achieved statistical significance, with each 1-unit increase in the population density term associated with a 47% reduction in MVT (IRR = 0.53) and each 1-unit increase in the poverty term associated with a 55% increase (IRR = 1.55). The three statistically significant parks interaction terms were associated with increased levels of MVT. Each 1-unit increase in the no high school (IRR = 1.92) and population density (IRR = 2.00) terms was associated with approximately a doubling of MVT while a 1-unit increase in the young male population term (IRR = 7.29) was associated with an over seven-fold increase in MVT. Each of the four significant commercial zoning interaction terms was associated with decreased levels of MVT: young male population (IRR = 0.21), geographic mobility (IRR = 0.49), population density (IRR = 0.71) and poverty (IRR = 0.46).

Table 5 displays the findings of the MVR negative binomial regression model. Similar to the MVT model, variability was observed for each risk factor. Four of the disorder calls terms were statistically significant for MVR, as compared with two in the MVT model. The terms for young male population (IRR = 12.77) and geographic mobility (IRR = 0.36) were associated with increased and decreased MVR, respectively, similar to their influence in the MVT model. One-unit increases in the no high school (IRR = 3.03) and poverty (IRR = 2.24) terms were each associated with MVR rate increases. Only a single foreclosure term achieved statistical significance, with each 1-unit increase in the population density term associated with a 25% reduction in MVR (IRR = 0.75), nearly identical to the effect observed in the MVT model. Two of the multi-family housing complex interaction terms achieved statistical significance, with both the population density (IRR = 3.20) and poverty (IRR = 1.86) terms associated with increased MVR. Both of these terms exerted a similar effect in the MVT model. The racial heterogeneity term, significant in the MVT model, was insignificant for MVR. Two of the hotels & motels terms were statistically significant. Each 1-unit increase in the young male population term was associated with a 99% reduction in the rate of MVR, identical to its observed effect in the MVT model. The geographic mobility term, insignificant in the MVT model, was associated with reductions in MVR (IRR = 0.47). For sit-down restaurants, the population density term was associated with reduced levels of MVR (IRR = 0.48), similar to the MVT findings. The other significant term in the MVT model (poverty) was insignificant for MVR. The three parks terms associated with MVT increases were similarly associated with MVR: young male population (IRR = 5.14), no high school diploma (IRR = 3.22), and population density (IRR = 2.81). The racial heterogeneity term, insignificant in the MVT model, was associated with decreased MVR (IRR = 0.46). For commercial zoning, the four significant terms exhibited similar effects on MVT as MVR: young male population (IRR = 0.10), geographic mobility (IRR = 0.65), population density (IRR = 0.58), and poverty (IRR = 0.48).

Three risk factors associated with MVR were not associated with MVT (convenience

Table 5. Negative binomial regression findings, interaction terms IRR (RSE). Motor Vehicle Recoveries.

	Racial heterogeneity	Young male population	Geographic mobility	No High School	Population density	Poverty
Disorder calls	0.95	12.77	0.36	3.03	1.00	2.24
	(0.36)	(12.09)**	(0.08)**	(1.18)**	(0.29)	(0.73)*
Foreclosures	1.45	0.32	0.99	0.75	0.75	1.10
	(0.35)	(0.29)	(0.21)	(0.16)	(0.11)*	(0.31)
Multi-family	0.82	1.51	0.79	0.67	3.20	1.86
housing complexes	(0.25)	(1.09)	(0.17)	(0.22)	(0.31)**	(0.53)*
Hotels & motels	0.52	0.01	0.47	3.09	0.42	0.44
	(0.55)	(0.00)**	(0.15)*	(2.57)	(0.32)	(0.32)
Sit-down restaurants	1.22	1.06	0.95	1.15	0.48	1.27
	(0.36)	(0.87)	(0.22)	(0.34)	(0.09)**	(0.33)
Parks	0.46	5.14	0.77	3.22	2.81	1.19
	(0.11)**	(4.29)*	(0.16)	(0.90)**	(0.48)**	(0.34)
Commercial zoning	1.62	0.10	0.65	0.82	0.58	0.48
	(0.43)	(0.05)**	(0.12)**	(0.18)	(0.11)**	(0.12)**
Convenience stores	0.89	0.04	0.61	0.27	0.68	3.41
	(0.60)	(0.01)**	(0.15)*	(0.19)	(0.36)	(2.08)*
Gas stations with	3.00	0.01	0.80	0.71	1.16	0.59
convenience stores	(1.47)*	(0.00)**	(0.22)	(0.52)	(0.40)	(0.22)
Schools	1.54	0.36	0.90	0.90	0.37	1.37
	(0.47)	(0.29)	(0.18)	(0.22)	(0.08)**	(0.33)
Spatial lag	1.18 (0.03)**					
Log =	−4150.96					
Wald X^2 =	18,398					
Wald d.f. =	61					
N =	76,528					

