The Relationship between Near-Repeat Street Robbery and the Environment: Evidence from Malmö, Sweden

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Received: 25 February 2020; Accepted: 24 March 2020; Published: 25 March 2020

Abstract: Near-repeat crime refers to a pattern whereby one crime event is soon followed by a similar crime event at a nearby location. Existing research on near-repeat crime patterns is inconclusive about where near-repeat patterns emerge and which physical and social factors influence them. The present research addressed this gap by examining the relationship between initiator events (i.e., the first event in a near-repeat pattern) and environmental characteristics to estimate where near-repeat patterns are most likely to emerge. A two-step analysis was undertaken using data on street robberies reported in Malmö, Sweden, for the years 2006–15. After determining near-repeat patterns, we assessed the correlations between initiator events and criminogenic places and socioeconomic indicators using a negative binomial regression at a street segment level. Our results show that both criminogenic places and socioeconomic indicators have a significant influence on the spatial variation of initiator events, suggesting that environmental characteristics can be used to explain the emergence of near-repeat patterns. Law enforcement agencies can utilize the findings in efforts to prevent further street robberies from occurring.

Keywords: near-repeat crime; street robbery; spatio-temporal modelling; urban analytics; GIS

1. Introduction

Crime is a societal problem in most countries. In addition to substantial criminal justice system and victim costs, crime also adversely affects social life [1]. Crime prevention strategies that directly or indirectly prevent crime from occurring can therefore generate substantial societal benefits [2].

In efforts to prevent crime, much research has focused on explaining how environmental characteristics influence the spatial variation of crime [3,4]. Several studies have shown that crime is concentrated in environments with certain physical and social environmental characteristics, such as places where people carry out activities (e.g., grocery stores) [5–8] or neighborhoods with low social cohesion [9,10]. Law enforcement and crime prevention resources can therefore efficiently target such environments to deter or detect criminal activity [11].

However, crime is concentrated not only in space, but also in time [12–16]. This is known as the near-repeat phenomenon and refers to a crime pattern, whereby one crime event is soon followed by a similar crime event at a nearby location [17–19]. The phenomena of near-repeat crimes have been observed not only for burglaries [20–22], but also for vehicle thefts [23] and street robberies [13]. To explain the emergence of near-repeat patterns, two hypotheses have been put forward [24,25]. One of them, the boost hypothesis, suggests that as a crime is carried out, the offender will learn about opportunities nearby and return to capitalize on these within a short period of time [26]. The other one, the flag hypothesis, suggests that certain risk factors make some environments more opportune to commit crime in and therefore attract more offenders [26].
To identify where initiator events—a crime event that initiates a near-repeat pattern—are most likely to occur, a growing body of literature has tried to explain how environmental characteristics influence the spatial variation of initiator events [27–30]. Informed by crime pattern theory [4] and social disorganization theory [3], findings from these studies demonstrate that there is an increased probability of initiator events occurring close to criminogenic places, such as grocery stores, restaurants, and parks [27–29] and in residential areas with a high proportion of socially disadvantaged individuals (i.e., individuals living below the poverty line, unemployed individuals, etc.) [30]. This suggests that both physical and social environmental characteristics influence the spatial variation of initiator events. However, the studies also have some limitations.

First, a majority of the studies [27–29] employ a risk terrain model technique [31] to estimate the influence of criminogenic places on initiator events. While such a model provides an accurate measurement of the accumulated influence of criminogenic places, the method does not measure the influence of individual criminogenic places [31]. If the influence of individual criminogenic places could be measured, it would also be possible to determine which criminogenic places affect the spatial variation of initiator events the most. Second, studies usually measure the influence on initiator events by applying a distance-based threshold value whereby criminogenic places within that distance are considered spatially close. However, this operationalization is problematic, because a criminogenic place located nearby may have a more pronounced influence than one that is further away [32]. An approach in which the distance between initiator events and criminogenic places is explicitly considered may, therefore, yield more accurate measurements of the criminogenic influence. Finally, although socioeconomic characteristics have been found to influence the spatial variation of crime [9,10], to our knowledge only one study has tested whether socioeconomic characteristics influence the occurrence of initiator events [30]. Existing research on near-repeat patterns focus only on pattern detection but do not assess correlations with local environmental characteristics [33]. Thus, little is known about the relationship between initiator events and socioeconomic characteristics, calling for more research.

