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Predicting Initiator and Near Repeat Events in Spatiotemporal Crime Patterns: An Analysis of Residential Burglary and Motor Vehicle Theft

Eric L. Piza and Jeremy G. Carter

Near repeat analysis has been increasingly used to measure the spatiotemporal clustering of crime in contemporary criminology. Despite its predictive capacity, the typically short time frame of near repeat crime patterns can negatively affect the crime prevention utility of near repeat analysis. Thus, recent research has argued for a greater understanding of the types of places that are most likely to generate near repeat crime patterns. The current study contributes to the literature through a spatiotemporal analysis of residential burglary and motor vehicle theft in Indianapolis, IN. Near Repeat analyses were followed by multinomial logistic regression models to identify covariates related to the occurrence of initiator (the first event in a near repeat chain) and near repeat (the subsequent event in a near repeat chain) events. The overall findings provide additional support for the argument that neighborhood context can influence the formation and context of spatiotemporal crime patterns.

Keywords near repeat analysis; crime-and-place; spatiotemporal clustering; residential burglary; motor vehicle theft

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Introduction

Criminological research has long demonstrated that crime clusters during certain times of the day (Cohen & Felson, 1979; Felson, 2002; Lemieux & Felson, 2012; Rengert & Wasilchick, 2000). Despite such research findings, crime-and-place studies have primarily reported that crime spatially concentrates in hot spots while leaving the temporal dimension unexplored (Braga & Weisburd, 2010; Eck & Weisburd, 1995). As argued by Pitcher and Johnson (2011, p. 101), this creates a situation in which "for one type of analysis, time is typically ignored whereas for the other space is neglected." Near repeat analysis has emerged as a method for simultaneously incorporating spatial and temporal dimensions in the study of crime patterns. Since its introduction, near repeat analysis has provided evidence that a number of crime types occurring across disparate study areas cluster not only geographically, but temporally as well. Such spatiotemporal analyses have contributed greatly to the crime-and-place literature by bridging the aforementioned spatial and temporal considerations of crime patterns.

Recently, researchers have disentangled near repeat patterns by classifying incidents based upon their role in spatiotemporal clusters. A number of studies have emphasized incidents occurring within near repeat chains (Haberman & Ratcliffe, 2012; Nobles, Ward, & Tillyer, 2016; Townsley, Homel, & Chaselin, 2003) while other studies have further disaggregated near repeat patterns by emphasizing initiators,[1] the first event in one or more near repeat pairs (Caplan et al., 2013; Kennedy et al., 2016; Lockwood, 2012; Moreto, Piza, & Caplan, 2014; Ratcliffe & Rengert, 2008; Wells, Wu, & Ye, 2012). Research has further highlighted the importance of diagnosing the locations most at risk of near repeat patterns, specifically through the use of data measuring structural aspects of the physical environment as well as the sociodemographic characteristics of surrounding neighborhoods (Nobles et al., 2016; Zhang, Zhao, Ren, & Hoover, 2015). Such analytical techniques have practical benefits, as early prediction of both initiator and near repeat events may inform coordinated law enforcement responses to incidents that are most likely to generate subsequent crime.

The current study contributes to the literature by measuring the factors significantly related to initiator and near repeat events of residential burglary and motor vehicle theft occurring during 2013 in Indianapolis, IN. For both crime types, a near repeat analysis was conducted to examine spatiotemporal clustering over the 1-year study period. After the diagnosis of near repeat patterns, multinomial logistic regression models were incorporated to identify variables significantly related to the occurrence of initiator and near repeat events. The regression models included 19 explanatory variables categorized

1. The literature has used the terms initiator (Lockwood, 2012; Ratcliffe & Rengert, 2008), originator (Haberman & Ratcliffe, 2012; Nobles et al., 2016), and instigator (Caplan, Kennedy, & Piza, 2013; Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016) to describe the first event in a near repeat pair. For consistency purposes, we use the term initiator throughout the manuscript.

across 4 groups: crime generators (6), geographic edges (4), social disorganization (5), and controls for date of occurrence (4).

This study makes three primary contributions to the near-repeat, crime and place, and crime prevention literatures. First, near repeat research has yet to incorporate place-based characteristics that have been shown to generate crime as well as influence the geographic concentration of crime. Second, and relatedly, the integration of place-based features with neighborhood characteristics to identify near repeat events refines the focus for police to develop actionable crime prevention strategies and for scholars to more efficiently specify near repeat models. Third, spatiotemporal studies of crime and place (i.e., near repeat literature) have not emerged at the same frequency as spatial studies of crime. Thus, the current study progresses the near repeat literature by generating additional knowledge of spatiotemporal patterns of crime in a new city of study, Indianapolis, IN. For these reasons and those we discuss in more detail in the conclusions, we believe the findings make an important and unique contribution to the near repeat, crime and place, and crime prevention literatures.

Review of Relevant Literature

Spatiotemporal analysis was pioneered in the Epidemiology field for the purpose of studying the spread of infectious diseases (Knox, 1964). Such research incorporated the Knox method to identify when the spatial and temporal distances between incidents of disease contagion were more clustered than would be expected on the basis of random distribution. Criminologists have recently applied the Knox method in the study of urban crime to diagnose spatiotemporal patterns. Each study testing the near repeat phenomenon has found statistically significant spatiotemporal clusters. Initial studies focused on residential burglary (Bowers & Johnson, 2004; Johnson & Bowers, 2004; Johnson et al., 2007; Townsley et al., 2003) with more recent research also testing this crime type (Chainey & da Silva, 2016; Moreto et al., 2014). To our knowledge, Ratcliffe and Rengert (2008) were the first to test the near repeat phenomena in a crime type outside of burglary, analyzing shootings in Philadelphia. Following Ratcliffe and Rengert (2008), scholars have increasingly tested the near repeat phenomenon across an array of crime types, including shootings and gun assault (Sturup, Rostami, Gerell, & Sandholm, 2017; Wells et al., 2012), armed robbery (Haberman & Ratcliffe, 2012), arson (Grubb & Nobles, 2016), maritime piracy (Marchione & Johnson, 2013), motor vehicle theft (Block & Fujita, 2013; Lockwood, 2012), and both insurgency (Townsley, Johnson, & Ratcliffe, 2008) and counter insurgency (Braithwaite & Johnson, 2012) activity in Iraq. Additional studies have assessed the generalizability of near repeats by measuring spatiotemporal clustering across multiple crime types. In each case, researchers found significant clustering for each crime type, though unique patterns were observed across crime types (Grubesic & Mack, 2008; Johnson, Summers, & Pease, 2009; Youstin, Nobles, Ward, & Cook, 2011; Zhang et al., 2015).

Despite the predictive capacity of near repeat analysis, its crime prevention utility has previously been called into question due to the typically short time frame of spatiotemporal patterns. Haberman and Ratcliffe (2012) found that near repeat robbery chains lasted an average of only 4.2 days in Philadelphia. Common forums for police strategy development, such as Compstat, occur too infrequently to respond to such a concise time frame (Haberman & Ratcliffe, 2012). The insights of Haberman and Ratcliffe (2012) suggest that new analytical procedures may be necessary to improve the utility of near repeat analysis. In particular, Haberman and Ratcliffe (2012) argue that data on characteristics of the surrounding environment can be used to predict the occurrence of near repeat patterns, an observation that has appeared elsewhere in the literature (Nobles et al., 2016; Pitcher & Johnson, 2011; Sagovsky & Johnson, 2007).

Such analytical techniques suggest a strategy whereby analysts identify incidents most at-risk of generating spatiotemporal crime patterns and police then focus resources directly to the incidents and/or places worthiest of intervention, rather than responding to all incidents as if they each pose the same likelihood of generating a near repeat pattern. A review of near repeat research suggests that such an approach may be promising, as researchers have identified factors associated with spatiotemporal crime clusters. Townsley et al. (2003) found that a greater number of near repeat events occurred in suburbs with homogenous housing stock than suburbs with more heterogeneous stocks. Zhang et al. (2015) found that near repeat clusters more often occurred in low income and racially/ethnically diverse neighborhoods, though this observation was much more evident for residential burglary and aggravated assault than robbery. Nobles et al. (2016) classified burglary incidents into two categories: single burglaries (incidents not linked in space and time) and repeat/near repeat burglaries (incidents that are linked in space and time). Nobles et al. (2016) found that measures of social disorganization were significantly associated with neighborhood levels of both single and repeat/near repeat residential burglary.