Notes: Abbreviations: IRR, Incident rate ratio; RSE, Robust standard error. $*p < 0.05$; $**p < 0.01$.

stores, gas stations with convenience stores, and schools) so a comparison of interaction terms across models is not possible. For convenience stores, three interaction terms achieved statistical significance. Each 1-unit increase in the poverty term was associated with a more than tripling of the MVR rate (IRR = 3.41) while the young male population (IRR = 0.04) and geographic mobility (IRR = 0.61) terms were associated with a reduction in MVR. For gas stations with convenience stores, each 1-unit increase in the racial heterogeneity term was associated with a tripling of MVR (IRR = 3.00) while each 1-unit increase in the young male population term was associated with a 99% reduction of MVR (IRR = 0.01). Only a single interaction term was significant for schools, with each 1-unit increase in population density associated with a 63% reduction of MVR (IRR = 0.37).

Discussion and conclusion

This study contributed to the literature in two primary ways. First, we identified the spatial correlates of both MVT and MVR, two crime types that have appeared sparingly in the geospatial literature. The top four risk factors, in terms of relative risk value, were identical for MVT and MVR: disorder related calls for service, foreclosures, multi-family housing units, and hotels and motels. In addition, each of the risk factors significant for MVT were also significant for MVR (disorder related calls for service, foreclosures, multi-family housing complexes, hotels and motels, sit-down restaurants, parks and commercial zoning). An additional three risk factors (convenience stores, gas stations w/convenience stores and schools) influenced the occurrence of MVR, but not MVT.

The nature of the significant risk factors suggests the importance of deniability, which St Jean (2007) describes as the ability to deny that one is present in an area for criminal purposes. Prior research has identified deniability as an important factor for offenders looking to 'blend-in' at a particular area for extended periods of time, such as drug sellers (Piza and Sytsma, 2016; St Jean, 2007). However, research suggests that deniability is also important for offenders looking to quickly flee an area, such as armed robbers (St Jean, 2007). The current study findings suggest deniability may be an important consideration for motor vehicle thieves. Outside of disorder related calls for service, all of the significant risk factors are legitimate features of land usage, rather than centers of illicit behaviour. In the lexicon of Environmental Criminology, these risk factors represent crime generators: places to which large numbers of people are attracted for reasons unrelated to criminal motivation but that nonetheless offer increased opportunities for crime (Clarke and Eck, 2005: 17). Searching for targets in such areas allows offenders to maintain an inconspicuous presence because other persons are frequenting the area for legitimate reasons. Deniability seems to be even more important for MVR, given the nature of the three risk factors related to MVR but not MVT. Convenience stores and gas stations with convenience stores provide thieves an opportunity to park a motor vehicle in an area where many other motorists do the same. In such an environment, an offender not returning to the vehicle is unlikely to be noticed by any on-lookers. Areas around schools similarly attract people who must leave their vehicles unattended for extended periods.

We further found the effect of each significant risk factor to be heterogeneous across neighbourhood context. This suggests that the convergence of particular spatial and neighbourhood-level factors may maintain or heighten criminogenic effects, while the convergence of other factors may result in a null or mitigating effect. Moreover, certain interaction terms were statistically significant in one model but not the other. This suggests that the interaction of risk factor spatial influence and neighbourhood disadvantage differently influence MVT and MVR.