The present research addressed these research gaps by examining the relationship between initiator crime events and environmental characteristics in Malmö, Sweden. Our objective was to test whether the combined influence of potentially criminogenic places and socioeconomic indicators explain the spatial variation of street robbery initiator events. Street robberies have not been examined in the environment– initiator events literature, but they are a major source of overall fear of crime in cities [1], making street robbery an important crime to prevent from a societal viewpoint. Confirming that street robberies exhibit near-repeat patterns has significant implications for crime prevention strategies, as it suggests that future crime events can be predicted based on past ones [25]. Thus, if an initiator event is identified, law enforcement agencies can allocate resources more efficiently to prevent subsequent events from occurring [30].

2. Materials and Methods

2.1. Study Area and Data

Malmö is the third largest city in Sweden, and in 2015, it had approximately 320,000 inhabitants. Malmö has received much attention in both politics and the media for its social and criminal problems, and especially its problem with violent crime such as street robbery, which is significantly more prevalent there than in other Swedish cities. This made Malmö an ideal location for this research.

Data were gathered from three sources. Data on street robberies were obtained from the police authority, which provided a database of 7744 crime events reported for the years 2006–15. The crime location of each street robbery was georeferenced based on the coordinates that correspond to the actual crime location. Of the events, 7434 (95.9%) could be georeferenced successfully, while the remaining 310 events had an unknown location, resulting in a successful georeferencing rate, well above the minimum reliable threshold of 85% suggested by Ratcliffe [34], given that data are missing at random.
Data on criminogenic places were collected from Malmö municipality. The selection of criminogenic places was informed by crime pattern theory to capture geospatial features of the environment that are thought to influence street robbery probability [4]. We included restaurants, bars, cafés, fast-food restaurants, grocery stores, ATMs, train stations, bus stops, high schools, and public parks [5,6,35]. These were all geocoded based on existing street addresses.

Finally, area-based socioeconomic data were collected from Statistics Sweden. The data are represented in squared grid cells with a spatial resolution of 100 x 100 m and 250 x 250 m. Guided by social disorganization theory [3], we considered the following variables: The total number of persons, the number of persons classified by country of birth (i.e., Swedish, Nordic (Denmark, Finland, Iceland, Norway), EU 28, Other), the number of persons classified by income level (i.e., low, medium, high, based on the national average income), the number of persons classified by employment (i.e., employed, unemployed), and the number of persons classified by education level (i.e., low, medium-low, medium-high, high, based on diploma).

2.2. Unit of Analysis and Aggregation of Data

Street segments, as recommended elsewhere [36], were used as the unit of analysis because they more accurately represent the setting where crime occurs [37] and are less susceptible to aggregation and zoning bias compared to area units [38,39]. Street network data for 2015 were retrieved from the Swedish Transport Administration. Highway and highway access points (n = 890) were removed as pedestrians are not allowed to use them, and street segments outside the urban parts of Malmö (n = 2457) were removed to reduce the number of units with no observations (potential boundary effects were taken into account). Thus, the final street network dataset consisted of 9769 street segments with a mean length of 103.8 m (standard deviation (SD) = 102.5 m).

To aggregate the data on criminogenic places and to match the socioeconomic characteristics to the street network, two separate approaches were used. First, data on the geocoded criminogenic places were attached to the corresponding street segment. Because an individual street segment is not an isolated feature but part of the larger street network, and therefore, the probability of crime occurring in that segment might be influenced by adjacent segments [32], we used a network-based approach in which the shortest path distance along the street network to the closest facility of each criminogenic place was calculated. Each street segment was consequently assigned the distance from its midpoint to the closest facility of each criminogenic place. We assumed that criminogenic places located close to a street segment have a pronounced influence on the probability of crime occurring, and vice versa.

