

# The Predictive Policing Challenges of Near Repeat Armed Street Robberies

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**Abstract** New research methodologies like the near repeat phenomenon provide police with a potentially powerful predictive technique, if law enforcement possesses the capacity to capitalize on identified patterns in time. The current study examines armed street robbery data from Philadelphia in order to identify and quantify the existence of multiple-event near repeat chains. The impact of near repeat chains on the temporal stability of micro-level armed street robbery hot spots is also explored. The findings demonstrate that near repeat armed street robbery chains tend to be relatively short in terms of chain length, and the number of days between the initiation and termination of a chain is rarely longer than 7 days. These results suggest that if police are to proactively address short-term crime event predictions, a range of complex organizational and analytical capacities have to be in place. Furthermore, despite the fact that a number of hot spots were found to be primarily derived of near repeat events, the results show that the temporal stability of armed street robbery hot spots is not associated with the proportion of near repeat events within the hot spots, a finding supportive of long-term opportunity reduction measures.

## Introduction

A common ethos amongst street-level police commanders and patrol officers is that the police should focus on emerging crime problems (Buerger, 2010). It is not surprising then that police departments have traditionally engaged in 'whack-a-mole' (Ratcliffe, 2008) or 'fire-brigade' (Tilley, 2003) policing where calls for service are dealt with in rapid succession and a high dosage of police presence is assumed to be an effective policing tactic (Eck and Maguire, 2000). The basic principles of Compstat (for example) attest to this by including

timely and accurate intelligence followed by effective tactics that are deployed rapidly (McDonald, 2002). To move beyond a generalized response to crime requires a range of organizational capacities; the ability to monitor crime events frequently, the analytical skill to identify emerging trends, a decision-making system adept at demanding differential responses, and an operational capacity to quickly implement new tactics.

Other strategies, such as problem-oriented policing, also begin with the identification of crime patterns (Eck and Spelman, 1987); however, the

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proliferation of computer crime mapping and Compstat has not resulted in a shift from flooding areas where crimes have recently occurred with police personnel to more holistic strategies such as problem solving as many policing reformers had hoped (Weisburd *et al.*, 2003, p. 443–444). Thus, saturation patrol (or equivalents) remains the first port of call for many Basic Command Unit (BCU) commanders focusing on emerging crime patterns. This ‘cops on corners’ approach also assumes that crime is spatially and temporally concentrated to the extent that a quick response can efficiently disrupt crime, even though research examining the spatial and temporal concentration of crime is still developing. Therefore, we can add to the list of organizational requirements (above) that the crime type under examination should also display spatial and temporal characteristics that are amenable to a rapid, saturation patrol preventative effort. In other words, this requires the crime in question to have predictable patterns that are reasonably constrained spatially (so patrols do not have to spread too far) and last long enough in time for there to be time to organize a suitable response.

Recent research into the near repeat phenomenon may provide some of this required analytical power. It has long been known that some victims and places are repeatedly victimized (Bowers *et al.*, 1998; Farrell and Pease, 1993; Polvi *et al.*, 1991). This understanding has been enhanced by the discovery of a near repeat phenomenon: not only are locations at risk of repeat victimization, but nearby locations are also at increased risk of crime up to a certain distance and for a certain time (Bowers and Johnson, 2004; Ratcliffe and Rengert, 2008; Townsley *et al.*, 2003).

The present study examines patterns of armed street robberies in Philadelphia (Pennsylvania), USA, in order to develop a more robust understanding of the extent to which violent crime concentrates in space and time simultaneously. For this study, armed street robbery refers to crimes known as ‘stick-ups’: a person with a weapon, predominantly a firearm, demanding cash or other valuables

from another person on the street. The term does not refer to armed robberies at banks, petrol stations, or other locations, and does not include robberies that do not involve the use of a weapon. We are therefore dealing with the most potentially lethal form of robbery. Specifically, this study quantifies the extent of armed street robbery in Philadelphia at the event-level by identifying and describing how near repeat armed street robberies occur in multiple-event chains. Second, the impact of near repeat armed street robberies on the temporal stability of micro-level armed street robbery hot spots is examined. The study concludes with a discussion of the results’ implications for the allocation of police resources. This article adds to the existing literature in three ways. First, it is the first near repeat study of armed street robberies. Second, by examining the multiple-event chains, it provides empirical clarity to the temporal characteristics of emergent robbery patterns. Third and perhaps most importantly, it does all of this within the context of an operational policing response, comparing the quantitative findings with a range of viable police reactions.

### **What do we know about near repeats?**

The near repeat phenomenon originated as an epidemiological concept to study the transmission of infectious diseases (Knox, 1964). More recently, environmental criminologists have incorporated epidemiologists’ space–time concept and methodology in the study of crime. The idea is that a previous crime event creates a heightened risk of victimization for spatially proximate targets that decays over time (Johnson *et al.*, 2007a; Johnson and Bowers, 2004b; Ratcliffe and Rengert, 2008). Simply stated, the near repeat phenomenon shows that crime clusters in space and time. Using epidemiological methods, recent research has found support for the near repeat crime hypothesis. While researchers proposed hypotheses about why

near repeat crime patterns would exist, early research focused on simply determining whether near repeat crime patterns existed. Townsley and colleagues (2003) demonstrated that a greater number of burglary event pairs in Queensland, Australia, were clustered within a distance of 200 m and 2 months than would be expected on the basis of chance. A similar near repeat burglary pattern was also found in Merseyside, UK, at distances of 400 m and 2 months (Johnson and Bowers, 2004a). Furthermore, an analysis of data from 10 separate cities from five different countries (Australia, Netherlands, New Zealand, UK, and US) revealed near repeat burglary patterns were ubiquitous. The results showed that near repeat burglary patterns were consistent across all studied locations; burglary point pairs were clustered within distances of about 100 m and 2 weeks (Johnson *et al.*, 2007a). Finally, a near repeat analysis conducted using burglary and theft from motor vehicles (TFMV) data from Bournemouth, UK, found a near repeat pattern for both the burglary events (400 m and 6 weeks) and TFMV events (400 m and 6 weeks) separately, but a modified analysis that examined burglary and TFMV simultaneously failed to find any evidence of a bivariate space–time concentration (Johnson *et al.*, 2009).

