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"A Plague on both Your Houses?": Risks, Repeats and Reconsiderations of Urban Residential Burglary

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Research has shown that mapping techniques are useful in forecasting future crime events. However, the majority of prospective mapping techniques has focused on the event-dependent influence of instigator incidents on subsequent incidents and does not explicitly incorporate the risk heterogeneity of the setting. The study here discussed is a modest attempt to address this issue by using a two-step process: first, using risk terrain modeling, we operationalized the "environmental backcloth," (the risk heterogeneity of an area) to forecast locations of residential burglaries in the urban city of Newark, New Jersey. Second, using the near repeat calculator, we assessed the variability of underlying risk between different types of residential burglaries. A discussion of the findings and the joint utility of these approaches is provided.

Keywords environmental criminology; spatial risk analysis; risk terrain modeling; near repeat phenomenon; GIS

With the exception of some studies (e.g. Groff & La Vigne, 2001, 2002; Johnson, Bowers, Birks, & Pease, 2009), the majority of prior research on prospective residential burglary mapping has focused on "hot spots" and

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incident-based maps without including the place-based factors that provide an optimal setting for burglaries. Specifically, research has been limited in the conceptualization and operationalization of the environmental backcloth (Brantingham & Brantingham, 1993a) that is most conducive for burglaries. Hot spot and incident-based approaches primarily address the concept of "event dependency" and leave questions pertaining to varying levels of *initial* risk or "risk heterogeneity" unanswered.

Research has shown that crime is not evenly distributed, tends to concentrate, and is stable at places over time (Braga, Hureau, & Papachristos, 2011; Braga, Papachristos, & Hureau, 2010; Sherman, 1995; Sherman, Gartin, & Buerger, 1989; Weisburd, Bushway, Lum, & Yang, 2004). Arguably, such concentration and stability is a manifestation of the underlying variability of risk among neighborhoods and places within neighborhoods. Heightened levels of risk can be associated with increased opportunities for criminal acts (Caplan, Kennedy, & Miller, 2011a). Indeed, it has been argued that measures of risk can be used as a proxy to measure opportunities of crime (Kennedy & Van Brunschot, 2009). In this paper, we assess whether underlying concentrations of risk—as defined by the criminogenic environmental backcloth—is associated with incidents of residential burglary, even when controlling for the contagion effects related to the near repeat phenomenon. We hypothesize that micro-level places with higher values of risk will provide more suitable opportunities for offenders to commit burglaries and will, therefore, have more residential burglary incidents compared to places with lower risk values. Additionally, we hypothesize that underlying levels of risk will vary between different types of residential burglary incidents.

The current study employs a two-part analytical approach to forecast locations of residential burglaries, including instigator[1] incidents and near repeat incidents in the urban city of Newark, New Jersey, USA. An instigator incident refers to the initial burglary in a near repeat pairing, while the near repeat refers to a subsequent incident that is both spatially and temporally close to the instigator. First, risk heterogeneity was measured using the risk terrain modeling (RTM) approach. Risk heterogeneity was conceived to be the spatial influence of place-based characteristics of the environmental backcloth and person-environment interactions. In other words, risk heterogeneity was proposed as the baseline level of risk of an area; therefore, places with high levels of risk should have more residential burglaries compared to areas of lower risk.

Second, the near repeat calculator was used to assess whether the near repeat phenomenon was present in Newark in 2010. When found, the baseline level of risk for instigator and near repeat (the subsequent burglary in a near-repeat pairing) residential burglaries was compared, and assessed to determine whether near repeat burglary incidents were also explained by differences in

1. Other authors have referred to the initial event in a near repeat pair as "originators" as well. We use the term "instigators" since the term appears more frequently in the literature.

underlying levels of place-based risk rather than strictly event-dependent incidents alone.

Theoretical Background

The Environmental Backcloth

The "environmental backcloth" refers to the "elements that surround and are part of an individual and that may be influenced by or influence his or her criminal behavior" (Brantingham & Brantingham, 1993b, p. 6). Both the physical characteristics of places (e.g. buildings, public transportation stops, etc.) and the influence of such characteristics on the surrounding landscape based on individual cognitive assessments and routine activities contribute to the environmental backcloth. In other words, the environment is not merely a setting or a backdrop in which criminal and non-criminal behaviors occur, but rather a dynamic context comprised of the person-environment nexus involving interactional feedback loops and day-to-day situations, including both criminal and non-criminal activities.

The surrounding environment is very much a part of any criminal activity—as the environment emits cues which may or may not affect an offender's decision making or daily routines. For example, crime generators and attractors will invariably impact how individuals view their environment; what signals they receive from it; and what type of behavior they believe they can participate in (Brantingham & Brantingham, 1995). Additionally, the presence of particular risky facilities (Clarke & Eck, 2007) can provide criminogenic opportunities. Other aspects like the demographic, economic, socio-cultural, legal and spatiotemporal characteristics of an area may also be considered (Brantingham & Brantingham, 1993b). Most factors that comprise the environmental backcloth fit into three broad categories[2]: (i) physical characteristics; (ii) demographic, socio-economic, and cultural characteristics; and (iii) person-environment characteristics. For the specific purposes of this study, we focused on the physical and person-environment aspects of the environmental backcloth that influence burglary target selection.

Factors Influencing Target Selection of Residential Burglars

Target selection for residential burglary has been explained in several ways. Numerous studies viewed it as a sequential, multi-level process typically involving general site selection first (e.g. neighborhood) and then the selection of a specific target (e.g. residence) (Bennett & Wright, 1984; Brown & Altman, 1981; Cromwell, Olson, & Avary, 1991; Wright & Decker, 1994). From a routine

2. These categories are not mutually exclusive and overlap can occur.

activities perspective (Cohen & Felson, 1979), target selection most likely occurs during the course of "everyday movement" rather than journeys undertaken for the explicit purpose of identifying crime opportunities (Felson & Clarke, 1998). Brantingham and Brantingham (1993b) have illustrated crime patterns to be shaped by an offender's specific activity nodes and the paths traveled between them. An offender's daily temporal behavior patterns may constrain their level of movement, resulting in low-levels of familiarity with areas outside of their routine travels (Ratcliffe, 2006). Recognizing such constraints is vital in understanding the variability in risk amongst seemingly equal targets (Beavon, Brantingham, & Brantingham, 1994).