Additional research has further disentangled near repeat chains by more precisely classifying individual crime incidents according to their role in spatiotemporal crime patterns. In particular, research has emphasized initiator events, those incidents that are the first event in one of more near repeat pairs. Ratcliffe and Rengert (2008, p. 71) demonstrated that initiator shootings were distributed across police sectors in a manner that differed from the cumulative shooting incidents, suggesting that initiators operated "under a different spatial regime than the general shooting pattern." Ratcliffe and Rengert (2008) argued that understanding such nuances of initiator events may allow police to more precisely focus their crime prevention activities. Lockwood (2012) found that neighborhood disadvantage was associated with an over twofold increase in initiator motor vehicle theft counts in Lincoln, NE. Wells et al. (2012) found that business locations and gang-linked shootings were more likely to generate near repeat shootings in Houston, though the findings only approached statistical significance. A number of studies have recently demonstrated how the co-location of crime generators and attractors, operationalized through the Risk Terrain

Modeling technique, predicts initiator events. Caplan et al. (2013) found that the 1-block area surrounding initiator violent crime events had significantly higher spatial risk levels than non-initiator events in Irvington, NJ. Moreto et al. (2014) and Kennedy et al. (2016) observed similar findings for residential burglary in Newark, NJ and aggravated assault in Chicago, IL, respectively.

Scope of the Current Study

The current study seeks to contribute to the literature through an analysis of the geospatial characteristics associated with the formation of spatiotemporal residential burglary and motor vehicle theft patterns in Indianapolis, IN. The current study expands upon previous near repeat analyses in a number of ways. First, we conduct a multi-crime test of the near repeat phenomenon in a new study setting of Indianapolis, IN. Furthermore, we address calls to enhance the crime prevention utility of near repeat analysis by disentangling near repeat patterns. Each incident occurring during the study period was classified as an isolate (not in a near repeat chain), initiator (the first event in a near repeat chain), or near repeat (the subsequent event in a near repeat chain) event. We believe this creates a hierarchy by which police may maximize their crime prevention efforts. On the low end of the hierarchy are isolates, which are spatiotemporally unconnected to other incidents. Police interventions in response to isolates have the lowest crime prevention utility, as isolates are not followed closely in space or time by other events. Near repeat events are next on the hierarchy. Because near repeat events extend spatiotemporal chains, responses to near repeat events may provide additional benefits by preventing additional incidents that may have occurred subsequently. Initiator events sit on top of the hierarchy, as the effective response to an initiator prevents the occurrence of all additional incidents that would have comprised a spatiotemporal pattern. When possible, police should direct efforts towards near repeat and initiator events because the halting or prevention of spatiotemporal clusters can have greater impact than a strategy predicated on responding to isolates. Finally, the current study follows the recently advanced approach of diagnosing the place-based characteristics of near repeat patterns. Multinomial logistic regression models were incorporated to identify variables significantly related to the occurrence of initiator and near repeat events. Findings highlight factors that can be used to prioritize the deployment of crime prevention resources, specifically by emphasizing incidents at a greater likelihood of falling within the upper tiers of the aforementioned hierarchy.

Methodology

Study Area and Data Sources

Indianapolis, Indiana is the largest city in the state, the state capital, and a consolidated city-county municipality. In 2013, Indianapolis had a population of 843,393 persons with a population density of 2,129 persons per square mile. The majority of citizens are White (59%) with much smaller proportions of ethnic minorities (28% Black, 9% Hispanic, and 2% Asian). Median household income was $41,361, with 20% living below the poverty line (as compared to 15.4% statewide), and 24 percent of the population had a bachelor's degree or higher (U.S. Census Bureau, 2016). Compared to other cities of similar size (500,000—999,999 population) in the United States during 2013, Indianapolis exhibited higher rates of burglary (1,594 vs. 959), and motor vehicle theft (595 vs. 522) per 100,000 population (Federal Bureau of Investigation, 2013).

This study is an artifact of on active research partnership between the authors and the Indianapolis Metropolitan Police Department (IMPD) wherein the authors regularly communicate with IMPD personnel and analysts regarding data processing procedures and the potential application of advanced data-driven techniques to combat crime and allocate resources. Crime data for the year 2013 were provided electronically from the IMPD, with *XY* coordinates provided for the crime incidents. All crime data are geocoded by the Information & Intelligence Branch of the IMPD. The IMPD geocodes crime incidents within ArcGIS using a composite address locator. The address locator first attempts to geocode incidents to parcels and then geocodes any unmatched incidents to street centerlines using an offset distance of 40 feet. Both the street centerlines and parcels are updated on a daily basis by IMPD and built into the address locators every night to ensure the accuracy of each day's geocoding. The use of dual reference data tables (parcel and street centerlines) helps to maximize the geocoding hit rate, as certain common police reporting practices, such as recording incident addresses as street corners (e.g. "Main St. and Central Ave.") rather than precise addresses (e.g. "100 Main St.") (Braga, Papachristos, & Hureau, 2010), generates incident locations that cannot be matched to parcels. We found that 70.10 and 62.79% of residential burglaries and motor vehicle thefts, respectively, were geocoded to parcels.[2] This demonstrates that relying on parcel geocoding alone was not an option in this study, as the hit rate would have been below the minimum geocoding rate of 85% suggested by Ratcliffe (2004). The composite address

2. To determine these percentages, we re-geocoded the data using the composite address locator provided by the IMPD, as the data provided to us did not capture the geocoding method as a variable in the attribute tables. To quantify differences in placement across geocoding type, we identified the 8,075 residential burglaries and 3,149 motor vehicle theft incidents successfully geocoded to parcels and re-geocoded them to street centerline. Using the "point distance" tool in ArcGIS 10.3 we calculated the distance between the parcel-geocoded point and street centerline-geocoded point for each incident. We found that the distance between parcel and street centerline points averaged 138.25 feet (with a median of 103.67 feet) for residential burglary and 193.98 feet (with a median of 129.25 feet) for motor vehicle theft. Both of these distances are less than half of the spatial bandwidth (the average length of a city block in Indianapolis) used in the near repeat analysis, which suggests that difference across geocoding methods have minimal implications for the current study.

locator successfully geocoded over 99% of incidents for each crime type, meaning that the near totality of incidents was used in the analysis.

In operationalizing explanatory variables, we were informed by both the environmental criminology (Cohen & Felson, 1979; Cornish & Clarke, 1986; Brantingham & Brantingham, 1993) and social disorganization (Shaw & McKay, 1942) perspectives. We first collected data on various geospatial features, as informed by environmental criminology. Six of these features are commonly considered crime generators in the literature: ATMs and banks, bars, liquor stores, parks, pawn shops, and trailer parks. A number of studies have found these features to be associated with increased levels of crime, including the crime types included in the current study: residential burglary (Caplan, Kennedy, Barnum, & Piza, 2015; Groff & La Vigne, 2001; Moreto et al., 2014) and motor vehicle theft (Levy & Tartaro, 2010; Piza, Feng, Kennedy, & Caplan, 2016; Rice & Smith, 2002). While trailer parks were not included in any of the aforementioned studies, they are an important feature in the context of Indianapolis. Trailer parks are often comprised of low-income residents and inadequately secured properties, similar to public housing complexes often considered crime generators (Haberman & Ratcliffe, 2015; Kennedy et al., 2011; Moreto et al., 2014) and thus warrant inclusion in the study. The parks and trailer park files were provided by the Indiana Geographic Information Council with the remainder obtained from InfoGroup (www.infogroup.com), a leading provider of residential and commercial data for reference, research, and marketing purposes.[3]

Four additional geospatial features are included and considered geographic edges, areas "where there is enough distinctiveness from one part to another that the change is noticeable" (Brantingham & Brantingham, 1993, p. 17): railroad tracks, rivers, trails, and police patrol zone boundaries. Edges can play either a mitigating or aggravating role in crime pattern formation depending upon the opportunity structure they offer potential offenders. Brantingham and Brantingham (1993) observed that edges may create areas where strangers are more easily accepted because they are frequently and legitimately present, as opposed to the interior of neighborhoods where the presence of strangers is subject to challenge. Edges can also offer certain land usage and physical features that concentrate crime (Brantingham & Brantingham, 1993).