After determining that near repeat property crime patterns existed, more recent studies have focused on directly testing why. Two hypotheses have been presented: 1. the ‘boost’ and 2. ‘flag’ hypotheses. The ‘boost’ hypothesis suggests that past victimization boosts the likelihood of future victimization (Farrell *et al.*, 1995; Johnson, 2008; Pease, 1998). This event-dependency hypothesis is an offender-based dynamic where it is argued that the same offender (and/or colleagues) returns to the area of a previous offence to capitalize on the opportunities the offender learned about during the previous offence. Conversely, the ‘flag’ hypothesis argues that target risk factors concentrate opportunity and, as a result, concentrate crime (Farrell *et al.*, 1995; Johnson, 2008; Pease, 1998). In other words, the attractiveness of targets means crime will be

concentrated among those targets regardless of whether it is the work of the same offender.

Most studies have tested the boost hypothesis. A study using data from Merseyside, UK, found that burglaries occurring close in space and time (near repeat pairs) were more likely to have been carried out with the same modus operandi than burglaries at greater distances in space and time (Bowers and Johnson, 2004). This finding suggested that the same offender(s) returned to the area to use a previously successful burglary tactic on other houses, perhaps because the original victim implemented crime prevention measures. Similarly, near repeat burglaries from the Netherlands were found to be cleared to the same offender more often than non-near repeat burglaries (Bernasco, 2008). Finally, Johnson *et al.* (2009b) found that pairs of burglaries as well as thefts from motor vehicles were more likely to be cleared to the same offender(s) when the events occurred closer in space and time than events that occurred farther apart in space and time. On the other hand, support for the flag hypothesis was found in Queensland, Australia, by comparing the level of near repeat burglary in suburbs with homogenous and heterogeneous housing stocks, and it was determined that a greater number of near repeat events occurred in the suburbs with a homogenous housing stock than the suburbs with a heterogeneous housing stocks (Townsley *et al.*, 2003).

There have been only a few studies conducted to determine if violent crimes follow a near repeat pattern. Ratcliffe and Rengert (2008) applied the near repeat phenomenon to shootings in Philadelphia. While the authors did not have data to directly test their theory, they used a body of literature suggesting that inner city violence often results in retaliation to frame their rationale for expecting a near repeat shooting pattern. Using operational knowledge of the nature of gun violence from the Philadelphia Police Department to guide the spatial and temporal parameters of their analysis, a near repeat pattern was found at the distances of about one block and 2 weeks.

Wyant and colleagues (in press) examined a bivariate near repeat phenomenon for illegal firearm carrying (Violations of the Uniform Firearms Act (VUFA)) and shootings from 2004–07 in Philadelphia. They worked from two hypotheses: 1. arresting people for illegally carrying firearms would suppress later shootings and 2. shooting events would result in increased police presence and thereby increase VUFA arrests in an area. In concordance with their hypotheses, shootings were: 1. found to significantly decrease anywhere from 28 to 47% after a VUFA arrest (the effect varied by police district) and 2. VUFA arrests were found to increase for about a week and up to a distance of about 0.2 miles after a shooting.

Finally, although not a traditional street crime, a near repeat pattern has also been demonstrated for improvised explosive device (IED) attacks in Iraq (Townsend *et al.*, 2008). Townsend and colleagues (2008) framed their study in the context of rational choice, assuming that terrorists would carry out attacks close in space and time in order to minimize the amount of effort exerted to carry out an attack. After analysing the locations and dates of 916 IED attacks occurring in a 3-month time frame, it was revealed that the greatest risk for a future IED attack was within the distances of about 1 km and 2 weeks after a previous attack. The authors concluded that this supported their assumption that insurgent attacks involved rational planning.

For all this research, the practical policing benefits from this area of study are still embryonic. Studies exploring the near repeat nature of violent crimes are scarce. Since recent research has shown that the near repeat nature of crime can be used for short-term crime forecasting (Bowers *et al.*, 2004; Johnson *et al.*, 2007b, 2009a), understanding the near repeat nature of violent crime may have value for proactive policing and crime prevention. Therefore, in this study we focus on identifying a near repeat armed street robbery pattern and developing a more robust understanding of the extent to which it occurs.

### Near repeats and street robbery

Adapted versions of the boost and flag hypotheses (Farrell *et al.*, 1995; Johnson, 2008; Pease, 1998) for armed street robbery underpin the present study. First, it is plausible that near repeat armed street robbery can also be explained by an offender-based boost process. In short, the success of a previous event most likely teaches the offender that a general location provides quick escape routes and suitable targets that lack adequate guardianship; traits reported in ethnographic research by street robbers as necessary for successful street robbery (St. Jean, 2007; Wright and Decker, 1997). Because active street robbers typically live the ‘fast life’, which includes partying, drug use, and gambling, their lifestyle creates a constant need for cash and likely drives continuous offending (Wright and Decker, 1997). When an offender decides to hunt for robbery victims in the area where he or she was previously successful, these continuous acts result in the space–time concentration of armed street robbery.