While the levels of target selection are categorized separately, they are not independent from one another. Neighborhood-level characteristics will affect individual-level decisions and behaviors and vice versa. This is especially the case with respect to target attractiveness and spatial attractiveness (Rhodes & Conly, 1981). Target attractiveness refers to the rewards and costs (e.g. investments[3] and risk of apprehension) associated with a particular neighborhood; spatial attractiveness refers to the favorable or unfavorable spatial characteristics of a neighborhood landscape from an offender's perspective.

As argued by Bernasco (2006, p. 141), assessing neighborhood level (or place-based) attributes for burglary is a crucial starting point in any assessment of burglary since it unravels important "implicit or explicit rules regarding which areas are suitable for burglary and which areas are not." The spatial influence of neighborhood characteristics can be divided into how places influence neighborhoods and how individuals influence neighborhoods. Place-based influence refers to physically identifiable infrastructure while individual-based influence refers to identifiable behavior of individuals or groups. For example, a pawn shop is a physical structure that can be identified and measured by land use data. On the other hand, open-air drug markets, while commonly correlated with certain environs (Harocopos & Hough, 2005; McCord & Ratcliffe, 2007), are primarily identifiable through the behaviors of individuals. The spatial influence of neighborhood characteristics has been well founded through spatial analyses and ethnographic offender-based research (e.g. Brantingham & Brantingham, 1993b; Caplan, 2011; Freundschuh & Egenhofer, 1997). For example, it has been argued that the presence of connectors, such as public transit and major highways, facilitates the expansion of offenders' cognitive awareness and activity spaces for both non-criminal and criminal activities (Brantingham & Brantingham, 1984, 1993b).

Another place relevant to residential burglary is the residence of the burglars themselves. Both spatial analysis and ethnographic interviews with known burglars have shown that they tend to offend within close proximity to their homes or other nodes (Bennett & Wright, 1984; Bernasco, 2006; Bernasco & Nieuwbeerta, 2005; Forrester, Chatterton, & Pease, 1988; Rengert &

3. Investment refers to the costs, tools and general requirements of "doing business" to execute an offense for an offender (Rhodes & Conly 1981, 170).

Wasilchick, 1985; Wright & Decker, 1994). Additionally, Kleemans (2001) argues that residences located near burglars are not only at higher risk of an initial burglary, but also of a repeat burglary. Most burglars offend in order to obtain cash or products that can be easily converted into cash (Bennett & Wright, 1984; Wright & Decker, 1994). Quick access to cash may be required in order to sustain their drug or alcohol use (Cromwell et al., 1991; Mawby, 2001; Wright & Decker, 1994). While some burglars may use a professional fence to sell their stolen goods, or sell merchandise in street-level transactions, others may use pawn shops (Wright & Decker, 1994).

Repeat Victimization and the Near Repeat Phenomenon as Indicators for Target Selection

Realization that a disproportionate amount of victims/targets are victimized on two or more occasions within a specific time period has spawned much research on victimization[4] and offenders (Bernasco, 2008; Farrell & Pease, 1993; Tseloni & Pease, 2003). Explanations for repeat burglaries include burglars coming back to steal items left after the first incident (early repeats), burglars coming back to steal replacement items (delayed repeats), and burglars telling other burglars that a particular residence is a favorable target (Clarke, Perkins, & Smith, 2001; Polvi, Looman, Humphries, & Pease, 1991). On the other hand, near repeat refers to when an incident occurs to two nearby targets within a specific period of time (Morgan, 2001; Pease, 1998; Ratcliffe & Rengert, 2008; Short, D'Orsogna, Brantingham, & Tita, 2009). Near repeats have received a significant amount of interest within the last decade, resulting in fascinating research promoting prospective mapping techniques (Bowers, Johnson, & Pease, 2004; Johnson & Bowers, 2004a, 2004b; Johnson et al., 2007; Townsley, Homel, & Chaseling, 2000). Importantly, near repeat research has not been limited to studying residential burglaries and has been used to analyze shootings (Ratcliffe & Rengert, 2008; Wells, Wu, & Ye, 2012), insurgent activities (Townsley, Johnson & Ratcliffe, 2008) and auto thefts and robberies (Youstin, Nobles, Ward, & Cook, 2011).

As an instigator, incident needs to occur prior to a near repeat, the majority of near repeat research has been incident-based. In other words, studies have looked at the relationship between subsequent incidents to an earlier incident. Some research, however, has recognized the importance of the surrounding physical environment and spatial influence of such structures. In an attempt to include environmental factors in their analysis, Johnson et al. (2009) utilized an event-driven risk surface combining the structural factors of the environment. In another study, Groff and La Vigne (2001, 2002) incorporated an opportunity raster cell surface premised solely on environmental factors that

4. See the edited text by Farrell and Pease (1993) for a comprehensive overview on repeat victimization.

were theoretically supported and found to be empirically related to residential burglary.

With particular relevance to the current discussion on near repeat analysis and the importance of the surrounding environment, Wells et al. (2012) found that clusters of near repeat shootings differed from the concentration of overall shootings. A disaggregate analysis found business locations to be slightly more likely to generate near-repeats than houses and open areas; gang-related shootings generated higher levels of subsequent violence than other incident types. However, none of these differences were statistically significant. Furthermore, the researchers were limited to data on the gun violence incidents themselves (e.g. location type and motivation) and lacked data on environmental features of places (e.g. crime generators and attractors), comprising the environmental backcloth of the near-repeat incidents. Despite this, it is evident that the spatial influence of particular features of the environment is an important component in understanding the occurrence of near repeat incidents as well as instigator incidents.

RTM and Risk Heterogeneity

Building upon the underlying principles of hotspot mapping, environmental criminology and problem-oriented policing, the RTM approach was recently developed as a technical and analytical method to forecast where criminal events are most likely to occur. Originally created to forecast shootings in Irvington, New Jersey (Caplan et al., 2011a), the RTM approach has also been used to successfully forecast other criminal incidents in different settings (e.g. Caplan, Moreto, & Kennedy, 2011b; Kennedy, Caplan, & Piza, 2011). Notably, while RTM has proven useful in forecasting criminal event locations, it also has the added potential of measuring the risk heterogeneity of an area at the micro-level. RTM is based on identifying, conceptualizing, and operationalizing factors to be associated with the specific outcome variable (e.g. residential burglary), and is not dependent on an instigator event to occur. RTM utilizes Geographic Information System (GIS) to attribute qualities of the real world to places on a digitized map. It operationalizes the spatial influence of target selection indicators (e.g. crime risk factors) to common geographic units and then combines separate map layers together to produce "risk terrain" maps showing the presence, absence, or intensity of all risk factors at every location throughout the landscape. In other words, it provides an explanation as to where *both* instigator and subsequent events may occur by shifting attention from the crime events themselves to the underlying factors of the environment.