3. InfoGroup uses a multi-pronged approach in collecting and ensuring the accuracy of their business data, incorporating business record information from thousands of sources (see: http://www.infogroupdatalicensing.com/why-infogroup-data-licensing/what-we-do). InfoGroup's data research specialists manually verify the accuracy of data, making over 100,000 calls a day to ensure listed business are in operation (see: http://www.infogroupdatalicensing.com/why-infogroup-data-licensing/how-we-do-it). The data files we obtained included all businesses verified during our study period of 2013. A number of crime-and-place studies have incorporated data from InfoGroup (e.g. Caplan et al., 2015; Kennedy et al., 2016; Miller, Caplan, & Ostermann, 2016) as well as other commercial providers that provide similar information (e.g. Bernasco & Block, 2011). InfoGroup data is also used in the Business Location platforms of ESRI, developer of the ArcGIS software suite and the recognized industry leader in GIS technology (Environmental Systems Research Institute, [ESRI], 2015).

However, other research suggests that certain geographic edges may dissuade crime by restricting offender movement (Clare, Fernandez, & Morgan, 2009). In the current study, railroad and rivers can physically restrict offender mobility patterns either prior to or following crime commission. Trails, conversely, are edges between roadway and forest spaces that can facilitate offender movement patterns between crime scenes and areas of preparation and/or escape. Therefore, trails may be classified as a criminogenic geographic edge since they can easily connect potential offenders to various areas within the urban landscape (Clare et al., 2009). Police patrol zone boundaries are not physical entities, but represent areas where police patrol areas overlap. Because multiple police commands have responsibilities at patrol zone boundaries, they may represent areas where a higher dosage of patrol occurs. Alternately, since command "ownership" is less obvious at boundaries than within patrol zones, these edges may actually represent areas of decreased dosage because officers may concentrate their patrol activities in areas that are more clearly under their responsibility. All geographic edges were provided as GIS shapefiles by the IMPD.[4]

Lastly, the analysis included neighborhood-level data collected from the U.S. Census Bureau's American Community Survey 5-year estimates (2009–2013), as informed by social disorganization theory. Data were collected at the census-tract level, which prior research has consistently used as an operationalization of neighborhood (Griffiths & Chavez, 2004; Kubrin & Herting, 2003; Stucky, Payton, & Ottensmann, 2016). First, we measured concentrated disadvantage, a standardized index composed of the percentage of residents receiving public assistance, the percentage of families living below the poverty line, the percentage of female-headed households with children under the age of 18, and the percentage of unemployed residents (Morenoff, Sampson, & Raudenbush, 2001; Sampson, Raudenbush, & Earls, 1997).[5] The remaining four Social Disorganization variables measure racial heterogeneity[6] (Berg, Stewart, Brunson, & Simons, 2012); geographic mobility: percentage of persons who lived at a different address the previous year (Bruce, Roscigno, & McCall, 1998); the young male population: percentage of persons that are male between the ages of 15 and 24 (Kubrin & Herting, 2003); and population density: persons per square mile (Osgood & Chambers, 2000; Sampson, 1983).

4. Additional geoprocessing was required to operationalize the police patrol zone boundaries. Patrol zones were provided as polygon features representing the entirety of the patrol zones. The research team converted the polygons to line features, representing only the boundary of the zones while excluding all other areas.

5. While prior measures of social disadvantage have also included percentage of black residents, racial composition was addressed via a separate variable, which is discussed subsequently.

6. Racial heterogeneity was calculated via the following formula: [(%White, non-Hispanic * %non-white, non-Hispanic) + (%black, non-Hispanic * %non-black, non-Hispanic) + (%Hispanic * %non-Hispanic)]/3 (Smith, Frazee, & Davison, 2000; Smith & Jarjoura, 1988; Weisburd, Groff, & Yang, 2012). The Asian population was not included in the formula due to its low level in Indianapolis, in recognition of the need to tailor the formula to the study setting (Weisburd et al., 2012).

For the residential burglary analysis, we used housing density rather than population density because it more accurately represents the number of targets at-risk (Zhang et al., 2015).

Analytical Approach

The analysis begins by testing the near repeat phenomenon for residential burglary and motor vehicle theft incidents using the Near Repeat Calculator (NRC) version 1.3 (Ratcliffe, 2009). This software incorporates the Knox test to identify significant spatiotemporal clusters. The Knox test compares each event in a data-set with every other event and records the spatial and temporal distances between them. Observed cell counts within a contingency table are compared with the expected counts to identify spatiotemporal clustering. In determining statistical significance, the NRC incorporates a Monte-Carlo simulation technique developed by Johnson et al. (2007) to overcome limitations of the original Knox test, specifically violation of the assumption of independent observations. The null hypothesis of spatiotemporal randomness is rejected when more events in the original contingency table occur close in space and time than a pre-determined percentage of the random permutations (Johnson et al., 2007).

The NRC incorporates user-specified spatial and temporal bandwidths in the analysis. In recognition of prior research (Grubb & Nobles, 2016; Haberman & Ratcliffe, 2012; Moreto et al., 2014; Kennedy et al., 2016; Ratcliffe & Rengert, 2008), we used a spatial bandwidth of 1 block.[7] The spatial distance between events was calculated using Manhattan distances, which adds the difference between the *X* coordinates of two points to the difference between the *Y* coordinates of the two points, approximating a travel pattern in which one first travels horizontally and then vertically (Ratcliffe, 2009, pp. 8–9). This is a more accurate representation of urban travel patterns than Euclidean distance, which simply measures the distance between two points via a straight line ("crows flight") (Chainey & Ratcliffe, 2005; Rossmo, 2000).

We conducted the near repeat analysis three times with the following temporal bandwidths: 4 days (Grubesic & Mack, 2008; Youstin et al., 2011), 7 days (Braithwaite & Johnson, 2012; Haberman & Ratcliffe, 2012), and 14 days (Johnson et al., 2007; Ratcliffe & Rengert, 2008). Prior research suggests that the temporal dimension of near repeat patterns may differ across crime types (Youstin et al., 2011). The use of various temporal bands allows us to diagnose when an observed near repeat pattern is most salient. For example, significant clustering during the 4-day period but not the 7-day period would suggest that the near repeat pattern is best operationalized as a 4-day phenomena.

7. The average block in Indianapolis was measured as approximately 434 feet in ArcGIS 10.3. This distance was used in the NRC.

Conversely, clusters significant at each of the 4-day, 7-day, and 14-day intervals suggests that the near repeat pattern persists over an extended period of time.

We selected a statistical significance level of $p < .001$ in the NRC, which ran 999 Monte Carlo simulations. The NRC output is a table displaying Knox Ratios for each spatiotemporal combination, which can be interpreted the same way as odds ratios (Haberman & Ratcliffe, 2012, p. 156). As per the guidelines offered by Ratcliffe (2009, p. 10), cells must exhibit a statistical significance level of $p < .05$ and a Knox Ratio of 1.20 or greater (i.e. at least 20% greater than we would expect by chance) for crime to be considered overrepresented and, thus, a spatiotemporal cluster.

Following the near repeat analysis, we used the "other functions" utility of the NRC to identify how many times each incident was either an initiator event or a near repeat event in a spatiotemporal cluster (Ratcliffe, 2009, p. 12). Multinominal logistic regression models (in STATA 13.0) were used to explore the explanatory factors of initiator and near repeat events, building upon the approach of Kennedy et al. (2016). The dependent variable is an unordered categorical measure classifying each incident as an initiator event, near repeat event, or an isolate event (i.e. not part of a near repeat pattern).[8] Isolates are considered the reference category, tailoring the analysis to the identification of factors related to the occurrence of the alternate categories (Britt & Weisburd, 2010). Said differently, the model is structured to identify factors associated with the occurrence of initiator events and subsequent near repeat events.

The models include 19 explanatory variables grouped into four categories. Six dichotomous variables measure proximity to the *Crime Generators* while 4 dichotomous variables measured proximity to the *Geographic Edges*. For each of these covariates, any incident within 2 blocks (868 feet) of these features was considered in close proximity and coded as "1" with all other incidents coded as "0."[9] The 2-block distance was chosen in light of recent research finding that crime generators influence crime levels on both immediate and adjacent blocks (Bernasco & Block, 2011; Haberman & Ratcliffe, 2015). Five standardized continuous variables measure the *Social Disorganization* variables. These variables were measured at the census tract level, with each crime incident assigned the value of its encompassing census tract (see Table 1 for descriptive statistics of all variables). Four dichotomous variables controlled for the incident's *Date of Occurrence*. Three variables measured the

8. In following the aforementioned hierarchy classification, incidents classified as both an initiator event and near repeat event in separate chains were coded as initiators for the analysis.