Alternatively, the flag hypothesis can also be reiterated for armed street robbery. Simply stated, the characteristics of certain areas may provide increased levels of street robbery opportunities within a specific temporal rhythm. Wright and Decker’s (1997) interviews with active street robbers found that the interviewees preferred locations where people were likely to be carrying cash and provided access to quick escape routes. Specifically, the street robbers noted preferences for areas with automatic teller machines (ATM), check cashing businesses, supermarkets, and shopping malls. Similarly, ethnographic research in Chicago’s Wentworth neighbourhood with both offenders and police officers found that areas with distracted persons carrying cash were the most likely place for a robbery to take place (St. Jean, 2007). St. Jean (2007) argued that these areas have ‘ecological (dis)advantage’, while environmental criminologists would describe these locations as crime generators or crime attractors (Brantingham and Brantingham, 1993).

The current literature establishes that, for some crimes, there are more point-pairs close in space and time than would be expected on the basis of chance in official crime data, but little is known about the extent to which these patterns occur (see, Townsley, 2007, for a notable exception). Understanding the extent to which near repeat victimization occurs at the event level may be useful for the allocation of crime prevention resources. If near repeat victimization occurs in extensive multiple-event chains then allocating resources to disrupt these chains will be a useful crime prevention strategy. On the other hand, if these chains are short-lived then it is probably more beneficial and practically feasible to focus on long-term crime problems rather than chasing crime outbreaks. By quantifying the extent of the armed street robbery near repeat phenomenon at the event level, this study will begin to shed light on whether focusing on multiple-event near repeat armed street robbery chains can be an efficient crime prevention strategy.

Finally, if the near repeat process results in multiple-event near repeat chains, then it is possible that near repeat chains contribute to the formation of crime hot spots. Crime hot spots are abstract entities that are difficult to parsimoniously define (Buerger *et al.*, 1995; Taylor, 2010), but have generally been thought of as places—'addresses, buildings, block faces, street segments, or clusters of addresses' (Mastrofski *et al.*, 2010, p. 251)—with a greater than average concentration of crime (Chainey and Ratcliffe, 2005, pp. 241–245; Eck and Weisburd, 1995; Sherman *et al.*, 1989). While an accumulating body of successful hot spot policing evaluations has led to significant policy discussions (Mastrofski *et al.*, 2010), scholars have discussed the importance of understanding the temporal stability of crime hot spots before designing strategies focused on hot spots (Johnson *et al.*, 2008; Ratcliffe, 2004b). In short, hot spots that are stable over time will likely require more complex

crime prevention efforts, such as redesigning the physical environment and a greater allocation of crime prevention resources than compared to temporally unstable hot spots, or in other words, a short-term crime outbreak (Johnson *et al.*, 2008). A hot spot created by a multiple-event near repeat chain actually only represents a short-term, geographically concentrated risk even though it may appear as an area in need of police resources during retrospective data analysis. Because the temporal instability of hot spots is one of the more serious critiques against hot spots policing (Rosenbaum, 2006), understanding how the near repeat process impacts the temporal stability of hot spots has significant import for the allocation of police resources.

In summary, the research literature is still sparse regarding patterns of near repeats in violent, or potentially violent, crime. Furthermore, there is next-to-nothing known about the temporal length of near repeat chains, and whether they persist long enough for there to be a viable policing response. These questions are addressed in the remainder of this article.

## Methodology

### Data

The present study uses 2009 armed street robbery event data from the City of Philadelphia. Philadelphia is located in the north-eastern region of the US, and the nearly 1.5 million residents of Philadelphia make it the fifth most-populated city in the country.<sup>1</sup> Philadelphia's population is predominantly made up of African American (43.5 %) and white (42.5%) residents with the remaining 14% of citizens consisting of a fair proportion of Hispanic residents. The city's median household income of \$36,222 is almost \$16,000 below the national level (US Census Bureau, 2006–08).

The Philadelphia Police Department (PPD) polices an area of roughly 150 square miles with

<sup>1</sup> According to the 2010 US Census.

an authorized force of 6,600 sworn officers (Philadelphia Police Department, 2010). In 2009, Philadelphia reported a total of 9,037 robberies for a rate of 584 robberies per 100,000 residents compared to the national rate of 133 robberies per 100,000 (Federal Bureau of Investigation, 2009). The present study, however, only focuses on armed street robberies or robberies in which the offender used a deadly weapon (most frequently a firearm) to forcefully take someone else's property on a city street. Of the 3,611 total armed robberies recorded in 2009, 3,556 contained adequate data for geocoding (98.5% geocoding hit rate) and are the subject of this study (Ratcliffe, 2004a).

### Identifying near repeat patterns

Near repeat scholars have employed virtually the same methodology,<sup>2</sup> the Knox method (Knox, 1964), to identify the space–time clustering of events. The first step of the Knox method is to measure spatial and temporal distances between each event and every other event within the dataset. The total number of space–time distance measurements will equal  $n(n-1)/2$ , where  $n$  is the total number events in the dataset. Next, the researcher specifies the spatial and temporal bandwidths that will be used construct a contingency table. These parameters are placed on the X and Y axis of the contingency table and the total number of point-pairs within each cell of the contingency table, a space–time distance interaction, is calculated. A Monte Carlo simulation is then used to create an expected distribution of cell frequencies in order to determine if the observed cell frequencies are greater than would be expected on the basis of chance. For each Monte Carlo simulation, the spatial locations of the events are held constant while the dates of the events are reassigned to a

new location using a random number generator. After each simulation, the space–time distances for all points in the simulated dataset are re-measured and the cell frequencies in the contingency table are recalculated. Statistical significance can then be determined by computing the number of times the observed cell frequency exceeded the expected cell frequency values for all of the simulations. The likelihood of near repeat victimization for each space–time distance pair can be calculated by dividing the observed cell frequency by the mean of the expected cell frequencies. Values below 1 indicate repeat victimization is less likely than expected on the basis of chance and values above 1 indicate repeat victimization is more likely than expected on the basis of chance. By subtracting the Knox ratio from 1, the effect size can be interpreted as an increased/decreased percentage of near repeat victimization likelihood, similar to the interpretation of an odds ratio (for alternative explanations, see Johnson *et al.*, 2007a; Ratcliffe and Rengert, 2008).