Study Objectives and Research Setting

This study had two primary objectives. First, we operationalized the environmental backcloth for burglaries to a digital map to articulate the risk heterogeneity of the research setting: Newark, New Jersey, USA. We utilized RTM methods to create a risk surface based on the spatial influence of place-based factors related to residential burglary. Like previous studies using the RTM approach, it was expected that residential burglaries would occur at places with higher levels of risk.

The second objective was a two-pronged test to determine whether the place-based risk levels (e.g. derived from the risk terrain model) influenced the locations of instigator and near repeat incidents of residential burglary in Newark. The first step was to use the near repeat calculator[5] to ascertain whether repeat victimization and/or near repeats occurred. The near repeat calculator was also used to identify how many times an incident was the instigator or near repeat in a near-repeat pair. If the near repeat phenomenon was present, the next task was to map and overlay both instigator and near repeat residential burglary incidents onto the risk terrain map and to assess the place-based risk levels of each type of event locations. As mentioned earlier, prior research has attributed near repeats to the heightened level of risk communicated by an instigator event. Our research objective was to determine whether heightened levels of place-based risk were also present before an instigator event occurred there.

The urban city of Newark, New Jersey was the study setting. Newark is the largest city in New Jersey and one of the most culturally diverse cities in the USA, both in terms of land use and population. Burglary rates are more than double the national average rate with 1,947 compared to 716.3 burglaries per 100,000 people in 2009, respectively (Federal Bureau of Investigation, 2010). The actual study area did not include areas largely comprised of Newark Liberty Airport and the (shipping) Port of Newark. This was done in recognition of the fact that residential burglary does not typically occur in this area,[6] and because large portions of these areas fall within the jurisdiction of the New York/New Jersey Port authority police, and not the Newark Police Department (who are responsible for all other crime in the city). The chance of a "residential" burglary is highly unlikely in an environment entirely comprised of commercial establishments, highways, and industrial parcels.

5. The near repeat calculator is a free, stand-alone software application developed by Ratcliffe of Temple University. It uses the x-, y-coordinate and date of criminal incidents (e.g. in this case, residential burglaries), and assesses any statistically significant spatiotemporal patterns between *all* points within a data set. Spatial and temporal bandwidths and bands are user-defined, but should be based upon empirical research or theoretical explanations. The actual spatiotemporal patterns found in the data set are then compared to an expected pattern if no near repeat phenomenon were to exist using the Monte Carlo method. The near repeat calculator can be downloaded from: http://www.temple.edu/cj/misc/nr/

6. Outside of the airport and port Newark, the only populated portion of this area is a small stretch of highway with hotels, restaurants, and other commercial (non residential) properties. The remainder of the area is comprised of interstate highways with no rest stops in Newark boundaries (e.g. the New Jersey Turnpike) and vacant, inaccessible land.

Methodology and Results

Objective 1 Methods: Operationalizing the Environmental Backcloth to Represent Risk Heterogeneity

The first objective in the study was to operationalize the environmental backcloth, and articulate (with a digitized map) the risk heterogeneity of the study area that was particularly pertinent to residential burglaries. Place-based risk factors of burglary were selected based on the empirical research evidence described earlier. Additionally, discussions with personnel of the Newark Police Department's CompStat unit provided practical experience-based justification for the use of some other factors included in this study. As described by Ratcliffe and McCullagh (2001), the experience of analysts and practitioners should be considered in order to unravel potentially relevant factors.

Initially, there were six risk factors identified for inclusion in the study—land use parcels, at-risk housing complexes, pawn shops, burglar residences, public transportation nodes (bus stops and light rail), and drug markets. Data for this project was collected from the GIS systems of the Newark Police Department and the City of Newark. The following layers were extracted from the Newark Police Department's GIS System: 2010 burglary incidents, "at-risk" housing complexes, 2009 drug arrests, "pawn shop" locations, and residences of known burglars. On a daily basis, Newark Police personnel geocode Part 1 crimes and merge them to "year-to-date" data layers containing all incidents previously occurring in the calendar year. Arrest data is geocoded and updated in a similar manner.[7] In addition to the aggregate "arrest" file, separate data layers capture arrests based on the offense type; Drug arrests data were used in this study. While criminologists have long debated the validity of arrest as a measure of crime, numerous studies have operationalized drug arrests as a proxy for drug markets (Caplan et al., 2011a; Jacobson, 1999; Kennedy et al., 2011; Weisburd et al., 2006; Weisburd & Green, 1995).

In addition to crime and offense activity, Newark's CompStat unit maintains GIS files of facilities of interest throughout the city, one such layer being pawn shops. Newark only has two "pawn shops" in the traditional sense: a commercial establishment that provides a monetary loan to customers who use their personal property as collateral. However, a number of businesses purchase

7. The Newark Police Department has undertaken specific processes to ensure the accuracy of their GIS data. The agency conducted an in-depth audit of their street centerline in 2009 for the purpose of conducting necessary updates to the address data. GIS personnel added streets of newly built housing complexes into the street file and conducted field visits to "unmatched" addresses to determine whether faulty address ranges contained within the street file were preventing the incidents from being mapped. In addition, the agency's GIS "address locator" incorporates a large alias table with over 15,000 records, which automatically corrects common errors in Newark's address data. These processes result in rather high geocoding rates. For example, the hit rate for the burglary data used in this study was near 100%, with only 4 of 2,028 and 1 of 2,401 incidents unable to be geocoded for the years 2010 and 2011, respectively.

used property (e.g. jewelry and electronics) from customers, and are licensed as "second-hand distributors of precious metal, gold, and electronics" by the city of Newark. Since these establishments provide similar opportunities for burglars to fence stolen merchandise as traditional pawn shops, they were considered along with the pawn shop as a singular risk layer in the study. In total, 36 facilities were included in the pawn shops layer.