Second, data on socioeconomic characteristics were disaggregated to the street network by calculating an area-weighted average based on the proportion of each street segment that intersected the variable’s cell [40]. A uniform distribution of values within each cell was assumed. Based on the socioeconomic input data, the following indicators were computed. Ethnic heterogeneity was represented through Simpson’s diversity index [41] to estimate the likelihood of two individuals living on the same street, having a similar background, based on four ethnic subdivisions: (1) Proportion of people born in Sweden (%), (2) proportion of people born in a Nordic country (%), (3) proportion of people born in another EU country (%), and (4) proportion of people born outside of the EU (%). Deprivation and affluence were calculated as composite measures using the sum of the unit-weighted z-scores. Deprivation comprised the proportion of people: (1) With a low education level (%), (2) with a low income level (%), and (3) who were unemployed (%). Affluence comprised the proportion of people: (1) With a high education level (%), (2) with a high income level (%), and (3) who were employed (%).

2.3. Analytical Strategy

The analysis was undertaken in two steps. First, near-repeat patterns were estimated with a near-repeat calculator to assess spatio-temporal interactions between street robberies using the Knox test [42]. The Knox test assesses the interaction of crime occurrences across space and over time in a
pairwise manner. For the spatial bandwidth, Haberman and Ratcliffe [13] suggested the average length of a city block. As proxy for a city block, we used the average length of street segments (103.8 m were rounded-up), which resulted in a spatial bandwidth of 105 m. Six spatial bands were employed to test the spatial extent of potential near-repeat patterns (i.e., 1–105 m, 106–210 m, etc.). Manhattan distance was chosen as a spatial distance calculation method, as it more accurately approximates people’s movement in a city, compared to Euclidean distance [43]. For the temporal bandwidth, previous studies showed that street robbers often go on crime sprees, meaning that several offenses are committed by the same offender within a short period of time [44]. We assumed a temporal bandwidth of 1 day and 4 temporal bands to test the temporal extent (i.e., 1 day, 2 days, etc.), similar to Youstin et al. [45]. However, as the temporal dimension of near-repeat patterns can vary considerably depending on the threshold value, sensitivity tests were performed with bandwidths of 4 days and 7 days [46]. Finally, to estimate the significance for a near-repeat pattern to emerge, 1000 Monte Carlo iterations were conducted to create a pseudo p-value and an observed-to-expected ratio for each spatial and temporal distance [42]. Higher observed-to-expected ratios indicate an increased probability that a near-repeat pattern will emerge.

Second, the relationship between initiator events and environmental characteristics was tested using a negative binomial regression model. Such models are well-suited to modelling discrete count response variables when data are overdispersed (i.e., the variance exceeds the mean) [14]. As a response variable, significant initiator events of near-repeat street robbery patterns were employed. As predictor variables, we considered the 10 criminogenic places and the four socioeconomic indicators at a street network level. Of importance, since the street network is interconnected, the dependent variable was expected to be spatially autocorrelated [40]. A spatially lagged version of the response variable, using the queen contiguity as neighborhood specification, was consequently added as predictor variable. Furthermore, to appropriately model the geographical exposure, an offset variable measuring the length of each street segment was added to control for differences in size of the segments [47].

For comparability, the predictor variables were standardized. The variables based on network distance (i.e., the criminogenic places) were also reverse coded to ease interpretation (i.e., instead of measuring the decrease in probability as the distance increases, a one-unit increase in the predictor variables measures the increase in probability as the distance decreases). For each predictor we report the incident rate ratios (IRR) (i.e., the exponentiated coefficients). Likelihood-ratio tests, Akaike information criterion (AIC) scores, and the Pearson’s dispersion statistic (PDS) were used to determine whether the negative binomial model provided a better fit than a basic Poisson model [47]. Multicollinearity was assessed through variance inflation factors (VIF). Values above 5 were considered to be critical [48].