A free computer program that automates the methodologically and computationally rigorous Knox method is currently available online (Ratcliffe, 2009). In order to test for a near repeat pattern, the program requires the input of a correctly formatted data set with the XY-coordinates and date of occurrence for the events of interest. The user then specifies the spatial and temporal bandwidths, the geographic distance measurement technique to be used, and the statistical significance level (which determines the number of Monte Carlo simulations used). Manhattan distance and a  $P$ -value  $< 0.001$  (999 Monte Carlo simulations) is used in the present study.

The spatial bandwidth for this analysis is 400 ft, the average length of a city street block in

<sup>2</sup> Earlier studies (Townseley *et al.*, 2003; Johnson and Bowers, 2004a) did not utilize the Monte Carlo simulation technique to create an expected distribution of cell frequencies and determine statistical significance. Johnson *et al.* (2007) introduced this modification to avoid the fact that the original Knox method violated the assumption of independent observations by assuming 'that in the absence of contagion, the statistical distribution of the expected values for the cells of the Knox [contingency] table would conform to a Poisson distribution, and can be computed using the marginal totals of the table' (p. 208).

Philadelphia (McCord and Ratcliffe, 2009; Ratcliffe and Rengert, 2008). The street block is considered the unit of analysis that best depicts variations in crime across the urban landscape (Taylor, 1997). Practically speaking, the term 'street block' is in the vocabulary of many and provides a simple heuristic for interpreting and applying the results. The temporal bandwidth used in the present analysis is 7 days. The 7-day bandwidth supplies both a short timeframe as well as a conceptually simple measure for interpreting, understanding, and applying the results. Since police commanders are typically focused on emerging crime problems (Buerger, 2010), a short temporal bandwidth will make the results practically appealing, especially for departments with Compstat-type organizational responses to crime (Weisburd *et al.*, 2003).

### Identifying near repeat armed street robbery chains

The second phase of the analysis involved connecting near repeat armed street robbery events into multiple-event chains. Near repeat events were considered part of the same chain if the temporal and spatial distances between events were within the statistically significant spatial and temporal parameters established by the Knox analysis. The Near Repeat Calculator provides an additional feature to examine which events from the data set are points within a near repeat pattern (Ratcliffe, 2009). These results are provided in a new data file that reports each event's XY-coordinates, date of occurrence, and counts for the number times the point was an originator in a near repeat pair, or a repeat in a near repeat pair (i.e. the second incident). A total of 888 (25% of all geocoded armed street robberies) near repeat armed street robbery points were identified as being part of an event pair. The near repeat data file was displayed in a Geographic Information System (GIS) and the related near repeat points were linked. In the present analysis, any events occurring within 7 days and 1200 feet of another near repeat event were aggregated into the same chain. After each near repeat event had been

assigned to a chain with a unique identifier, the number of originating points and near repeat points within each chain were summed and compared. Since each near repeat should have a preceding originator, the totals for these two categories for each chain should be equal. This was confirmed. Descriptive statistics describing the extent of the near repeat chains were then calculated.

### Near repeat chains and the temporal stability of armed street robbery hotspots

The final phase of this analysis was designed to examine the extent to which near repeat armed street robberies impact the temporal stability of armed street robbery hot spots. The hierarchical nearest neighbour (HNN) clustering routine available in CrimeStat v3.2 (Levine, 2009) was used to identify micro-level armed street robbery hot spots in the 2009 Philadelphia armed street robbery data. HNN creates an output of clusters at different orders. Only first-order clusters are examined in the present analysis because first-order clusters are event-based or 'hot spots' of events; whereas, higher-order clusters (i.e. second-order or third-order) are clusters of clusters formed by aggregating clusters at a lower order into larger clusters (Levine, 2009). First-order clusters are also a more micro-level hot spot and, more theoretically, representative of the variation in crime levels typically found within larger areal units (Andersen and Malleson, 2011). A researcher must specify the minimum number of events that each first-order cluster must encompass. Events are then grouped on the basis that the spatial distance between each event and its nearest neighbour is shorter than would be expected under the assumption of complete spatial randomness (Eck *et al.*, 2005). In the present analysis, first-order clusters are specified to have at least 10 armed street robbery events.

In order to examine how near repeat events impact the temporal stability of micro-level hot spots, a homogeneity index, commonly used in social science research to summarize the distribution of data across nominal categories

(Blau, 1977; Chainey and Ratcliffe, 2005; Gibbs and Martin, 1962), was calculated. The homogeneity index was computed using the formula:  $h = 1 - \sum p_i^2$  where  $p_i$  is the proportion of data within each category of the nominal variable of interest. The homogeneity statistic is bounded by a maximum of  $1 - 1/n_i$ , where  $n_i$  is the total number of observed categories, and a minimum of 0. A value close to the maximum indicates the data are heterogeneous or equally dispersed across the observed categories. A value of 0 indicates complete homogeneity or that the data are entirely concentrated within just one category.

In the present study, each hot spot's homogeneity index was calculated using the count of armed street robberies that occurred within each of the thirteen ( $n = 13$ ) 28-day intervals that made up the 2009 calendar year. A hot spot with the maximum value (0.923) would indicate the events within the hot spot were equally dispersed across all of the 28-day intervals for 2009 and a value of zero would indicate that robberies within the hot spot occurred within just one of the 28-day intervals for 2009. The relationship between the temporal stability statistic (homogeneity index) and the proportion of near repeat events within each hot spot is reported using a Pearson's correlation coefficient.