Residences of known burglars are frequently updated and maintained by the Newark Police Department. Individuals are entered into the "Known Burglar" database for three reasons. Firstly, anyone who has been arrested for committing a burglary (or has been issued a warrant for this offense) in Newark is entered into the database. Secondly, through a partnership with surrounding police departments, the Newark Police is notified when a Newark resident is arrested for committing a burglary in a surrounding jurisdiction. Lastly, through a partnership with the State Parole Board, the Newark Police is notified when parolees are released from prison to a Newark residence. Parolees with multiple burglary convictions are entered into the known burglar database.

The "at-risk" housing file is maintained by the Newark Police Department's Compstat unit through a partnership with the Newark Housing Authority and various City of Newark departments. Two facility types are included in this layer. The first is the public housing complexes under the direct control of the Newark Housing Authority. Secondly, in recognition of previous analyses conducted in Newark that have found certain privately-owned housing complexes to contribute to crime in a similar manner as public housing (Kennedy et al., 2011; Piza & O'Hara, 2012; Zanin, Shane, & Clarke, 2004), the at-risk housing file also includes privately-owned complexes similar in scope to public housing complexes. The CompStat unit in conjunction with the City of Newark License Unit first identified all residential buildings in the city with 10 or more units. CompStat personnel then identified all of these complexes with similar structural attributes as public housing (e.g. large buildings with single entrances, limited automobile accessibility to the courtyard, etc.) as well as complexes that received government subsidies for renting to low-income individuals.[8] Privately owned complexes that fit both of these criteria were merged with public housing to create the "at-risk" housing layer. The final two risk-layers—areas of the city zoned as "residential" and public transportation nodes—were extracted from the City of Newark's GIS platform.

As shown in Table 1, the spatial influence of each risky feature of the landscape was informed from prior empirical literature. It should be noted, however, that some operationalizations were more conservative than typically

8. The CompStat unit informed us that they received this information from the City of Newark's Office of housing Assistance.

found in the literature.[9] Once the spatial influence of each risk factor was operationalized (Caplan, 2011; Caplan et al., 2011a), it was mapped using ArcGIS 10 software. The Spatial Analyst extension in ArcMap was then used to convert these vector maps into raster map layers; each map layer had identically-sized: 145 feet by 145 feet raster cells.[10] Each raster map layer was then re-classified into dichotomous values for each cell (+1 for highest risk, 0 for not highest risk) based upon the cell's presence or absence within each buffer distance of greatest operationalized risk.

Prior to generating a composite risk terrain map, negative binomial regression analysis was conducted to determine which factors should be included in the risk terrain model. This "best fit" approach was utilized in order to identify which risk factors were significantly related to residential burglaries in Newark and which risk factors should be included in the final composite risk terrain map. The unit of analysis for each negative binomial regression analysis was 145 foot by 145 foot cells that comprised the grid surface for the entire City of Newark ($N = 13{,}801$).

To-date, prior studies using the RTM technique have used binary logistic regression to test for predictive validity (Caplan et al., 2011a, 2011b; Kennedy et al., 2011). However, given that some residences may be victimized repeatedly, the use of binary logistic regression may undercount the total number of residential burglaries in 2010 as multiple incidents are classified as a single unit to fulfill the requirements of running logistic regression analyses. This is even despite the fact that there is a high frequency of cells *without* residential burglaries and low frequency of cells *with* more than one incident[11] (see Table 2). Since burglary incidents, like most crime incidents, are distributed as rare event counts, negative binomial regression is a more appropriate statistical test than a linear regression model (Braga & Bond, 2008). Indeed, the problems associated with treating event count variables as continuous values are well documented (see Gardner, Mulvey, & Shaw, 1995; Osgood, 2000).

Recognizing this issue and because the dependent variable is a count-based non-negative account of residential burglaries, Poisson and negative binomial regression models were used to assess the predictive validity of RTM for residential burglary incidents that occurred during 2010 in Newark. The choice of model depends on the distribution of the count-data at hand. Poisson regression models assume that the conditional mean and variance are equal, which scholars have argued is rarely met in criminological datasets (MacDonald & Lattimore, 2010). Thus, there is strong support for negative binomial

9. For example, literature on burglar residence and journey-to-crime has shown that close proximity and short journey-to-crime can be as far as one mile (see Rossmo, 2000). Using a one mile buffer for each known burglar residence would "black-out" our entire study area leading to potentially misleading results; thus, a more conservative and meaningful approach was utilized (see Table 1).

10. This cell size was selected because it is half the median length of a Newark city block (290 feet). The average length of Newark streets was not used due to highway street segments acting as outliers and skewing the street measurements in residential areas.

11. A consequence of the very small 145 foot by 145 foot units of analysis.

Table 1 Conceptualization and operationalization of the spatial influence of risk factors

Factor	Spatial influence*	Risk value**	Justification	Source
Land use	Residential parcel data converted into 145 foot raster cells	+1	Residential parcels will be at higher risk of residential burglary since only residences could be targets	Spatial influence: Groff & La Vigne (2001) Justification: Groff & La Vigne (2001)
At-risk housing	300 foot buffer around and including at-risk housing polygons	+1	At-risk housing will be at higher risk of residential burglary due issues related to drug activity and other crimes. Such areas may also have low forms of guardianship	Spatial influence: *Current study* Justification: *Current study*
Pawn shop	Greater than 300 foot to 900 foot donut shaped dissolved buffers	+1	Residences within close proximity to pawn shops are at higher risk due to quick disposal of goods for cash	Spatial influence: *Current study* Justification: Wright and Decker (1994)
Burglar residence	Greater than 300 foot to 900 foot donut shaped dissolved buffers	+1	Residences in close proximity to burglars' residences are at higher risk due to (i) increased awareness and activity spaces of offenders, (ii) familiarity with routine activities of neighbors, and (iii) easier accessibility. More conservative measures were used for the current study in comparison to many studies that found around a one-mile journey-to-crime distance	Spatial influence: *Current study* Justification: Bernasco (2006); Bernasco and Nieuwbeerta (2005); Rossmo (2000); Wright and Decker (1994); Forrester et al. (1988); Rengert & Wasilchick (1985); Bennett and Wright (1984)

(continued)

Table 1 (continued)