3. Results

3.1. Near-Repeat Analysis

Table 1 shows the results of the near-repeat analysis. The greatest probability of near-repeat patterns emerging exists 0–1 day after an initiator event. The highest probability levels can be observed for spatial bandwidths of 1–105 m ($p < 0.050$) and 211–315 m ($p < 0.001$), where the probability that one street robbery event will be followed by another is increased by 60 percent. For bandwidths of 106–210 ($p < 0.050$), 316–420 ($p < 0.050$), 421–525 ($p < 0.001$), and 526–630 m ($p < 0.050$), there is also a significantly higher probability that a near-repeat pattern will emerge, but the probability decreases as the spatial distance from the initiator event increases. For temporal bandwidths of 2-2 days (i.e., 25–48 h from the initiator event), spatial bandwidths of 106–210 ($p < 0.001$) and 316–420 m ($p < 0.050$) demonstrate an increased probability, indicating that the probability remains higher for 2 days for some distances. For the longer temporal bandwidths that were employed as a sensitivity test, an increase in probability can be observed for the spatial bandwidth of 0–4 days. However, this increase is most likely driven by the high probability observed for 0–1 day, especially since similar patterns can also be found for the
temporal bandwidth 0–7 days. For other temporal bandwidths, significant patterns can be found for some spatial bandwidths, except for bandwidths of 5–8 days and 211–315 m ($p < 0.001$), the increase in probability is less than 20 percent, which is low.

Table 1. Observed-to-expected mean frequencies for street robberies in Malmö in 2006–15 with temporal bandwidths of 1, 4, and 7 days.

| Location  | Days  | 0–7  | 8–14 | 15–21 | 22–28 |
|-----------|-------|------|------|-------|-------|
| Same location | 5.16 ** | 2.25 ** | 1.93 ** | 1.84 ** |
| 1–105 m    | 0.97  | 0.89 | 0.81 | 0.74  |
| 106–210 m  | 1.18 ** | 1.13 * | 1.04 | 1.0   |
| 211–315 m  | 1.20 ** | 1.0  | 1.03 | 1.06  |
| 316–420 m  | 1.15 ** | 1.13 ** | 1.03 | 1.03  |
| 421–525 m  | 1.12 ** | 0.98 | 1.01 | 1.01  |
| 526–630 m  | 1.08 * | 1.0  | 0.98 | 0.95  |

| Same location | 7.41 ** | 2.44 ** | 2.26 ** | 1.9 ** |
| 1–105 m    | 0.97  | 1.0  | 0.78 | 0.98  |
| 106–210 m  | 1.26 ** | 1.07 | 1.17 * | 1.05  |
| 211–315 m  | 1.16 ** | 1.23 ** | 0.98 | 1.04  |
| 316–420 m  | 1.15 ** | 1.14 * | 1.07 * | 1.11 * |
| 421–525 m  | 1.09 * | 1.16 * | 0.92 | 1.0   |
| 526–630 m  | 1.09 * | 1.07 * | 0.97 | 1.0   |

| Same location | 32.35 ** | 4.0 ** | 2.39 ** | 1.32  |
| 1–105 m    | 1.60 * | 0.87 | 0.93 | 0.76  |
| 106–210 m  | 1.56 * | 1.46 ** | 1.28 | 0.86  |
| 211–315 m  | 1.60 ** | 1.14 | 1.02 | 1.08  |
| 316–420 m  | 1.25 * | 1.25 * | 1.06 | 1.09  |
| 421–525 m  | 1.37 ** | 1.07 | 1.05 | 1.0   |
| 526–630 m  | 1.36 * | 1.1 | 1.12 | 0.91  |

* $p < 0.05$, ** $p < 0.001$

Following this, significant initiator events ($n = 1569$) were extracted from the dataset and aggregated to individual street segments (descriptive statistics are provided in Table A1 in the Appendix A). Only initiator events that were a part of a near-repeat pattern that occurred within a temporal distance of 0–2 days and a spatial distance of 1–630 m were extracted, as these distances demonstrated the most significant and highest probabilities that near-repeat patterns will emerge, which is also in line with previous studies [44,45].