## Results

### The near repeat nature of armed street robbery

A statistically significant near repeat armed street robbery pattern was identified. The results from the

near repeat analysis are displayed in Table 1. As expected, the increased chance for a near repeat armed street robbery to occur after an originating robbery diminishes as the distance and time from an originating event increases. Specifically, the Knox ratio of 1.80 for the 0 to 7 days and 1 to 400 feet cell in Table 1 indicates that a subsequent armed street robbery is 80% more likely to occur within one block and 1 week after an initial armed street robbery than if a near repeat pattern was not identified. The Knox ratio of 1.31 within the same 0 to 7 days time frame and 401 to 800 feet cell indicates that a near repeat armed street robbery is 31% more likely on the second block away and within the week following the originating event. Finally, the increased likelihood for a subsequent armed street robbery to occur after an originating event decreases to only about 16% more likely than if a near repeat pattern was not identified at the distance of about 2 to 3 blocks (801 to 1200 feet) and within the same 0 to 7 day time frame after the originating event (though still statistically significant). In total, there is a greater likelihood for a subsequent armed street robbery event to occur within 1200 feet and 7 days of an initial armed street robbery event than would be expected if a space-time interaction for armed street robberies was not identified within the data.<sup>3</sup>

### The extent of near repeat armed street robbery chains

The second phase of this analysis focused on aggregating close pairs of armed street robberies into multiple-event chains in order to quantify the

<sup>3</sup> Additional analyses were performed using slightly different spatial and temporal parameters: (1) 400 ft and 14 days; (2) 800 ft and 7 days; and (3) 800 ft and 14 days. In sum, the results were not substantively different, but less sharp than the analysis reported above. In all three analyses, it was found that increasing the temporal and spatial parameters slightly increased the geographic extent and temporal length of the near repeat pattern, but only in the contingency table cells that also included the events from the 400 ft and 7 days analysis. For example, in the 400 ft and 14 days analysis, the cell for events 400 ft and 14 days was significant, but this cell also contained all events from the statistically significant 400 ft and 7 days cell in the analysis discussed above. More importantly, the spatial and temporal parameters of 400 ft and 7 days (discussed in the findings) provided the most robust results: all Knox likelihood ratios were larger than those from the other analyses. Because the strongest effects were found in the 400 ft and 7 day analysis and those parameters provide the most conceptually simple and practically useful results, they are presented above. Nonetheless, results from the sensitivity analyses can be provided upon request.

**Table 1:** Armed street robbery near repeat analysis: Knox ratios

Time Distance	0 to 7 days	8 to 14 days	14 to 21 days	22 to 28 days	More than 28 days
Same location	2.49**	1.89**	1.18	0.89	0.90
1 to 400 feet	1.80**	0.89	0.85	1.11	0.97
401 to 800 feet	1.31**	1.01	0.86	0.99	0.99
801 to 1200 feet	1.16*	1.03	0.95	1.00	0.99
1201 to 1600 feet	1.09	1.02	1.01	0.94	1.00
More than 1600 feet	1.00	1.00	1.00	1.00	1.00**

\* $P < 0.05$ ; \*\* $P < 0.001$ . Source: Philadelphia Police Department, 2009.

extent to which near repeat armed street robbery occurred at the event level. The 888 individual armed street robbery events identified as part of the near repeat armed street robbery pattern in the first part of the analysis were aggregated into a total of 363 near repeat chains. Table 2 displays descriptive statistics for the near repeat armed street robbery chains. For the most part, near repeat armed street robberies occurred in close pairs. In fact, roughly 57% ( $n = 502$ ) of the individual near repeat armed street robbery events identified were either an originator or near repeat event in one of 251 close pairs identified. The second most frequently identified chain length was 3-event near repeat armed street robbery chains. In total, roughly 27% ( $n = 237$ ) of the individual near repeat armed street robbery events identified made-up 79 3-event near repeat armed street robbery chains. About 17% ( $n = 149$ ) of the individual near repeat armed street robbery events identified were part of the 33 chains identified having 4 or more events, distributed thus: 4-event chains ( $n = 21$ ), 5-event chains ( $n = 8$ ), 6-event chains ( $n = 3$ ), and a chain with 7 events ( $n = 1$ ).

In Table 2, what we refer to as the *risk time* is determined as the period in days during which a near repeat chain persisted. In other words, risk time counts the first event day as day one, and continues to the last event day inclusively. The short event length of the near repeat chains was reiterated in terms of risk time. As depicted in Table 2, when comparing the mean risk time for chains of varying event lengths individually, the average risk time

**Table 2:** Descriptive statistics for near repeat armed street robbery chains

Chain event length	Number of chains	Total events in all chains	Number of days chain persisted (Risk Time) <sup>a</sup>			
			Min.	Max.	Mean	SD
2	251	502	1	6	3.18	1.64
3	79	237	1	12	5.47	2.57
4	21	84	3	14	8.29	2.95
5	8	40	4	17	10.75	5.04
6	3	18	8	13	11.00	2.65
7	1	7	— <sup>b</sup>	—	—	—
All chains	363	888	1	17	4.20	2.77

Note that each event in a chain is within 1200 feet and 7 days of at least one other event in the chain. <sup>a</sup>Risk time is total number of days that a near repeat chain persisted, counting the first event day as day one, and continuing to the last event day (inclusive); <sup>b</sup>Only one chain 7 events long was identified, so descriptive statistics are not displayed. The risk time for the 7-event chain was 11 days. Source: Philadelphia Police Department, 2009.