9. For crime generators represented as points (ATMs & banks, bars, liquor stores, pawn shops), the 2-block distance was measured from the specific *XY* coordinate of the point. For crime generators represented as polygons (parks and trailer parks), the 2-block distance was measured from the boundary of the feature. Geographic edges were operationalized as lines, with proximity measured as the 2-block distance to either side of the line.

quarter of the year that the incident occurred: Quarter 1 (Jan.—Mar.), Quarter 2 (Apr.—Jun.), and Quarter 3 (Jul.—Sep.). The fourth Quarter of the year (Oct.—Dec.) was used as the reference category.[10] One variable measured whether the incident occurred on a weekend (Friday—Sunday).

Findings

Near Repeat Patterns

Table 2 displays the Knox Ratios for residential burglary. In the 4-day period, near repeat patterns were evident up to 3 blocks and within 4 days of the initiator event. The Knox ratio of 1.78 in the 1-block band indicates that near repeat residential burglary is 78% higher than expected by chance. The Knox Ratio of 1.33 indicates near repeats to be more than 33% more likely between 1 and 2 blocks while the Knox Ratio of 1.26 indicates that near repeats are more than 26% more likely between 2 and 3 blocks. Between 5 and 8 days, 9 to 12 days, and 13 to 16 days, a near repeat residential burglary pattern was present within 1 block. A very robust repeat victimization pattern was also evident, as burglaries were more than 7 times more likely to occur at the same location within 4 days of an initiator event. Repeat victimization patterns were evident for each period within 20 days. Spatiotemporal clustering extended 1 block less in the 7-day band (up to 2 blocks) than the 4-day band (up to 3 blocks) in the first temporal period (0 to 7 days). Near repeat residential burglary patterns were 39% more likely than expected between 8 and 14 days within 1 block. In the 14-day band, near repeat residential burglary patterns were evident only within 1 block between 0 and 14 days (Knox Ratio = 1.49). No other significant near repeat patterns were observed.

Table 3 displays the Knox Ratios for motor vehicle theft. Significant near repeat patterns were evident up to 3 blocks in the 4-day band. Within 0 to 4 days, Knox Ratios suggested that near repeat incidents were more than 45, 31, and 26% greater than expected by chance in the 1-block, 1—2 block, and 2—3 block bands, respectively. A repeat victimization pattern was also evident for motor vehicle theft, with victimized locations nearly 11 times more likely to experience an additional crime event within 4 days of an initial victimization. In the 5- to 8-day period, near repeat motor vehicle theft patterns exhibited a "donut" type pattern, with clustering more likely within 1-block (Knox Ratio = 1.31) and between 2 and 3 blocks (Knox Ratio = 1.48), but not between 1 and 2 blocks. A similar donut pattern was observed for the 9- to 12-day period, with significant near repeat patterns within 1 block (Knox Ratio = 1.35)

10. Including Quarter 4 as a covariate introduced problems of multicollinearity, influencing our decision to use it instead as the reference category. VIF statistics confirmed that no other variables introduced multicollinearity.

Table 1 Descriptive statistics

	Residential Burglary		Motor Vehicle Theft	
Dependent Variable	*N* (%)		*N* (%)	
Initiator Event	2,536 (21.98)		802 (16.03)	
Near Repeat Event	1,712 (14.84)		592 (11.84)	
Isolate	7,288 (63.18)		3,607 (72.13)	
Crime Generators	0 (%)	1 (%)	0 (%)	1 (%)
ATMs & banks	9,198 (79.73)	2,338 (20.27)	3,297 (66.1)	1,694 (33.9)
Bars	10,758 (93.26)	778 (6.74)	4,431 (88.8)	560 (11.2)
Liquor stores	10,908 (94.56)	628 (5.44)	4,557 (91.3)	434 (8.7)
Parks	9,013 (78.13)	2,523 (21.87)	3,919 (78.5)	1,072 (21.5)
Pawn shops	11,390 (98.73)	146 (1.27)	4,871 (97.6)	120 (2.4)
Trailer parks	11,181 (96.92)	355 (3.08)	4,814 (96.5)	177 (3.5)
Geographic Edges	0 (%)	1 (%)	0 (%)	1 (%)
Railroad tracks	10,128 (93.30)	1,408 (12.21)	4,208 (84.3)	783 (15.7)
Trails	10,763 (93.30)	773 (6.70)	4,588 (91.9)	403 (8.1)
Patrol zone boundary	8,900 (77.15)	2,636 (22.85)	3,680 (73.7)	1,311 (26.3)
River	11,207 (97.15)	329 (2.85)	4,813 (96.4)	178 (3.6)
Socio-Economics (z-scores)	Mean (SD)	Min (Max)	Mean (SD)	Min (Max)
Concentrated disadvantage	.33 (0.99)	−1.60 (2.92)	.33 (.96)	−2.15 (1.61)
Geographic mobility	.12 (.92)	−1.66 (5.39)	.16 (.98)	−1.66 (5.39)
Housing/Population density*	.14 (1.04)	−1.69 (4.32)	.13 (1.04)	−1.74 (2.89)
Racial heterogeneity	.24 (.92)	−2.15 (1.61)	.21 (.91)	−2.15 (1.61)
Young male population	.04 (.93)	−1.79 (4.13)	.09 (.97)	−1.79 (4.13)
Date of Occurrence	0 (%)	1 (%)	0 (%)	1 (%)
Qtr. 1 (Jan.—Mar.)	9,078 (78.69)	2,458 (21.31)	3,858 (77.3)	1,133 (22.7)
Qtr. 2 (Apr.—Jun.)	8,612 (74.65)	2,924 (25.35)	3,837 (76.9)	1,154 (23.1)
Qtr. 3 (Jul.—Sep.)	8,154 (70.68)	3,382 (23.32)	3,617 (72.5)	1,374 (27.5)
Qtr. 4 (Oct.—Dec.)	8,764 (75.97)	2,772 (24.03)	3,661 (73.3)	1,330 (26.7)
Weekend (Fri.—Sun.)	7,016 (60.82)	4,520 (39.18)	2,825 (56.6)	2,166 (43.4)

Note. Incidents classified as both an initiator event and near repeat event in separate chains were coded as initiators for the analysis.
*Housing density is reported for burglary. Population density is reported for motor vehicle theft.

Table 2 Near repeat analysis Knox ratios: residential burglary

	4 Days					
Time / Distance	0 to 4 days	5 to 8 days	9 to 12 days	13 to 16 days	17 to 20 days	More than 20 days
Same location	***7.56*****	***2.26*****	***1.84*****	***1.70*****	***1.34****	.78
1 Block	***1.78*****	***1.38*****	***1.42*****	***1.23*****	1.19**	.95
1–2 Blocks	***1.33*****	1.14**	1.11*	1.10*	1.02	.98
2–3 Blocks	***1.26*****	1.06*	1.12**	1.08*	1.07*	.99
3–4 Blocks	1.19**	1.09*	1.08*	1.00	.99	.99
4–5 Blocks	1.14**	1.06*	1.10**	1.04	1.00	.99
5–6 Blocks	1.09*	1.06*	1.05*	1.02	1.03	.99
More than 6 Blocks	1.00	1.00	1.00	1.00	1.00	1.00**
	7 Days					
Time / Distance	0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	More than 35 days
Same location	***5.14*****	***1.78*****	***1.54*****	1.26*	1.11	.74
1 Block	***1.59*****	***1.39*****	1.19**	1.12*	.99	.94
1–2 Blocks	***1.24*****	1.14**	1.04	1.03	1.00	.98
2–3 Blocks	1.17*	1.10**	1.07*	.99	1.01	.98
3–4 Blocks	1.15*	1.05*	1.01	1.03	1.05*	.99
4–5 Blocks	1.11*	1.08**	1.01	1.03	1.00	.99
5–6 Blocks	1.06*	1.06*	1.03	1.03*	1.05*	.99
More than 6 Blocks	1.00	1.00	1.00	1.00	1.00	1.00
	14 Days					
Time / Distance	0 to 14 days	15 to 28 days	29 to 42 days	43 to 56 days	57 to 70 days	More than 70 days
Same location	***3.41*****	***1.40*****	.95	.91	.93	.70
1 Block	***1.49*****	1.16**	.98	1.04	1.02	.92
1–2 Blocks	1.18**	1.04*	1.00	1.02	1.00	.97
2–3 Blocks	1.14**	1.03*	1.00	1.04*	.99	.98
3–4 Blocks	1.10**	1.02	1.05*	1.00	.96	.99
4–5 Blocks	1.09**	1.02	1.02	1.03*	1.00	.98
5–6 Blocks	1.06**	1.03*	1.03*	.97	.99	.99
More than 6 Blocks	1.00	1.00	1.00	1.00	1.00	1.00**

Note. Knox Ratios in ***bold italicized*** font indicate a near repeat pattern (KR ≥ 1.20 and $p < .05$).
$^{**}p < .001$; $^{*}p < .05$.