3.2. Negative Binomial Regression

The results of the negative binomial regression are presented in Table 2. The likelihood-ratio test ($p > 0.050$), AIC values, and PDS consistently confirmed that the negative binomial model (AIC = 4995; PDS = 1.23) provided a better fit than the Poisson model (AIC = 6632; PDS = 2.46). The PDS value is also well below the threshold value of 1.30 recommended by Hilbe [47], indicating that the negative binomial model accurately adjusted for overdispersion. Additionally, the VIF indicate that multicollinearity was not an issue (all VIF scores < 3).
Table 2. Results from negative binomial regression based on 1569 significant initiator events of street robberies in Malmö in 2006–15.

| Predictor Variables               | b       | IRR    | SE     | z        | p-Value |
|-----------------------------------|---------|--------|--------|----------|---------|
| Constant                          | −8.4758 | 0.0002 | 0.1010 | −83.935  | 0.000 ***|
| Criminogenic places                |         |        |        |          |         |
| Restaurant (alcohol)              | −0.0978 | 0.9069 | 0.1438 | −0.680   | 0.496   |
| Restaurant (no alcohol)           | −0.1846 | 0.8314 | 0.1202 | −1.537   | 0.124   |
| Cafe                              | 0.2157  | 1.2408 | 0.1300 | 1.660    | 0.097   |
| Fast-food restaurant              | 0.2569  | 1.2930 | 0.1259 | 2.041    | 0.041 * |
| Grocery store                     | 0.8698  | 2.3865 | 0.1366 | 6.369    | 0.000 ***|
| ATM                               | 0.3485  | 1.4169 | 0.1551 | 2.247    | 0.025 * |
| Bus stop                          | −0.2659 | 0.7666 | 0.0768 | −3.460   | 0.000 ***|
| Train station                     | 1.1171  | 3.0561 | 0.1022 | 10.935   | 0.000 ***|
| High school                       | 0.1474  | 1.1588 | 0.0977 | 1.509    | 0.131   |
| Park                              | 0.1938  | 1.2138 | 0.0840 | 2.306    | 0.021 * |
| Socioeconomic indicators          |         |        |        |          |         |
| Population                        | 0.0891  | 1.0933 | 0.0294 | 3.039    | 0.002 **|
| Affluence                         | −0.1048 | 0.9006 | 0.0747 | −1.403   | 0.161   |
| Deprivation                       | 0.4053  | 1.4997 | 0.0723 | 5.609    | 0.000 ***|
| Heterogeneity                     | 0.1123  | 1.1189 | 0.0743 | 1.513    | 0.130   |
| Spatially lagged response         | 0.4054  | 1.4999 | 0.0486 | 8.350    | 0.000 ***|

Fit statistics
- Nagelkerke’s $R^2$ = 0.38
- Pearson’s dispersion statistic = 1.23
- Moran’s $I$ = 0.032

Note: $n$ = 9769 street segments. Abbreviations: $b$ = beta coefficient; IRR = incident rate ratio; SE = standard error; $z = z$-value. * $p < 0.050$; ** $p < 0.01$, *** $p < 0.001$

Several of the theorized criminogenic places had a significant ($p < 0.050$) influence on the number of street robbery initiator events. Street segments near fast-food restaurants, grocery stores, ATMs, train stations, and parks all showed an increased probability of initiator events occurring. Areas close to train stations (IRR = 3.05, $p < 0.001$) had by far the highest probability, followed by grocery stores (IRR = 2.38, $p < 0.001$). For street segments near bus stops (IRR = 0.76, $p < 0.001$), however, the probability of an initiator event occurring was lower. No significant effects were found for restaurants serving alcohol, restaurants not serving alcohol, cafés, and high schools.