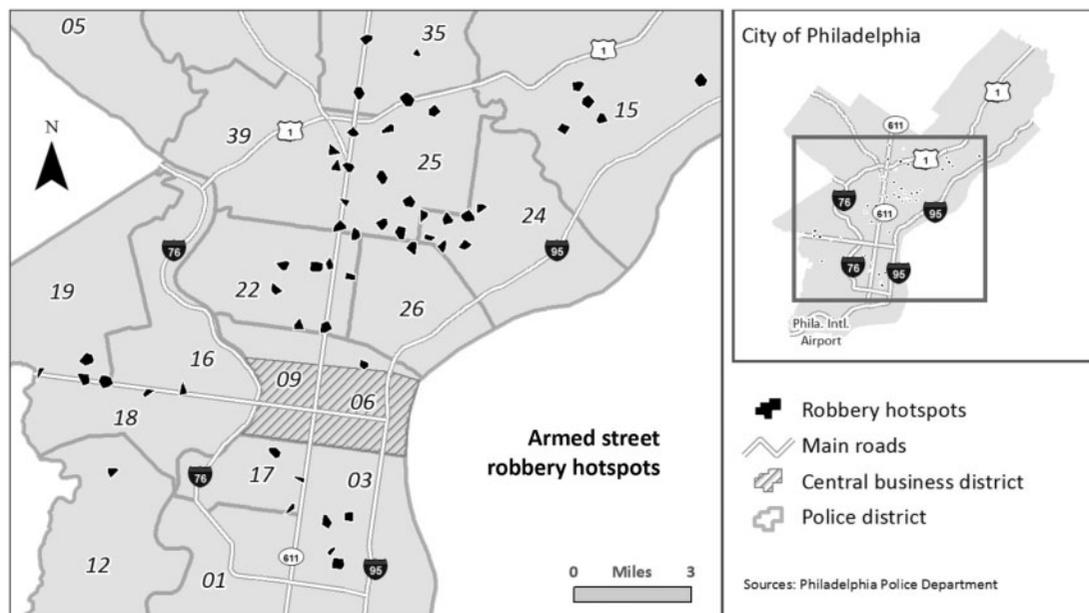
generally increased as the chain event length increased. Nonetheless, the average risk time for all chains was still only 4.2 days, and 89.5% of all chains, regardless of event length, expired within 7 days or less. Simply put, the risk time variable reflects the fact that most chains contained very few events that, by definition of the near repeat phenomenon, occurred within close temporal proximity to each other. While armed street robberies occurred close in both space and time more often than would be expected on the basis of chance, the extent of the heightened risk in the nearby area is minimal at the event level.

### Near repeats and the temporal stability of armed street robbery hot spots

A preliminary examination of maps showing the distribution of all armed street robbery events against all near repeat armed street events suggested that the distribution of near repeat armed street robbery events closely mirrored the spatial distribution of all armed street robbery events in the city. Thus, the final phase of this study was designed to examine how near repeat armed street robbery events contributed to the development and subsequent temporal stability of armed street robbery hotspots. HNN clustering was employed to identify micro-level armed street robbery hot spots (Levine, 2009). A total of 52 first-order clusters were identified (Fig. 1). Descriptive statistics for the 52 first-order hotspots are displayed in Table 3. The 52 first-order clusters contained 20.75% ( $n=738$ ) of all geocoded 2009 armed street robberies, but merely 2.73% ( $n=589$ ) of Philadelphia street intersections. Roughly 43% ( $n=317$ ) of the total armed street robberies within the 52 hot spots were part of a near repeat chain. The 317 near repeat armed

street robbery events within the armed street robbery hot spots represented only about 9% of all geocoded armed street robberies but about 36% of all near repeat armed street robbery events that occurred in Philadelphia during 2009. The locations of the robbery hotspots are shown in Fig. 1.

Table 3 shows that the proportion of near repeat events to total armed street robberies within each hotspot ranged from 0 to 0.8. The majority ( $\approx 60\%$ ;  $n=31$ ) of armed street robbery hotspots contained a proportion of near repeat armed street robberies to total armed street robberies of .5 or less. On the other hand, a total of 21 ( $\approx 40\%$ ) armed street robbery hotspots were identified where  $>50\%$  of the total events within the cluster were part of a near repeat process. The temporal stability statistics ranged from 0.72 to 0.90 with the average equalling 0.84 and a standard deviation of 0.04. The consistently high values across all 52 hot spots indicated that the robbery events that formed the hot spots were similarly dispersed over multiple 28-day intervals throughout the year. The scatter plot in Fig. 2



**Figure 1:** Armed street robbery hotspots, Philadelphia, PA, 2009.

depicts the relationship between the proportion of total armed street robberies that were near repeat events within each hotspot and the temporal stability statistics ( $r = -0.16$ ;  $P$ -value non-significant). The scatter plot visually demonstrates the temporally stable patterns across the hot spots, regardless of near repeat composition. In short, the hot spots

derived mostly from near repeat events experienced the same temporal pattern as the hot spots derived of only a few or no near repeat events. This finding suggests that even if a hot spot was driven by near repeat events, those near repeat events were spread out over the duration of 2009 rather than the result of one short armed street robbery outbreak.