Table 3 Near repeat analysis Knox Ratios: motor vehicle theft

	4 Days					
Time / Distance	0 to 4 days	5 to 8 days	9 to 12 days	13 to 16 days	17 to 20 days	More than 20 days
Same location	***10.96*****	1.12	***1.66****	.92	.93	.77
1 Block	***1.45****	***1.31****	***1.35****	1.12	.98	***1.35****
1–2 Blocks	***1.31*****	1.16	1.04	1.15	.95	1.11
2–3 Blocks	***1.26****	***1.48*****	1.10	.98	***1.21****	.99
3–4 Blocks	1.09	1.06	***1.23*****	.95	1.04	1.07
4–5 Blocks	1.06	1.08	1.04	1.02	1.03	.93
5–6 Blocks	1.09	1.07	1.01	1.10	1.01	1.02
More than 6 Blocks	1.03	1.07	1.03	.99	.94	1.01
	7 Days					
Time / Distance	0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	More than 35 days
Same location	***7.88*****	***1.61*****	***1.38****	.82	***1.35****	.84
1 Block	***1.52*****	***1.31*****	1.04	1.14*	***1.35*****	.97
1–2 Blocks	***1.26*****	1.15*	1.06	1.09*	1.04	.99
2–3 Blocks	***1.30*****	1.15**	1.10*	1.12*	.97	.99
3–4 Blocks	1.08*	1.15**	1.03	.99	1.11*	.99
4–5 Blocks	1.11**	1.07*	1.01	1.00	.98	1.00
5–6 Blocks	1.08*	1.12**	.96	1.01	1.02	1.00
More than 6 Blocks	1.00	1.00	1.00	1.00	1.00	1.00**
	14 Days					
Time / Distance	0 to 14 days	15 to 28 days	29 to 42 days	43 to 56 days	57 to 70 days	More than 70 days
Same location	***3.79*****	.81	1.19	1.01	.69	.80
1 Block	***1.36*****	1.09	1.06	.99	.96	1.07
1–2 Blocks	1.18**	1.05	1.03	1.01	1.06	.91
2–3 Blocks	***1.24*****	1.08*	.95	.97	.98	.95
3–4 Blocks	1.13**	.98	1.06	.95	1.02	1.01
4–5 Blocks	1.06*	1.00	.99	1.01	.99	1.09*
5–6 Blocks	1.07*	1.02	.98	1.00	.97	1.04
More than 6 Blocks	1.03	1.02	1.00	.97	1.03	.99

Note. Knox Ratios in ***bold italicized*** font indicate a near repeat pattern (KR ≥ 1.20 and $p < .05$).
$^{**}p < .001$; $^{*}p < .05$.

and between 3 and 4 blocks (Knox Ratio = 1.23). Motor vehicle theft exhibited a nearly identical near repeat pattern in the 7-day band as the 4-day band, with significant near repeat patterns present up to 3 blocks from initiator events. During the 8- to 14-day period, near repeat patterns were 31% more like within 1 block, with a repeat victimization pattern also observed (Knox Ratio = 1.61). In the 14-day band, near repeat patterns were only observed between 0 and 14 days within 1 block (Knox Ratio = 1.36) and within 2 and 3 blocks (Knox Ratio = 1.24). This suggests that the spatiotemporal patterning of motor vehicle theft remained stable from 4 to 7 days, with the elevated risk dissipating during the 14-day period.

The cumulative near repeat findings suggest that, for residential burglary, places nearby an initiator event are most at-risk during the subsequent 4-day period. The risk of spatiotemporal clustering for residential burglary significantly reduces when the temporal bandwidth extends to 7 and 14 days. For motor vehicle theft, spatiotemporal clusters were similar in the 4-day and 7-day bands, which suggests nearby areas are similarly at risk during both periods. 14-days after an initiator event, however, the spatiotemporal clustering of motor vehicle theft changes in scope.[11]

Explanatory Factors of Initiator and Near Repeat Events

Following the calculation of Knox Ratios, we used the near repeat calculator to classify each incident as an initiator, near repeat, or isolate event. The NRC requires users to specify the temporal and spatial bands to search for spatiotemporal chains. In doing so, we identified what Youstin et al. (2011) refer to as "gradient-like decay patterns" in the near repeat analysis findings. We sought instances where spatiotemporal clustering was evident across consecutive spatial bands. As previously mentioned, spatiotemporal patterning of residential burglary was most salient in the 4-day band, specifically within 0 and 4 days from an initiator event. For residential burglary, temporal parameters were set to between 0 and 4 days while the spatial parameters were set to between 0 and 1,302 feet (3 blocks). For motor vehicle theft, near repeat

11. To determine whether the 4-day patterns were driven by crimes occurring within 1-day bands, we ran near repeat models with 1-day temporal bands for both residential burglary and motor vehicle theft. In both situations, the observed 1-day patterns were unique from the 4-day patterns, which suggests that the 4-day and 1-day patterns are not interrelated. For residential burglary, near repeat patterns extended out to 5 blocks in the 0 to 1 day period. Within 2 days, a "donut" type pattern was observed where near repeat clusters occurred within 4 blocks and between 4 and 5 blocks, but not between 3 and 4 blocks. For motor vehicle theft, near repeat patterns extended through 2 blocks in the 0 to 1 day period with a significant repeat victimization pattern (i.e. same location) evident in the 2-day band. For both crime types, the 1-day patterns significantly differed from the gradient pattern used to classify initiator events: up to 3 blocks within 0 to 4 days. Given space constraints, findings of the 1-day models are not presented in text, but the interested reader can obtain the findings of the sensitivity analysis from the lead author upon request.

patterns were nearly identical in the 4-day and 7-day bands, so either band would have made an appropriate parameter for the identification of initiators. However, to allow for more valid comparisons with the residential burglary results, the temporal parameters for motor vehicle theft were set to between 0 and 4 days while the spatial parameters were set to between 0 and 1,302 feet (3 blocks). Out of 11,536 residential burglaries, the NRC identified 2,536 as initiator events and 1,712 as near repeat events. Out of the 4,991 motor vehicle thefts, the NRC identified 802 as initiator events and 592 as near repeat events.[12]

We began our exploration of initiator and near repeat events by visualizing their spatial distribution. We first employed the technique employed by Ratcliffe and Rengert (2008) in Philadelphia, which identified patterns of initiator events across police sectors. Ratcliffe and Rengert's (2008) technique was meant to aid in proactive police deployment by identifying sectors with disproportionate levels of initiator events. In Figure 1, we code Indianapolis patrol zones according to their observed location quotient, which compares the count of initiators in the patrol zone with the general distribution of crimes across Indianapolis. Location Quotients are calculated via the following formula:

$$\mathrm{LQ} = (i_n/t_n)/(i_N/t_N)$$

where *i* is the frequency of the disaggregate event of interest (initiator events), *t* is the frequency of the aggregate event of interest (all crime incidents), *n* is the subset location (police patrol zone) and *N* is the entire region (Indianapolis) (Brantingham & Brantingham, 1997). Adapted from regional planning, Location Quotients allow for the easy identification of areas with crime (in this case, initiator events) levels that are higher, lower, or at the expected region-wide rate.

12. To test the robustness of our findings to alternate geocoding methods, we re-conducted each of the near repeat analyses using the data entirely geocoded to street centerlines, as described in footnote 2. The results of these alternate models are not qualitatively different from the main analysis. While the Knox Ratios were often slightly different, all cells suggestive of a near repeat pattern (i.e. Knox Ratio ≥ 1.20 and $p < .05$) in the main analysis were maintained in the sensitivity analysis. While the street centerline data produced three additional significant near repeat patterns (2 for residential burglary and 1 for motor vehicle theft) these cells fell far outside of the gradient-like pattern described by Youstin et al. (2011). For residential burglary, one additional near repeat pattern was observed within 1-block from 29 to 42 days in the 14-day model and an additional near repeat pattern was observed within 3–4 blocks from 9 to 12 days in the 4-day model. The lone additional significant pattern for motor vehicle theft was observed within 3–4 blocks from 8 to 14 days in the 7-day model. In each instance, the additional significant near repeat pattern would not have informed our identification of the near repeat gradient given that they did not fall within clusters of near repeat patterns (i.e. significant findings across consecutive bands). While space constraints prevent us from displaying the contingency tables in text, the interested reader can obtain the findings of the sensitivity analysis from the lead author upon request.