The significance of the interaction terms supports the notion of Environmental Criminology and Social Disorganisation as complementary, rather than competing, theoretical perspectives. Despite the tendency for scholars to consider these theories as contrasting, their conceptual frameworks overlap. In particular, both place premium importance on the notion of informal social control (Bossen and Hipp, 2015: 400). Social Disorganisation scholars argue that collective efficacy is maintained through informal mechanisms, such as the 'monitoring of spontaneous play groups among children, a willingness to intervene to prevent acts such as truancy and street-corner "hanging" by teenage peer groups, and the confrontation of persons who are exploiting or disturbing public space' (Sampson et al., 1997). Environmental criminologists emphasise the role of intimate handlers and place mangers in exerting informal control over potential offenders within neighbourhoods (Eck, 1994; Felson, 1995). Intimate handlers and place managers often include the same entities involved the development of collective efficacy, such as neighbourhood residents, business owners, apartment mangers and street pedestrians.

Findings in the current study suggest an interaction between Environmental Criminology and Social Disorganisation mechanisms. For example, the Risk Terrain Model found foreclosures to be related to increased levels of both MVT and MVR on a city wide basis. However, foreclosures within areas of high population density were significantly associated with reduced counts of both MVT and MVR. A potential explanation may be that, while foreclosures translate to the removal of homeowners, the residents most commonly associated with stability and investment (Immergluck and Smith, 2006; Katz et al., 2013), areas with high population densities may provide the necessary guardians to prevent high levels of MVT and MVR. In addition, the interaction between disorder calls and young male population generated the highest IRR values for both MVT and MVR. This suggests that disorder calls, criminogenic on their own, present maximum influence in areas where the size of the young male population challenges the formation of collective efficacy. Theorising the underlying mechanism of each statistically significant interaction term is beyond the scope of this paper, given the large number of terms. Rather, we present our findings as an illustration of the utility of jointly considering micro-level risk factors and neighbourhood-level measures in crime-and-place research. We recommend that future research continue to explore the joint utility of these perspectives.

The findings also have implications for the Policing field. While crime hot spots have been used to identify targets for police resources, crime forecasting techniques such as Risk Terrain Modelling can help further refine target areas (Caplan et al., 2013; Kennedy et al., 2011) while simultaneously identifying criminogenic spatial features that crime prevention activities should target (Caplan et al., 2015; Kennedy et al., 2015). The current study suggests that testing the interaction effects between risk factors and neighbourhood dynamics may help to further focus crime prevention responses. For example, while foreclosures exhibited a city-wide effect on MVT, police may want to prioritise foreclosures in neighbours with high levels of racial heterogeneity and geographic mobility, since crime risk was heightened in these contexts. For MVR, officials should consider diverting crime prevention resources away from foreclosures in neighbourhoods with high population densities, since this context was actually associated with decreased levels of crime. This suggests a two-step analytical procedure, the first step identifying the significant spatial risk factors and the second step measuring precise neighbourhood characteristics that aggravate or mitigate the criminogenic influence of said risk factors. While we focused on Motor Vehicle Crime in the current study, such an approach can be used to address any crime type.

Despite these implications, this study, like most others, suffers from specific limitations that should be mentioned. Officially reported crime data is always subjected to reporting bias as not all crimes get reported to the police. While MVT seemingly is not influenced by reporting bias as much as other offences, as 91.1% of completed MVTs are reported to police (BJS, 2015), reporting frequency of MVR is less clear. Regarding the RTM analysis, while we made every effort to include an exhaustive set of risk factors in the analysis, we were limited to what was obtainable via available data sources. It is possible that pertinent, and informative, spatial risk factors were excluded. In addition, while commonly used as proxies for neighbourhoods, census tracts may not accurately reflect resident perceptions of community. Basta et al. (2010) found that respondents' hand-drawn maps of their neighbourhoods did not correspond with administrative boundaries such as census tracts, and that respondents living in the same area had much different conceptions of their neighbourhoods. The reader should be aware of potential issues with face validity. Lastly, we alert the reader to the differing spatial scales of the data used to create the interaction terms. All spatial risk factors were operationalised at the micro-level (grid cell), with neighbourhood disadvantage measured at the meso-level (census tract). This approach mirrors the methodology of prior crime-and-place research, with scholars simultaneously incorporating Environmental Criminology and Social Disorganisation perspectives forced to use variables measured at different scales (e.g. Braga et al., 2012; Drawve et al., 2016; Rice and Smith, 2002; Taniguchi and Salvatore, 2012). This is due to the fact that socio demographic variables are primarily collected by census bureaus, with pre-defined administrative areas (e.g. census tracts) as units of analysis. While research incorporating such measures has greatly contributed to the crime-and-place literature, we echo recent calls for the improved measurement of social disorganisation at the micro-level (Braga and Clarke, 2014; Weisburd et al., 2014), which would better match the scale used to analyse crime and spatial risk factors. Future research should seek to address these study limitations.