Factor	Spatial influence*	Risk value**	Justification	Source
Drug market (based on 2009 drug arrests)	300 foot buffers around and including top 5% 2009 drug arrests polygon	+1	Research has indicated that some burglars offend in order to fund drug use; therefore, residences around drug markets will be at higher risk	Spatial influence: *Current study* Justification: Mawby (2001); Wright and Decker (1994); Cromwell et al. (1991)
Public transportation nodes	Greater than 300 foot to 900 foot donut-shaped dissolved buffers	+1	Public transportation nodes may place certain locations at more risk by (i) increasing offender awareness and activity templates, (ii) increasing ease of access to such places, and (iii) providing a means for exit	Spatial influence: *Current study* Justification: Clare et al. (2009); Brantingham and Brantingham (1991, 1993b)

Notes. *All buffers were converted into 145 foot × 145 foot raster cells. **Values are unweighted. All other values are classified as "0".

regression models, which do not assume an equal mean and variance and particularly correct for overdispersion in the data (Osgood, 2000; Paternoster & Brame, 1997). Following the approach of previous research (see Braga & Bond, 2008, p. 589), an exploratory Poisson regression model and accompanying Pearson Chi-Square goodness-of-fit test were conducted to measure the distribution of the data. The findings revealed that the count of 2010 burglary incidents was distributed as a negative binomial process.[12]

In light of the χ^2 results, and the low frequency of cells with *any* incident, negative binomial regression is considered an appropriate approach for the analysis. In addition to addressing the potential limitation of using binary logistic regression, the use of negative binomial regression is valuable in order to test another statistical technique to verify RTM studies, particularly those that rely on count data. It should be noted, however, that logistic regression analyses were also ran for each model in order to compare the results of

12. Pearson Chi-Square = 20,350.29 with d.f. = 13798; $p = 0.00$.

Table 2 Negative binomial regression: results for risk factors forecasting period 2 residential burglary incidents

Predictor variable	IRR (Std. err.)	95% C.I. lower	95% C.I. upper
Land use	1.31 (.86)*	1.15	1.49
At-risk housing	1.27 (.093)*	1.10	1.46
Pawn shop	1.42 (.12)*	1.20	1.69
Burglar residence	1.36 (.81)*	1.21	1.53
Drug market	1.39 (.71)*	1.26	1.53
Public transportation	1.02 (.062)	.91	1.15

Note. *$p < .001$ and **$p < .05$.

each type of analysis and that the results from both regression analyses were similar.[13]

As shown in Table 3, results of negative binomial analyses suggest that at-risk housing, burglars' residences, drug markets, land use, and pawn shops were significantly associated with residential burglary incidents. Conversely, public transportation nodes were found to be statistically non-significant. Therefore, with the exception of public transportation nodes, all the risk factors were included within the composite risk terrain map.

The recognition of contextually meaningful micro-places has increased within the criminological literature. For example, the recent work conducted by Weisburd et al. (2004), Weisburd, Groff, and Yang (2009) highlight the importance of analyzing street segments. Given the importance of micro-places, the current study focuses upon 145 by 145 foot cell sizes, approximately half the median length of a Newark block. As the current study incorporates raster grid cells, the modifiable areal unit problem (MAUP) is an issue that needs to be discussed. Akin to the ecological fallacy, whereby inferences about individuals are made based on aggregate-level information, the MAUP can alter findings based on varying spatial configurations and differing units of analysis (Amrhein, 1995). Comprised of the *scaling effect* and the *zoning* (or *aggregation*) *effect*, the MAUP can potentially impact research conclusions through the establishment of arbitrary boundaries and the aggregating of data to such boundaries (Openshaw, 1984). While MAUP may still be an issue in the current study, we believe that the use of a relatively small cell size may help alleviate concerns.

Once all five raster map layers were reclassified to permanent binary-valued map layers, they were combined to form the final risk terrain map that represented the compounded spatial influence of all risk factors—and the criminogenic risk of each 145 foot by 145 foot place throughout the study

13. Logistic regression results show the odds ratio suggests that for every one unit increase of risk, the log odds of all residential burglary increases by at least 13% ($p < .001$). In addition, the odds ratios suggests that for every one unit increase of risk, the log odds of a non-instigator and non-near repeat residential burglary increases by at least 18% ($p < .001$); only instigator incidents increases by 42% ($p < .001$) and; only near repeat incidents increases by 38% ($p < .001$). These results are all based on holding the spatial lag constant.

Table 3 Distribution of 145 foot by 145 foot cells within the study area ($N = 13{,}801$)

Incident type	n	Percentage of area coverage
Cell with more than one incident of residential burglary	289	2.1
Cell with only one incident of residential burglary	1,051	7.6
Cell with no incidents of residential burglary	12,461	90.3

setting. The Risk Terrain Toolset[14] was then used to convert the final risk terrain map into a vector grid of equally-sized cells (145 feet × 145 feet). The resultant vector risk terrain map was then spatially joined with all residential burglaries in 2010 (1 January—31 December; $n = 1{,}340$; the dependent variable) to produce a count of burglary incidents located within each cell (e.g. micro-level place).

Residential burglary incidents were then joined by spatial location to each respective cell (which also had a risk value—i.e. the independent variable—attributed to it), and the map was clipped to the study area so that only cells that intersected with street segments were included in the final analysis. This was done in order to properly reflect the manner by which the crime data was digitized. In Newark, as in other police departments, crime locations are identified by street name and number, and subsequently geocoded to their corresponding location on a street shapefile. This process holds true regardless of the actual location of occurrence (e.g. front of a property vs. back of a property; indoors vs. outdoors, etc.). Within a GIS, cells not containing streets have no chance of containing a crime incident given these aforementioned limitations of administrative police records and the geocoding process (Caplan et al., 2011a). Excluding cells which do not intersect streets ensure construct validity since crime incidents were only geocoded to street center lines.

Objective 1 Results

Prior to each model being analyzed, the presence of spatial autocorrelation was assessed. For the first objective, Moran's I was .05 ($p < .001$) indicating that spatial autocorrelation was present, so a spatial lag was needed to be incorporated as a control. The "Risk Value" (0—5)[15] was the independent variable; while burglary counts were the dependent variable in negative binomial regression. This format was the same for all subsequent tests. The results from the negative binomial regression analysis suggests that for every one unit

14. The Risk Terrain Toolset can be downloaded for free from: http://www.rutgerscps.org/rtm/.
15. It is important to remember that a risk-value of "0" does not mean that there is absolutely no risk of residential burglary within that vector cell, but rather that the spatial risk associated with risk factor(s) is not present within that vector cell.

increase of risk, the difference in the logs of expected counts of all residential burglary incidents is expected to change by 22% (incident rate ratio [IRR] $= 1.22$; $p < .001$), given that the spatial lag is held constant. These results suggest that the risk terrain map produced to articulate the environmental backcloth for residential burglary in Newark, NJ is statistically valid.