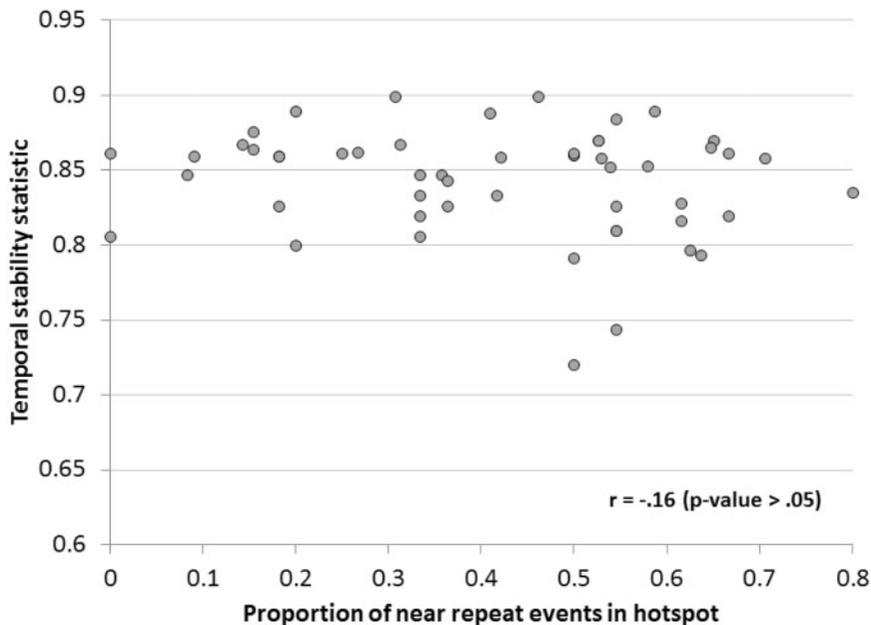
**Table 3:** Descriptive statistics for first-order armed street robbery clusters ( $n = 52$ )

	Min.	Max.	Mean	Median	Standard deviation
Robberies	10	29	14.19	12.00	4.17
Near repeat robberies	0	17	6.10	5.50	3.86
Proportion of near repeat robberies	0	0.8	41.30	44.13	19.80
Temporal stability	0.72	0.90	0.84	0.86	0.04
Area (sq. miles)	0.012	0.043	0.026	0.026	0.007
Intersections	4	22	11.33	11	4.16
Miles of street	0.917	3.08	1.76	1.74	0.50

Source: Philadelphia Police Department, 2009.

## Discussion

This study applied the near repeat phenomenon to a previously unexamined crime type, armed street robbery, and focused on quantifying the extent at which the near repeat phenomenon occurs. At least in Philadelphia, it is statistically more likely for an armed street robbery to occur within about three city blocks (1200 feet) and 1 week (7 days) of a previous armed street robbery than compared to a random spatio-temporal distribution. Linking near repeat armed street robberies into chains of multiple near repeat events, however, revealed that the heightened risk to nearby targets created



**Figure 2:** Relationship between the temporal stability statistic and the proportion of near repeat events for each armed street robbery hotspot ( $n = 52$ ).

by a previous armed street robbery event was short lived. In fact, roughly 90% of near repeat armed street robbery chains terminated after just 2 or 3 events and 7 days or less. The short extent of the near repeat armed street robbery chains also translated to the fact that individual armed street robbery outbreaks never led directly to the formation of any armed street robbery hot spots. The majority of armed street robbery hot spots were determined to be predominantly comprised of isolated armed street robbery incidents, but even those hot spots primarily consisting of near repeat events (21 of the 52) were found to be temporally stable across 2009. In other words, those near repeat chains occurred in multiple instances throughout 2009 rather than in one long chain of events or concentrated chains of events.

The statistically significant near repeat pattern suggests that past armed street robberies can be useful for forecasting the occurrence of future armed street robberies. This provides police with two options; a tactical short-term response and a strategic long-term response. Unfortunately, the evidence suggests a tactical short-term response would be difficult to muster within the time frame of even the longest near-repeat chains. Consider the analytical and organizational capabilities that have to occur before police can capitalize on the near repeat strategy. The organization must have:

- a surveillance mechanism adequate enough to monitor crime events with sufficient frequency;
- an analytical regime capable of recognizing a chain of events quickly and against a background noise of unrelated crimes;
- a decision-making framework capable of identifying the need for, and coordinating, a suitable tactical response; and
- the operational flexibility to adapt to changing conditions and implement a new tactic.

Furthermore, the crime type in question must have a near repeat pattern that persists with sufficient temporal length to still be viable once the organization has mustered a response.

In the case of near repeat armed street robbery, the vast majority of the chains lasted less than 7 days and only 38 of the 363 chains persisted beyond 7 days.<sup>4</sup> Of the 154 events in these 38 chains, only 58 actual repeat events occurred beyond 7 days (from an initial sample of 3,556). This provides the police with a considerable intelligence and organizational challenge, at least with regard to armed street robberies. In the case of Philadelphia, 30% (112/363) of new near repeat pairs will continue to have another event, which is a reasonable crime prevention opportunity; however, it must be recognized quickly as the overall pattern rarely lasts beyond a week. This draws into question the value of Compstat-type meetings that are held weekly and biweekly, lacking as they do the currency to identify and react with sufficient flexibility. Many Compstat meetings are conducted with data that are at least a day or two out of date in order to allow crime analysts time to prepare the (often compendious) books of statistics that accompany the meeting. This delay, while inevitable, further adds to the argument that the responses that emanate from a Compstat meeting may be starting too late to be effective.

The evidence in this article instead promotes the necessity for a rapid assessment of crime patterns conducted at the local level. Given the nascent state of 'predictive policing' (Johnson *et al.*, 2009a; Tompson and Townsley, 2010), a 30% chance that a near repeat pair will have a follow-on within a week and within 1,200 feet is a strong finding with real proactive potential; however, to capitalize on this opportunity requires a real-time analytical capacity, vigilant local mid-level command staff, or sophisticated automated systems capable of alerting commanders to an emergent crime fighting possibility.