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Notes

1. The use of a concise time frame means that any stolen vehicle recovered after 31 October 2013 is falsely classified as a permanent MVT, and thus not included in the current study. However, prior research suggests that stolen motor vehicles are typically recovered within a week (Roberts, 2012). Qualitative research on motor vehicle thieves suggests that the recovery time is accelerated in certain cases, with many offenders reporting that they abandon newer vehicles within two days because of increased risk of detection (Jacobs and Cherbonneau, 2014). Indeed, prior studies have acknowledged the inability to account for MVR outside of the study period as a threat to validity (e.g. Roberts and Block, 2012; Suresh and Tewksbury, 2013). Therefore, we feel that the presence of false positives is minimised in our sample, and commensurate with that of prior research on MVT.
2. The disorder calls for service include various incidents considered as social disorder in the literature: disorderly conduct, public intoxication, loitering, noise complaints, aggressive panhandling and trespassing.
3. After consulting with CSPD officials, we decided to not include gas stations in their entirety. This is because drivers do not typically leave their vehicles unattended at gas stations. Therefore, the seizing of a motor vehicle in these locations would be classified as a robbery (with the vehicle being forcefully taken from the victim) rather than a theft (with the vehicle being taken while not in the presence of the victim). Gas stations that also contain convenience stores, conversely, have parking areas for customers to leave their vehicles. Since vehicles are unattended in such circumstances, their loss is classified as a motor vehicle theft.
4. Bars, commercial zoning, disorder related calls for service, multi-family housing complexes, parks, sit-down restaurants, schools, liquor stores, malls, night clubs and takeout restaurants.
5. Bowling centres, convenience stores, foreclosed properties, hotels & motels, gas stations with convenience stores, parking stations & garages, retail shops and variety stores.

6. Racial heterogeneity was calculated via the following formula: [(%White, non-Hispanic * %non-white, non-Hispanic) + (%black, non-Hispanic * %non-black, non-Hispanic) + (%Asian, non-Hispanic * %non-Asian, non-Hispanic) + (%Hispanic * %non-Hispanic)]/4.
7. While RTMDx identified the best model for the RTM analysis as a negative binomial regression, we manually diagnosed the data distribution for the follow-up analysis since a different set of covariates (the interaction terms) were used as explanatory variables. First, a Kolmogorov-Smirnov test confirmed that both MVT ($D = 43.87$, $p < 0.01$) and MVR ($D = 48.50$, $p < 0.01$) had distributions vastly different from a normal distribution. Second, X^2 goodness-of-fit tests conducted after exploratory Poisson regression models confirmed that both MVT ($X^2 = 105{,}538.40$, $p < 0.01$) and MVR ($X^2 = 143{,}249.10$, $p < 0.01$) were distributed as negative binomial processes.
8. The inclusion of a spatial lag variable follows the approach of prior research measuring the effect of crime generators and attractors (e.g. Ashby and Bowers, 2015; Bernasco and Block, 2011; Moreto et al., 2014). First order Queen Continuity was used in the creation of the spatial lag variables. Moran's I was 0.06 ($p = 0.001$) for MVT and 0.11 ($p = 0.001$) for MVR. Moran's I statistics were calculated in GeoDa.
9. Owing to space constraints, VIF results are not presented in text, but are available from the lead author upon request.

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