Objective 2 Methods: Assessing Levels of Risk for Instigator and Near Repeat Residential Burglaries

The second objective was a two-pronged test. First, the near repeat calculator was used to determine whether repeat victimization and the near repeat phenomenon occurred in the study area during 2010. Based on the recommendations by Ratcliffe (2008), as well as the evidence from the literature, the spatial bandwidth used was 300 feet (just over one Newark block); six spatial bands were assigned. The temporal bandwidths used were 14 days and 26 temporal bands.

It should be noted that one of the issues raised about the near repeat phenomenon is the potential for establishing arbitrary spatial and temporal cutoffs for what constitutes as a near repeat pairing. Recognizing the potential limitations of user-defined spatial and temporal bandwidths, Youstin et al. (2011) sought to identify patterns at various spatiotemporal lengths of three different crime types: shootings, car thefts, and robberies. The researchers found notable differences within and between the three crime types, and concluded that while the near repeat phenomenon was present, each crime type displayed its own distinct pattern that needed to be disentangled in order to establish appropriate prevention strategies. Therefore, for proof of concept and ground-level practicality, shorter spatial and temporal bandwidths and bands are used for the current study.[16]

When the near repeat phenomenon was found, we then used the near repeat calculator to determine which incidents in a near repeat pair was the instigator and near repeat incident. Spatial and temporal parameters were once again based on Ratcliffe's recommendations as well as prior literature, and were up to14 days, and greater than 300 feet up to and including 600 feet, respectively. Originator and near repeat incidents were noted accordingly in the attribute table of the original geocoded point shapefile of all residential burglaries in the study setting.

As shown in Figure 1, instigators appear to cluster around areas with higher levels of risk. To test whether this observation is statistically significant, instigators and near repeats were extrapolated from the GIS dataset of all residential burglaries. All incidents that were "Instigators" *and* "Near Repeats" at

16. It should be noted that the authors also tested for longer spatial and temporal bandwidths (e.g. one month temporal bandwidths, 12 temporal bands), which also corresponded with prior studies (Johnson et al., 2007) and found similar results to the findings presented here.

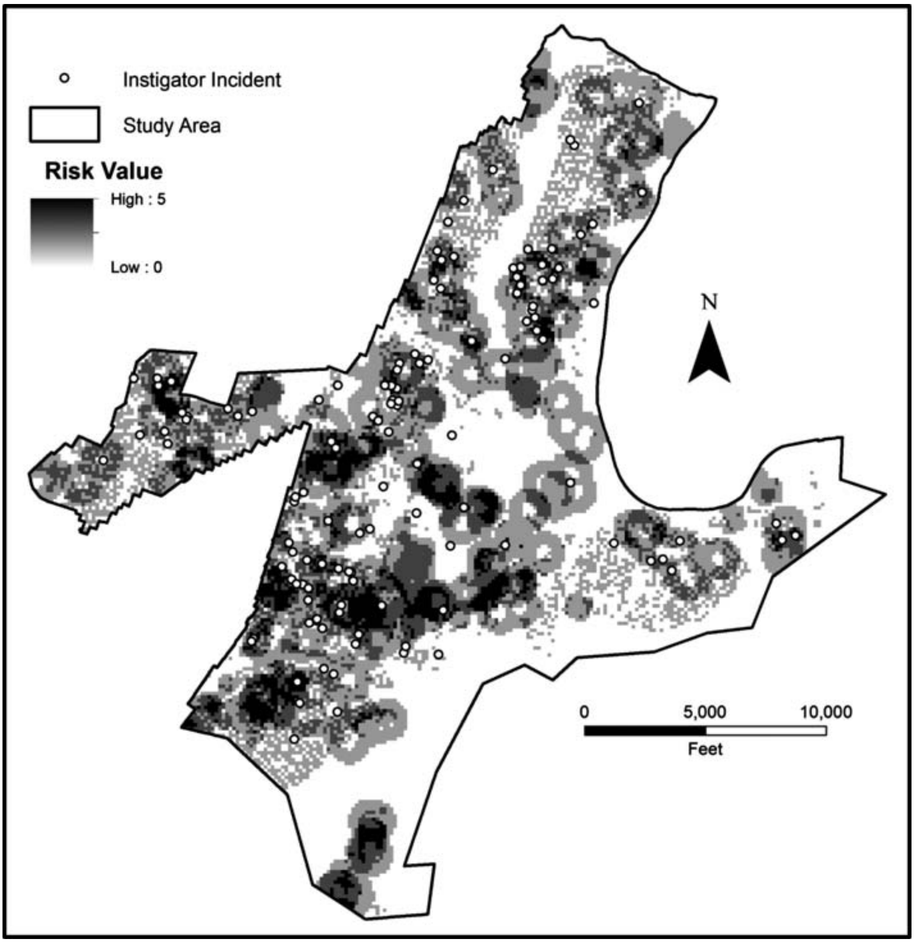

Figure 1 Risk terrain map with 2010 instigator residential burglaries ($n = 98$).

least once were exported as a separate shapefile ($n = 173$).[17] Then, only those incidents that were "Instigators" ($n = 98$) *or* "Near Repeats" ($n = 91$) at least once, respectively, were exported as two separate shapefiles. To compare instigators and near repeats to other residential burglaries, all incidents that were neither "Instigators" nor "Near Repeats" were exported as a separate shapefile ($n = 1{,}167$). Pearson Chi-Square goodness-of-fit tests run after exploratory Poisson regression models revealed that the "Instigators" and "Near Repeats" were distributed as negative binomial processes while incidents that were neither "Instigators" nor "Near Repeats" were distributed as a Poisson process.[18] The count models were then used to test the risk heterogeneity of

17. Some cells were associated with both an instigator and near repeat incident in different near repeat pairings.
18. For Instigators: Pearson Chi-Square = 15,429.13 with d.f. = 13,798; $p = 0.000$. For Near Repeats: Pearson Chi-Square = 15,831.74 with d.f. = 13,798; $p = 0.000$. For neither instigator nor near repeats: Pearson Chi-Square = 12,479.42 with d.f. = 13,798; $p = 1.000$.

each burglary event type (all non-instigators and non-near repeats, only instigators, and only near repeats).