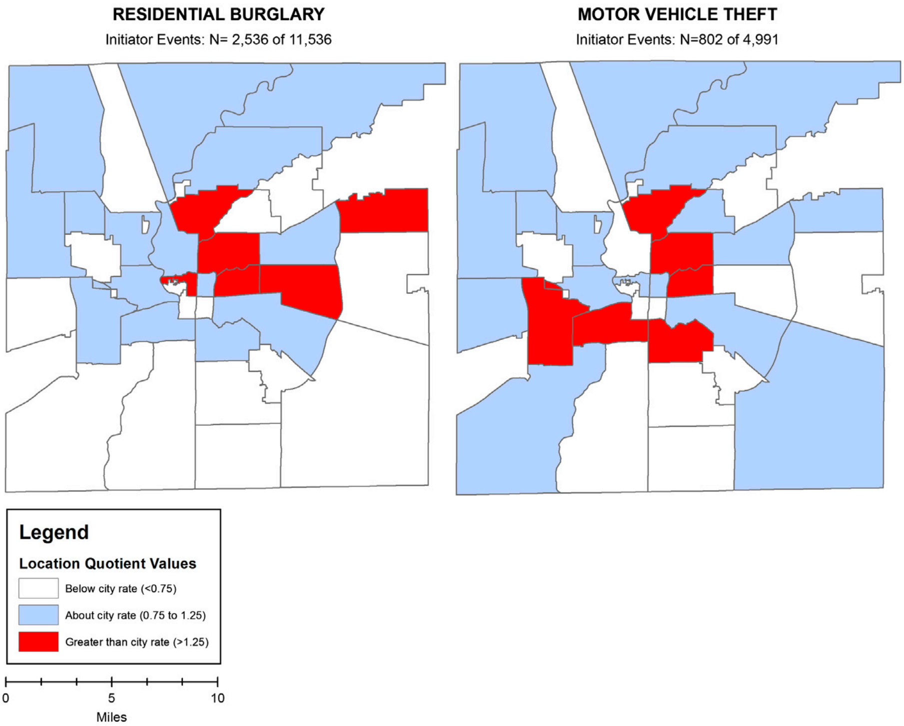

Figure 1 Location quotient values for initiator incident totals across police zones.

With a total of 2,536 of 11,536 residential burglaries classified as initiator events, we would expect about 23% of incidents in each Patrol Zone to be initiators. For motor vehicle theft, the expected rate of initiators is about 11% (529 of 4,991). As evident in Figure 1, 6 of Indianapolis' 33 Patrol Zones experienced a higher than expected initiator rate for residential burglary while 6 zones experienced a higher than expected initiator rate for motor vehicle theft. The three police zones in the central portion of the city had higher than expected initiator rates for both crime types. For residential burglary, 2 additional high-initiator zones appeared to the east of the city center while the remaining high-initiator zone lay adjacent, directly to the west of the city center. For motor vehicle theft, the 3 additional high initiator zones were southwest of the city center.

As argued by Ratcliffe and Rengert (2008), identifying zones with higher than expected initiator events can help identify target areas for crime prevention activity. However, while the aforementioned approach identifies meso-level areas worthy of intervention it does not highlight the micro-places within the patrol zones at highest risk for near repeat patterns. This is an important caveat, as the crime-and-place literature has consistently demonstrated that crime concentrates in micro-units, such as street segments and intersections, and that focusing resources towards such units generates consistent crime

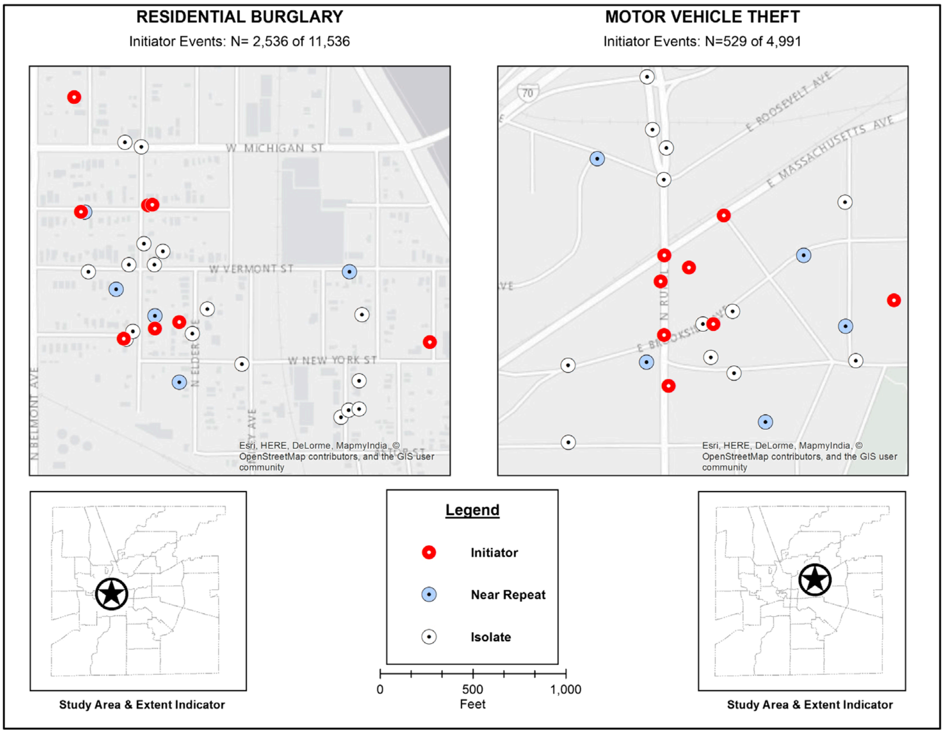

Figure 2 Residential burglary and motor vehicle theft in high-initiaor zones.

control benefits (Braga, Papachristos, & Hureau, 2014; Weisburd, 2008). With this in mind, Figure 2 displays residential burglary and motor vehicle theft incidents occurring in high-initiator patrol zones, with incidents coded according to whether they were an initiator event, a near repeat event, or an isolate. The initiator events can be considered the most influential of the incident types, as they are the causes of subsequent near repeat crime patterns, meaning their occurrence generates additional crimes. Figure 2 allows for more precise identification the micro-level places that could be targeted by police to prevent near repeat patterns. Of course, an incident becomes an initiator only after a near repeat pattern emerges. Police would need to first determine the likelihood of a given crime event generating a near repeat pattern before deploying resources to the immediate area. It is with this aim in mind that we conducted the multinomial logistic regression analysis.

Table 4 displays the results of the multinomial logistic regression models for residential burglary. Findings are reported as Relative Risk Ratios (RRR), exponentiated model coefficients commonly interpreted as Odds Ratios. Two *Geographic Edges* were significantly related to the occurrence of near repeat events, though in opposite directions. Proximity to railroad tracks was associated with a decreased likelihood (RRR = .83) while proximity to a river was associated with increased likelihood (RRR = 1.44) of an incident being a near repeat event. All 5 *Social Disorganization* variables were significantly related

Table 4 Multinomial logistic regression findings: residential burglary

	Near repeat event				Initiator event			
Independent variables	R.R.R.	S.E.	*z*	*p*	R.R.R.	S.E.	*z*	*p*
Crime Generators								
ATMs & banks	1.00	.07	.12	.90	.97	.06	−.44	.66
Bars	.88	.09	−1.14	.25	.87	.09	−1.41	.16
Liquor stores	1.11	.14	.86	.39	.91	.10	−.81	.42
Parks	.95	.07	−.73	.47	.90	.06	−1.62	.11
Pawn shops	.94	.22	−.28	.78	.79	.18	−1.03	.30
Trailer parks	.95	.17	−.32	.75	.89	.14	−.71	.48
Geographic Edges								
Patrol zone boundary	.83	.07	−.64	.54	.90	.05	−1.78	.08
Railroad tracks	.83	.07	−2.15	.03*	.86	.07	−2.00	.04*
River	1.44	.24	2.16	.03*	1.57	.23	3.10	.00**
Trails	.95	.12	−.43	.66	1.12	.12	1.10	.27
Social Disorganization (standardized scores)								
Concentrated disadvantage	1.32	.04	9.64	.00**	1.38	.04	12.57	.00**
Geographic mobility	1.08	.04	2.26	.02*	1.08	.03	2.62	.01**
Housing density	1.28	.04	8.80	.00**	1.36	.03	12.70	.00**
Racial heterogeneity	1.17	.04	4.92	.00**	1.23	.03	7.51	.00**
Young male population	.87	.03	−4.26	.00**	.87	.02	−4.98	.00**
Date of Occurrence								
Qtr. 1 (Jan.—Mar.)	.75	.06	−3.45	.00**	.81	.06	−2.98	.00**
Qtr. 2 (Apr.—Jun.)	.95	.07	−.63	.53	.97	.06	−.39	.70
Qtr. 3 (Jul.—Sep.)	1.12	.08	1.49	.14	1.19	.08	2.69	.01**
Weekend (Fri.—Sun.)	1.12	.06	2.07	.04*	.96	.05	−.83	.41
Model								
Log =	−10,063.37							
Wald X^2 =	783.04							
N =	11,536							