<sup>4</sup> These 38 chains included 3-event chains ( $n = 17$ ), 4-event chains ( $n = 12$ ), 5-event chains ( $n = 6$ ), 6-event chains ( $n = 3$ ), and a 7-event chain ( $n = 1$ ).

Given this context, prospective hot spotting techniques could be applied to armed street robbery. One prospective hot spotting technique (ProMap), that uses a revised kernel density equation to give more weight to recent crime events, has been demonstrated to be more predictive of future crime events than traditional kernel density estimation maps (see Bowers *et al.*, 2004; Johnson *et al.*, 2007b, 2009a). Further prospective mapping techniques that combine long-term risk heterogeneity with near repeat patterns are underway by researchers at Temple University's Center for Security and Crime Science. The implementation and use of these tools to effectively prevent crime, however, will likely need to be accompanied by fundamental organizational changes.

The finding that the armed street robbery hot spots were temporally stable regardless of their near repeat composition throughout 2009 suggests that the underlying processes contributing to the heightened opportunity for armed street robbery within each of the hot spots also remained constant across the study period. Though the chains were short-lived and would be difficult to address unless the organizational capacities in the previous paragraph existed, more holistic strategies designed to reduce crime opportunities in the more temporally stable armed street robbery hot spots are likely to be more fruitful than chasing short-term crime outbreaks. There is preliminary evidence to suggest that the same places within a city experience high levels of crime over the long periods of time (Braga *et al.*, 2011; Weisburd *et al.*, 2004). Therefore, considering that it has been shown that changes in crime levels at small geographies can impact city-wide crime levels (Ratcliffe, 2010) and the growing body of empirical research demonstrating the effectiveness of different hot spot policing tactics in crime hot spots (for general summaries, see, Braga, 2005; Lum *et al.*, 2011; for a specific example, see, Ratcliffe *et al.*, in Press), it seems to make more sense for police commanders to focus resources at the hot spots-level versus the event-level.

The finding that some temporally stable hot spots experience a relatively high number of near repeat events also provides new insight for designing strategies to address hot spots in general. Clarke and Eck (2003) explained the importance of understanding the underlying process fuelling a hot spot before attempting to design and implement a crime-prevention strategy and it is well-documented that problem-solving efforts commonly fail because the involved parties fail to fully analyse and understand the problem (Bullock *et al.*, 2006). Because the processes driving hot spots with an abundance of near repeat events are likely different than the processes driving hot spots of mostly isolated events, the current findings suggest that crime prevention planners should be aware of the targeted hot spot's near repeat composition before designing a crime-prevention strategy. In short, the crime prevention strategy undertaken to address a hot spot of isolated events might be different than a strategy designed to address a hot spot of predominantly near repeat events.

### Limitations

Although this study has answered a number of research questions, it has also illustrated the need for additional research examining the near repeat phenomenon. Although this study was framed by two hypotheses (boost and flag), available data did not permit directly testing them. Testing these hypotheses will likely require using a number of different methodologies and access to related offender information. For example, the boost hypothesis might be supported by using official arrest data to determine if strings of near repeat crimes are more likely to be cleared to the same persons than non-near repeat crimes (Bernasco, 2008; Bowers and Johnson, 2004; Johnson *et al.*, 2009b). In addition, interviews with street robbers about target selection and offending frequency might also provide important insight on the boost hypothesis. Alternatively, data on the physical environment might be used to predict the spatial patterning of near repeat events in order to support

the flag hypothesis. Finally, simulation and mathematical modelling might be used to test both theories individually and simultaneously (Groff, 2007, 2008; Johnson, 2008; Pitcher and Johnson, 2011).

This study is also limited in that only one crime type, armed street robbery, was examined; albeit reducing armed street robbery is of considerable concern to most police organizations. Examining near repeat chains for other crime types may produce different results with different implications for crime prevention and policing. The present analysis should be replicated using data from other locations before any police departments begin using the near repeat nature of armed street robbery to make operational decisions. Furthermore, the temporal stability statistic in this study suffers from a modifiable temporal unit problem that is similar to the modifiable areal unit problem (MAUP) that many geographic studies face. While using different temporal bounding units, such as months, did not substantively change the results of this study, future research should continue to develop new statistics for assessing temporal stability.

## Conclusion

While the present study identified a near repeat gunpoint robbery pattern, the results suggest that a range of challenging organizational capacities are required to capitalize on this pattern. These organizational challenges include possessing the analytical capacity to identify a pattern, the leadership mechanism to direct a new strategy, and the operational flexibility to rapidly respond, all within a timeframe of usually less than 1 week from the start to the end of the crime series. With these capacities in place, the nearly one-third of near repeat armed street robbery pairs that will have a subsequent event within a week and about three city blocks has the potential to aid proactive policing efforts.

That being said, exploring the influence of near repeat armed street robbery chains on the temporal

stability of hot spots suggests that chasing short-term outbreaks may not be the best use of police resources for addressing armed street robbery. In the future, crime scientists may be able to develop predictive models to aid police departments in formulating crime prevention strategies focused on short-term changes in crime, but the current body of literature on the stability of spatial crime patterns, the empirical evaluations of policing tactics, and the findings of this study still provide overall support for more holistic strategies that focus on reducing armed street robbery opportunities in long-term armed street robbery hot spots.

Predictive policing, while remaining largely undefined, is still mostly an analytical challenge and curiosity for crime analysts and computational scientists. It currently lacks integration with operational policing as found with more holistic and established frameworks such as problem-oriented policing and intelligence-led policing. The evidence from this article has one clear implication: to capitalize on the opportunities provided by predictive analytics requires a range of complex organizational capabilities to be in place. Without simultaneously and explicitly considering the analytic and organizational structures necessary to implement the findings of predictive regimes, police agencies will not be able to effectively utilize predictive research, and frustration and disillusionment will result.

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