Objective 2 Results

Part I: confirmation of repeat victimization and near repeats

Both repeat victimization and near repeats were present for residential burglaries in Newark in 2010. As shown in Table 4, there was a 318% ($p < .001$) greater chance of the same residence being burglarized within 14 days of the initial incident. Additionally, there was a 20% ($p < .01$) greater chance of residences being burglarized within 300 feet (one block) and within 14 days of an instigator incident; 30% ($p < .01$) within 300 feet and within 15 to 28 days; 21% ($p < .001$) within 301 to 600 feet and within 14 days; 23% ($p < .05$) within 601 to 900 feet; and 23% ($p < .001$) within 601 to 900 feet and within 14 days.[19]

Part II: place-based risk heterogeneity of instigators and near repeats

Since the near repeat phenomenon was found to exist in Newark during the study period, both binary logistic regression and count (negative binomial or Poisson) regression analyses were used to test the predictive validity of the risk terrain model on different types of incident locations. Similar to the test used for Objective 1, the independent variable for all four tests regarding Objective 2 was the "Risk Value". However, the dependent variable was based on counts of: non-instigator/non-near repeat; instigator only; and near repeat only. The Moran's I value for all non-instigators/non near repeats was .04, $p < .001$; only instigators was .02, $p < .001$; and near repeats was .02, $p < .001$, indicating spatial autocorrelation and the need to include a spatial lag control variable in the regression models. The following results are based on the spatial lag being held constant in each individual analysis.

Referring to Table 5, the predictive validity of the risk terrain map was statistically significant for all three burglary incident types. Results of the Poisson regression model suggest that for every one unit increase of risk, the difference in the logs of expected counts of a non-instigator and non-near repeat residential burglary increases by at least 16% (IRR = 1.16; $p < .001$). Results of negative binomial models suggest that only instigator incidents increases by 45% (IRR = 1.45; $p < .001$) and only near repeat incidents increases by 42% (IRR = 1.42; $p < .001$). Lastly, negative binomial regression analysis was conducted to determine the place-based influenced of risk values on near repeat incident locations while controlling for the presence of instigator incidents and a spatial lag. As shown in Table 6, risk value remains statistically significant:

19. Notably, the near repeat phenomenon was also found at greater distances and at longer time periods; however, the authors believed that for practical purposes, the aforementioned results would suffice for the current discussion.

Table 4 Near repeat calculator, Monte Carlo analysis for repeat victimization, and near repeats for 2010 residential burglaries*

Type of repeat	Distance/days	Observed over expected mean	Sig.
Repeat victimization	Same location/0–14 days	4.18	.001
Near repeat	1–300 feet/0–14 days	1.20	.01
Near repeat	1–300 feet/15–28 days	1.30	.01
Near repeat	301–600 feet/ 0–14 days	1.21	.001
Near repeat	601–900 feet/0 to 14 days	1.23	.05
Near repeat	601–900 feet/0–14 days	1.23	.001

Note. *Monte Carlo Analyses were based on 1,000 iterations, which ensures that the results would be at the highest level of reliability.

Table 5 Risk terrain forecasting 2010 residential burglaries with spatial lags included as control variable*

Incident group	Model type	IRR (Std. err.)	95% C.I. lower	95% C.I. upper
All non-instigators/non near repeats	Poisson	1.16 (.03)**	4.18	8.75
Only instigators	Negative binomial	1.45 (.15)**	1.18	1.78
Only near repeats	Negative binomial	1.41 (.15)**	1.14	1.74

Notes. *Due to space constraints, spatial lags which were used as a control for all variables are not presented; however, all spatial lags were statistically significant for all variables ($p < .001$). All tests were run independently. **$p < .001$.

every one unit increase of risk results in a 39% increase in the difference in the logs of expected counts of a near repeat incident occurring at that location (IRR = 1.39; $p < .05$).

Discussion

Residential burglaries generally occur at micro-level places with higher values of risk—as articulated by a risk terrain map. However, burglary incidents iden-

Table 6 Negative binomial regression: results for period 1 risk terrain forecasting period 2 near repeat incidents

Predictor variable	IRR (Std. err.)	95% C.I. lower	95% C.I. upper
Risk value	1.39 (.15)*	1.13	1.71
Instigator	23.22 (9.66)**	10.27	52.50
Spatial lag	32.25 (56.46)*	1.13	1.71

Notes. *$p < .01$, **$p < .001$ and ***$p < .05$.

tified as instigators and near repeats are even more likely to occur at *higher* risk places than non-instigators and non-near repeats. These findings show the combined utility of both the RTM approach and the near repeat calculator in analyzing residential burglary in the urban city of Newark. More importantly, this study yields evidence that analyzing the risk heterogeneity of an area along with event-dependent assessments is useful for generating a more complete understanding of a crime problem. This study highlights the underlying environmental contexts that are present before, during, and after instigator or near repeat incidents and that such contexts may influence whether a residence is targeted for burglary. While the immediate area surrounding an instigator incident may have heightened levels of risk *post factum*, such an area may already have been at high levels of risk in the first place. In fact, results suggest that instigator and near repeat events occur at places of higher risk in comparison to non-instigator/non-near repeat incidents, and that instigator and near repeat pairings are influenced by similar levels of risk.

As illustrated in Figure 2, burglaries that cannot be prevented and that serve as instigator incidents (for near repeats) are most likely to attract near repeat incidents at nearby places of high environmental risk—as opposed to micro-level places within the expected near repeat bandwidth that have very low risk. Stated another way, instigator burglary incidents may create a "pie" of a certain radius, within which near repeat incidents are most likely to happen during a certain timeframe. But within this pie, some "slices" are more likely to have burglaries than other slices.