For the socioeconomic variables, an increase in probability was observed for street segments with a larger population (IRR = 1.09, $p < 0.01$). Similarly, street segments with high deprivation levels (IRR = 1.49, $p < 0.001$) also experienced an increased probability, while indicators of affluence and ethnic heterogeneity showed no significant effects. The spatially lagged version of the dependent variable significantly captures most of the observed spatial autocorrelation in the response variable ($I = 0.134$, $p < 0.001$), but the 0.32 Moran’s $I$ statistic of the model residuals still indicates minor spatial autocorrelation at a 5% significance level.

4. Discussion

The aim of this study was to test whether a combination of criminogenic places and socioeconomic indicators would explain the spatial variation of street robbery initiator events, to improve the utility of the near-repeat concept as a crime prevention strategy. The findings showed that both criminogenic places and socioeconomic indicators indeed influenced the spatial variation of street robbery initiator events.

The increased probability of near-repeat street robbery occurring in areas near fast-food restaurants, grocery stores, ATMs, train stations, and parks suggests that the spatial variation of initiator events,
to some extent, follows an expected pattern and is concentrated close to criminogenic places that have previously been found to increase the risk of street robbery [1,5,6,35]. Drawing upon crime pattern theory, this may be explained by the increased presence of people who either run errands or entertain themselves regularly at such places, offering crime opportunities for a motivated street robber [4]. Similarly, the increase in the probability of initiator events occurring in areas with large populations and high deprivation levels is also in line with prior studies [9,10]. Consistent with social disorganization theory, this may be explained by the lack of social cohesion that socially disadvantaged neighborhoods often experience, which is expected to make them less capable of handling criminal behavior [3].

However, the decrease in the probability of an initiator event occurring near bus stops contradicts, for example, Bernasco and Block [5]. This difference could be explained by how bus stops are distributed across space. Past research has demonstrated that the probability of crime occurring close to a bus stop is often dependent on the types of places that are near the bus stop and the number of people who visit those places [49]. Thus, if a bus stop is in an isolated location, the probability of crime occurring might be lower, as there will be fewer crime opportunities.

Taken together, these findings suggest that crime pattern theory and social disorganization theory can be used to understand the spatial variation of initiator events and further confirm the findings of previous studies [27–30]. The results of the present study do, however, provide a much more nuanced picture, as the influence of individual criminogenic places is disentangled and the actual distance between initiator events and criminogenic places is considered.

The findings of this study also add to the theoretical knowledge on why near-repeat patterns emerge. The influence of criminogenic places and socioeconomic indicators on initiator events indicates that certain environmental risk factors increase the probability of near-repeat patterns emerging, as suggested by the flag hypothesis [26]. However, the results of the near-repeat analysis show that the probability that a near-repeat will emerge is highest 1–2 days after an initiator event. This indicates crime spree offending, meaning that the same offender is likely to be responsible for the observed near-repeat patterns, as proposed by the boost hypothesis [26]. This implies that both the boost and the flag hypothesis offer plausible explanations of why near-repeat patterns emerge. Thus, more studies that test the two mechanisms empirically to separate their individual influence are needed, especially since the boost mechanism was not directly tested in this study.

The following limitations should be considered when interpreting our findings. First, the data on street robberies do not include unreported crime events. It is likely that our study did not capture all near-repeat patterns and all initiator events of street robbery. This is not, however, a limitation that is exclusive to this study: It is a well-known bias when working with crime data [34]. Second, while this study used a wide set of variables to estimate the influence of environmental characteristics, the selection was still limited to the available data sources. Future studies should strive to include more criminogenic places and socioeconomic indicators to better understand the spatial variation of initiator events. Finally, although our results provide several novel insights into the spatial variation of street robbery initiator events, more research is needed to assess whether it is a common pattern. Future research should therefore focus on replicating the results of the present study in a different setting. This might yield interesting insights, as near-repeat patterns have previously been demonstrated to exhibit differences in frequency and occurrence depending on the setting [46].