Note. Qtr. 4 (Oct.—Dec.) is the reference category for the Qtr. variables.
$^{**}p \le .01$; $^{*}p \le .05$.

to the occurrence of near repeat events. Concentrated disadvantage (RRR = 1.33), geographic mobility (RRR = 1.08), housing density (RRR = 1.28), and racial heterogeneity (RRR = 1.17) were each associated with an increased likelihood of a motor vehicle theft being a near repeat event. Each 1-unit increase in the young male population decreases the likelihood of an incident being a near repeat event by a factor of .87. Two *Date of Occurrence* variables achieved statistical significance. Residential burglaries occurring during quarter 1 (Jan.—Mar.) were significantly less likely to be a near repeat event (RRR = .75) while incidents occurring on weekends were 12% more likely to be a near repeat event (RRR = 1.12). These findings were largely replicated for

Table 5 Multinomial logistic regression findings: motor vehicle theft

	Near repeat event				Initiator event			
Independent variables	R.R.R.	S.E.	*z*	*p*	R.R.R.	S.E.	*z*	*p*
Crime Generators								
ATMs & banks	1.30	.13	2.62	.01**	1.35	.12	3.37	.00**
Bars	1.06	.15	.26	.79	1.07	.14	.49	.62
Liquor stores	1.15	.18	.89	.37	1.04	.15	.24	.81
Parks	1.14	.14	1.10	.27	1.14	.12	1.21	.23
Pawn shops	1.46	.38	1.45	.15	1.49	.35	1.67	.10
Trailer parks	1.07	.26	.26	.80	.77	.19	−1.04	.30
Geographic Edges								
Patrol zone boundary	.99	.10	−.03	.97	.97	.09	−.28	.78
Railroad tracks	.98	.13	−.15	.88	1.11	.12	.97	.33
River	.89	.24	−.42	.67	.57	.16	−2.04	.04**
Trails	1.08	.20	.40	.69	1.05	.17	.29	.77
Social Disorganization (standardized scores)								
Concentrated disadvantage	1.20	.06	3.10	.00**	1.21	.06	4.18	.00**
Geographic mobility	1.07	.06	1.23	.22	1.14	.05	2.83	.01**
Population density	1.11	.05	2.12	.03*	1.10	.05	2.33	.02*
Racial heterogeneity	1.11	.06	1.94	.05*	1.13	.05	2.47	.01**
Young male population	.93	.05	−1.29	.20	.98	.05	−.51	.61
Date of Occurrence								
Qtr. 1 (Jan.—Mar.)	.84	.11	−1.42	.16	.83	.09	−1.67	.09
Qtr. 2 (Apr.—Jun.)	.79	.10	−1.82	.07	.74	.08	−2.61	.01**
Qtr. 3 (Jul.—Sep.)	.89	.11	−.96	.34	.86	.09	−1.44	.15
Weekend (Fri.—Sun.)	1.01	.09	.11	.92	1.11	.09	1.26	.21
Model								
Log =	−3812.58							
Wald X^2 =	157.68							
N =	4,991							

Note. Qtr. 4 (Oct.—Dec.) is the reference category for the Qtr. variables.
$^{**}p \leq .01$.; $^{*}p \leq .05$.

initiator events. Each of the variables significant for near repeat events maintained significance for initiator events, with similar RRR values suggestive of a relationship of comparable magnitude and identical direction. There were two exceptions. Weekend, significant for near repeats, did not achieve statistical significance for initiator events. Furthermore, while unrelated to near repeat events, occurrence during quarter 3 (Jul.—Sep.) was associated with a 19% greater likelihood of an incident being an initiator event.

Table 5 displays the results of the multinomial logistic regression models for motor vehicle theft. Incidents occurring in close proximity of ATMs & Banks were

30% more likely to be a near repeat event. All other statistically significant predictors of near repeat motor vehicle thefts were *Social Disorganization* variables. 1-unit increases in concentrated disadvantage, population density, and racial heterogeneity were associated with 20, 11, and 11% increased likelihoods, respectively, of a motor vehicle theft being a near repeat event. Findings for initiator events were similar. Motor vehicle thefts occurring in close proximity to ATMs & banks were 35% more likely to be an initiator event. As with near repeat events, initiator events were most often predicted by *Social Disorganization* variables. The likelihood of a motor vehicle theft being an initiator event was significantly related to increased levels of concentrated disadvantage (RRR = 1.21), geographic mobility (RRR = 1.14), population density (RRR = 1.10), and racial heterogeneity (RRR = 1.13). A single *Geographic Edge* achieved statistical significance, with proximity to a river was associated with decreased likelihood (RRR = .57) of an incident being an initiator event. As for the *Date of Occurrence* variables, motor vehicle thefts occurring during quarter 2 (Apr.—Jun.) were significantly less likely to be an initiator event (RRR = .74).

Discussion and Conclusion

Findings from the present study are discussed in terms of the nuanced spatiotemporal patterns of crime in Indianapolis as well as in the context of near repeat, crime and place, and crime prevention literatures. To begin, findings of the near repeat analyses support prior research. While near repeat patterns were evident for both residential burglary and motor vehicle theft, spatiotemporal footprints differed. The observed near repeat pattern for motor vehicle theft was more spatially expansive than residential burglary, with spatiotemporal clusters extending out to three blocks for each tested temporal band (4, 7, and 14 days). Prior research testing multiple crime types has similarly found motor vehicle theft to have the most expansive pattern (Youstin et al., 2011), as research suggests motor vehicle offenders are willing to travel further in search of crime opportunities than other offenders (Wiles & Costello, 2000).

The present study employed measures of social disorganization and environmental placed-based features to explain near repeat patterns of burglary and vehicle theft. In sum, these measures attempt to capture what Brantingham and Brantingham (1993, p. 6) refer to as the environmental backcloth, "elements that surround and are part of an individual and that may be influenced by or influence his or her criminal behavior." While crime-and-place scholars have operationalized the environmental backcloth in explaining crime at the micro-level, it has also been used to explain the variation of micro-level crime within meso-level areas (Groff, 2015). While community structure is central to patterns of crime, these factors do not solely predict where crime occurs. Weisburd et al. (2012) observed that a few streets within both low and high socially disadvantaged neighborhoods consistently accounted for a high proportion of crime in larger community areas. As noted by Braga and Clarke (2014), such micro-places have place-level characteristics that distinguish them from low crime places in the same neighborhoods and future spatiotemporal inquiries should include place-based variables that help to define urban form and accessibility. The present study incorporated measures of social disorganization in addition to crime generators and geographic edges in an attempt to capture the environmental backcloth in which initiator events and near repeat patterns of burglary and motor vehicle theft occur in Indianapolis.

Findings of the multinomial logistic regression models found that *Social Disorganization* variables were most predictive in both the residential burglary and motor vehicle theft models. All five *Social Disorganization* variables were significantly associated with the occurrence of both near repeat and initiator residential burglary events. Young male population was associated with decreased likelihood of both near repeat and initiator events, while the other four social disorganization measures were positively associated with both types. The effect of *Social Disorganization* on motor vehicle theft was more nuanced. Concentrated disadvantage, population density, and racial heterogeneity were each positively associated with both near repeat and initiator events. Geographic mobility, while not associated with near repeat events, was significantly related to increased likelihood of initiator events. The disparate findings of the models suggest that all *Social Disorganization* variables provide comparable utility in the analysis of residential burglary, while, for motor vehicle theft, predictive value varies across variables.