This study helps to answer the critical question of "Where do *instigator* incidents occur?" Indeed, the concept of the "communicability of risk" (Bowers et al., 2004; Johnson & Bowers, 2004a, 2004b; Townsley, Homel, & Chaseling, 2003)—which is analogous to the contagion effect of disease—does not incorporate determining whether the area was "sick" already, and overlooks the underlying, latent causes of the "disease" by only addressing the symptoms (e.g. instigators and near repeat incidents). Results presented here support the

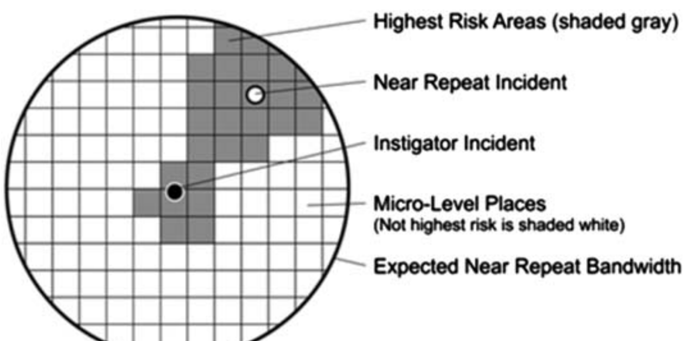

Figure 2 Instigator incident and near repeat incident within expected near repeat spatial bandwidth on risk terrain surface.

idea that the underlying environment is associated with *both* instigator and near repeats events. The combination of higher values of baseline risk levels coupled with the heightened risk produced by instigator and near repeat events provides a meaningful and actionable explanation as to why specific places are targeted for burglaries over others.

Looking at the bigger picture, this formative approach to crime analysis recognized that "each crime has its particular *chemistry*" (Felson & Boba, 2010, p. 45; emphasis added). Each burglary likely has its basic elements, compounds, and reactions. Viewing criminal activity as being analogous to a chemical reaction (Felson, 2008) underscores that the potential for *criminogenic combustion* (i.e. crime) is latent in any circumstance given the appropriate formula of elements and compounds. Generally speaking, the risk factors included in this study (e.g. proximity to pawn shops, proximity to burglar residence, etc.) can be viewed as elements that comprise an environmental compound (e.g. the environmental backcloth or the risk heterogeneity of an area) suitable for criminogenic reactions to occur. The recognition of crime in this manner provides a potential explanation as to the formulation, continuation, and cessation of *current* or ongoing crime hot spots. Essentially, the involvement and actions by offenders, targets, and guardians can impact the criminogenic structure of an environment through feedback loops and mechanisms (Eck, 2003) as would be the case with instigator events and the amount of surveillance and enforcement utilized by the police. Such actions could be considered along the line of dosage effects, as increased suppression tactics and guardianship would inversely impact the risk level of an area, while the presence of motivated offenders and suitable targets would inherently increase risk levels—both of which could be operationalized as qualities of space and included in a risk terrain model for the articulation of an environmental backcloth.

From a practical perspective, this study sheds light into the importance of understanding place-based, baseline levels of risk when performing prospective mapping for strategic policing operations. It identified specific places worthy of attention in Newark's anti-burglary efforts. For example, drug markets and pawn shops may be susceptible to the common strategies of the Newark police, particularly the disruption of narcotics-related activity through proactive, street-level enforcement (Jacobson, 1999; Weisburd & Green, 1995; Weisburd et al., 2006). Thus, officials could choose to also conduct intensive narcotics enforcement at drug markets nearby burglary hot spots. Additionally, the recognition of risky areas may also help in the identification of important stakeholders that might have otherwise been overlooked (e.g. place managers), who may be directly responsible for facilitating such a risky environment or who may have a vested interest and can be incorporated as informal guardians (Felson, 1995). If risk factors (that were included in the risk terrain model) are not mitigated effectively, then burglaries will continue to occur and will cluster at the same places over time, creating hot spots (Johnson et al., 2007).

It is important to note that the study, like most others, contains limitations. First, the urban city of Newark may not be representative of other cities, particularly those that are suburban. Indeed, as found by Bowers and Johnson (2005), while repeat victimization tended to occur in more impoverished areas, space-time clustering was more apparent in more affluent areas. Future research analyzing the underlying risk levels of different types of residential burglaries in different communities would be needed in order to determine whether the results presented here are limited to the current study area. Studies attempting to replicate the findings here in both urban and suburban communities are welcomed.

Second, the study only utilized five components to create the environmental backcloth or the risk heterogeneity of the study area. While the factors that were included in the study were theoretically grounded and empirically supported, it can be argued that more factors may need to be included in order to generate a more representative environmental backcloth of an area. While beyond the scope of the current discussion, the authors caution that particular types of information (e.g. demographic) may be limited for the current application due to limitations in data itself (e.g. census data collected every ten years in the USA). Moreover, from a practical perspective, the inclusion of particular demographic variables (e.g. unemployment) may be of little use to policing authorities since such factors may go beyond their capabilities or resources. However, we encourage future research to incorporate demographic data in a manner that has tangible implications for law enforcement. Stucky and Ottensmann (2009), for example, found that the criminogenic influence of certain land uses were heightened within disadvantaged areas. Such information may improve upon the spatiotemporal analysis of crime.

Conclusion

This study contributed to the work of other scholars (e.g. Bowers et al., 2004; Groff & La Vigne, 2001; Johnson & Bowers, 2004a, 2004b; Johnson et al., 2007; Johnson et al., 2009; Townsley et al., 2003) by combining the strengths of place-based risk assessment and incident-based crime analysis, and by joining the information products of RTM and the near repeat calculator to produce intelligence that can be used to forecast locations of residential burglaries, including instigator and near repeat incidents. It highlights how police can seek to prevent burglaries by allocating resources to places that are most attractive to motivated offenders given certain characteristics of the environment (Weisburd, 2008), by trying to mitigate environmental risk factors at these places, and by using unpreventable burglary incidents to anticipate the distal and temporal limits of repeat victimization and near repeat events at certain high risk places.

In the longstanding debate in criminology concerning what promotes crime, it is not enough to say that risk of burglary increases when the absolute numbers of burglary incidents increase throughout a jurisdiction. What is more likely is that the risk of burglary at places that have certain criminogenic attributes is higher than other places because these locations attract motivated offenders and are conducive to allowing burglary events to occur. Prevention strategies addressing residential burglary, therefore, must incorporate both the spatial and temporal patterns of recent known burglary incidents and the environmental risks of micro-level places if it is to yield the most efficient and actionable information for police resource allocation and prevention efforts.

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