The major policy implication of the findings is that crime prevention strategies, such as more intense police patrolling, can be efficiently directed toward potential initiator events (i.e., crime events that will develop into a near-repeat pattern) to prevent subsequent events from occurring [11]. For example, if a street robbery occurs close to a grocery store, our findings call for a close-proximity intervention in both space and time to prevent subsequent crime events, as initiator events were more likely to occur close to grocery stores. Conversely, if a street robbery occurs close to a bus stop, our results imply that close-proximity intervention might not be necessary, as initiator events were less likely to occur close to bus stops. Such prioritization will assist law enforcement agencies to more efficiently deploy resources to prevent subsequent crimes from occurring.
5. Conclusions

This present research examined the relationship between street robbery initiator events and environmental characteristics at a street segment level in Malmö. The findings showed that both criminogenic places and socioeconomic indicators had a significant influence on the spatial variation of initiator events. By explaining how these characteristics influence the spatial variation of initiator events, this study contributes to the literature on near-repeat patterns by providing unique evidence on where initiator events are most likely to occur. Our findings can be utilized in the crime prevention strategies of law enforcement agencies to prevent further street robberies from occurring.

Author Contributions: Conceptualization, M.R. and M.H.; methodology, M.R.; software, M.R.; validation, M.R.; formal analysis, M.R.; writing and editing, M.R.; supervision, M.H. All authors have read and agreed to the published version of the manuscript. This paper is based on M.R.’s research Master’s thesis.

Funding: This research received no external funding.

Acknowledgments: We would like to thank Malmö municipality and police authority for providing the research data for the analysis.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Descriptive statistics of response and predictor variables.

| Variables                      | Minimum | Median | Mean | Maximum   | SD    |
|-------------------------------|---------|--------|------|-----------|-------|
| **Street robberies**           |         |        |      |           |       |
| Initiator event a             | 0.00    | 0.00   | 0.15 | 22        | 0.90  |
| Spatially lagged response     | 0.00    | 0.00   | 0.17 | 10.43     | 0.58  |
| **Criminogenic places**        |         |        |      |           |       |
| Restaurant (alcohol) b         | 0.09    | 595.73 | 742.23| 4035.64   | 615.16|
| Restaurant (no alcohol) b      | 0.11    | 482.60 | 608.17| 4931.76   | 482.19|
| Café b                        | 0.09    | 518.88 | 604.87| 4279.51   | 467.88|
| Fast-food restaurant b         | 0.18    | 482.72 | 558.80| 4870.47   | 391.19|
| Grocery store b               | 0.06    | 417.01 | 482.90| 4198.00   | 353.97|
| ATM b                         | 0.40    | 845.92 | 975.60| 6733.42   | 651.55|
| Bus stop b                    | 0.01    | 283.35 | 311.56| 2654.96   | 202.37|
| Train station b               | 18.75   | 2953.17| 3087.81| 9170.43   | 1661.10|
| High school b                 | 0.46    | 1303.79| 1586.23| 8920.38   | 1148.70|
| Park b                        | 0.08    | 295.18 | 375.24| 3734.17   | 321.76|
| **Socioeconomic indicators**   |         |        |      |           |       |
| Population                    | 0.00    | 5.58   | 27.17| 1417.55   | 70.52 |
| Affluence                     | −1.70   | 0.19   | 0.00 | 2.56      | 0.89  |
| Deprivation                   | −1.15   | −0.13  | 0.00 | 5.31      | 0.88  |
| Heterogeneity                 | 0.00    | 0.17   | 0.17 | 0.67      | 0.11  |

a Street segment count of the variable (n = 9769 street segments). b Network distance (meters) from the street segment midpoint to the closest feature of the variable.

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