At the individual level, near repeat events are spurred by the boost hypothesis wherein offenders continue to victimize successful targets and also communicate information about successful crime to their co-offenders (Nobles et al., 2016). The flag hypothesis argues repeat events are best explained through the variation of time-stable risk factors across the landscape, as derived from risk heterogeneity theory (Sparks, 1981). Our findings indicate that near repeat patterns of burglary and motor vehicle theft largely occur at the same location or within a city block contained within larger communities. These findings, and that of other near repeat studies, provide further evidence for the need to more closely examine micro-place characteristics and the effects of collective efficacy in micro-places.

Our study is the first to our knowledge to incorporate both meso-level (*Social Disorganization*) and micro-level (*Crime Generators* and *Geographic Edges*) place-based features of near repeat crime patterns. The different levels of spatial measurement provide complimentary benefits to the analysis. The social disorganization variables highlight characteristics of neighborhoods that are more susceptible to near repeat crime patterns while the micro-level variables identify places within the neighborhood that can promote or mitigate the emergence of near repeat patterns. Crime generators and geographic edges differentiate these micro-places from the broader community structure of the area. Indeed, geographic edges have a significant effect on near repeat and initiator burglary events in Indianapolis, with rivers associated with increased risk of both near repeats and initiators and railroad tracks associated with decreased likelihood of both event types. Rivers were associated with a decreased risk of initiator events in the motor vehicle theft models. Interestingly, rivers seemed to differentially influence residential burglary and motor vehicle theft, creating increased risk of near repeat patterns in the former and decreased risk of the latter. An explanation for this finding may be that places located along rivers experience minimal non-criminal pedestrian traffic (railroad tracks are more easily traversed than a river) and are less populous relative to other areas in the city. Thus, burglary offenders perceive a lack of guardianship from persons other than the target's resident, thereby increasing the suitability of the target. Conversely, the lack of pedestrian traffic may have created a situation whereby motor vehicles were less at risk of theft, meaning that individual theft incidents were unlikely to generate near repeat patterns (i.e. less likely to be an initiator event).

Crime Generators were only significant in the motor vehicle theft model, with ATMs and banks positively associated with both near repeat and initiator events. Given the increased pedestrian traffic around such facilities, these places may have provided necessary levels of deniability for offenders to "blend-in" at a particular area prior to crime commission. Prior research has highlighted the importance of deniability for a range of crime types that occur in public, including motor vehicle theft and recovery (Piza et al., 2016), robbery (St. Jean, 2007), and open-air drug dealing (Piza & Sytsma, 2016; St. Jean, 2007). This suggests that pedestrian traffic may have differential effects for indoor and street-level crime. In the case of residential burglary, decreased pedestrian traffic may mean that offenders are less likely to be seen breaching the exterior of a dwelling. For motor vehicle theft, high levels of pedestrian traffic may allow offenders to remain inconspicuous in public while they prepare to steal a vehicle from the street.

These findings suggest that tenets of environmental criminology play a role in understanding the occurrence of near repeat and initiator events, but in a much more nuanced manner than social disorganization. In both models, most (and, in the case of residential burglary, all) social disorganization measures were significant, and most often indicative of increased likelihood of event (near repeat or initiator) occurrence. Fewer environmental criminology (crime generators and geographic edges) measures achieved statistical significance, with a greater mix of positive and negative associations. This suggests that social disorganization can primarily be used to identify incidents to direct crime prevention resources towards, while environmental criminology can also identify incidents where resources can be diverted away from, due to the significantly decreased likelihood of subsequent crime events.

Despite these findings, this study, like most others, suffers from specific limitations that should be mentioned. The robustness of the analysis would have improved with the inclusion of additional situational variables pertaining to the suspects and victims of the crime incidents. In addition, the type of housing structure and automobile make/model would have been welcome additions to the residential burglary and motor vehicle theft analyses, respectively.

Unfortunately, such data was not accessible. Regarding the geospatial variables, while we made every effort to include an exhaustive set of crime generators in the analysis, we were limited to what was obtainable via available data sources. In particular, commonly observed crime attractors, such as drug markets and prostitution strolls, were not able to be measured in the study area. Due to the fact that we did not have information on the suspects, we were unable to test whether the involvement of prior offenders influenced the occurrence of initiator events. While prior near repeat studies have suffered from the same limitation, future research should strive to include offender-specific variables when attempting to forecast initiator events thereby lending insight into the boost hypothesis. Lastly, our analyses leverages burglary and motor vehicle theft offenses reported to IMPD and does not capture incidents that go unreported. Estimates from the National Crime Victimization Survey (NCVS) suggest only 58% of residential burglaries (Walters, Moore, Berofsky, & Langton, 2013) and 87% of motor vehicles thefts (Truman & Rand, 2010) are reported to the police. Thus, our analyses do not capture all incidents that do occur and likely does not identify originator or near repeat events that may occur. However, given that all prior near repeat studies similarly uses reported crime incidents, this limitation is not exclusive to the current study.

Given these qualifications, we feel that this study is a valuable contribution to the near repeat, crime and place, and crime prevention literatures. Findings from this study can be considered in tandem with the established body of evidence in support of hot spots policing strategies (Braga et al., 2014) and the emerging literature focused on micro-time hot spots (Santos & Santos, 2015a) to inform recommendations for policy. As argued by Caplan et al. (2013, p. 260), an advantage of near repeat analysis is the ability to prioritize each new crime incident according to its propensity for generating or sustaining a spatiotemporal pattern. Such information can better focus police resources by identifying micro-places experiencing crime events that are most likely to generate subsequent near repeat events.

In a series of recent studies by Robert and Rachel Santos, a crime analysis approach akin to near repeat analysis has emerged to direct tactical police responses to micro-time hot spots, or crime "flare ups", of residential burglary and thefts from vehicles. This line of research comes from an *ex post facto* quasi-experimental study in Port St. Lucie, Florida where a micro-time hot spot was operationalized as (1) two or more crimes; (2) occurring from one to 14 days of another; and (3) within a .79 square mile radius (Santos & Santos, 2015a, 2015b, 2015c). The authors contend that micro-time hot spots are "… unpredictable, short in duration and, if left alone, will run its course and eventually end. Thus, an effective response implemented as soon as the micro-time hot spot begins will shorten its duration and severity" (Santos & Santos, 2015a, p. 682). Such an immediate tactical police response can reduce overall levels of crime by intervening in a sequence of near repeat crimes. Results demonstrated that tactical police intervention in micro-time hot spots led to a significant 20% decrease in both thefts from vehicles (Santos & Santos, 2015a) and residential burglary (Santos & Santos, 2015c).

Findings of the current study can also help refine and focus interventions such as those deployed in Port St. Lucie. Given the current fiscal environment, police departments may not have the necessary resources to respond to each micro-hot spot. Systematically responding to micro-hot spots may be especially challenging in large cities like Indianapolis, which has a land area (361.43 square miles) over three times the size of Port St. Lucie (113.95 square miles). Therefore, identifying explanatory variables significantly related to near repeat patterns can help police prioritize micro-hot spots for police response. Regarding the current study, IMPD can prioritize incidents occurring in areas with high levels of social disorganization. Within such areas, directed patrols can be deployed to the 3-block area surrounding residential burglary and motor vehicle theft events for a period of 4 days to prevent near repeat crime patterns. The environmental criminology measures can also be incorporated to further refine resource deployment. For example, residential burglaries nearby railroad tracks in Indianapolis should receive a lower priority for directed patrol response when weighed against events in areas absent these features. Conversely, events in close proximity to rivers should receive an immediate tactical response in the hopes of preventing near repeat burglaries. Motor vehicle thefts could be similarly prioritized based upon proximity to ATMs and banks as well as rivers. Criminologists should continue to advance this line of research and seek to further inform the theoretical foundation and practical outcomes of near repeat and initiator events.

Finally, our study highlights a pertinent underexplored issue within the near repeat literature. A review of the literature, and through the process of fully describing our analytic approach, reveals a troubling trend in transparency of near repeat studies—the failure of scholars to delve into the specifics of their data geocoding. Of the 22 near repeat studies cited in this article, 17 do not indicate how incidents were geocoded, 3 employ street centerline, 1 employs city block centroid, and 1 uses a combination of building, parcel, and street centerline. Though the findings of our sensitivity analysis suggest that geocoding method may not have much of an effect, we urge scholars to report their geocoding procedures, not only for near repeat studies, but any empirical examination that employs a geocoding process. This is increasingly important given the growing academic interest in place-based social inquiry.

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