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Near Repeat Space-Time Patterns of Canadian Crime[1]

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Des études antérieures ont trouvé que des cibles situées à proximité de cibles précédemment victimisées ont de plus grandes chances d'être victimisées elles aussi. Par contre, ce risque élevé de victimisation à cause de la proximité semble être temporaire et diminue avec le temps. Des données canadiennes ont rarement été utilisées pour étudier la victimisation à cause de la proximité, et il a été démontré que des modèles espace-temps exacts varient d'un endroit à l'autre. Cette étude aide donc à examiner une lacune dans la recherche en déterminant le regroupement espace-temps exact de crime répété à proximité pour trois types de crimes (cambriolage, vol dans un véhicule à moteur [VDVM] et voies de fait simples) dans trois villes canadiennes (Edmonton, en Alberta; Moose Jaw, en Saskatchewan; et Saint John, au Nouveau-Brunswick). Les résultats démontrent un regroupement espace-temps important de crime répété à proximité pour le cambriolage à Edmonton, le VDVM à Edmonton et le VDVM à Saint John, avec un modèle espace-temps exact qui varie d'un fichier de données à l'autre. Les conséquences de ces résultats, ainsi que certaines limites et directions pour des études futures, sont examinées.

Mots clés : analyse espace-temps, crime répété à proximité, victimisation répétée, cartographie des zones sensibles, crime canadien

Previous research has found that targets located in close proximity to previously victimized targets are at an increased risk of also being victimized. However, this elevated risk of near repeat victimization appears to be temporary and subsides over time. Near repeat victimization has rarely been examined using Canadian data, and exact space-time patterns have been shown to vary by location. Thus, the current study helps to address a gap in the research by determining the exact near repeat space-time clustering of three

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crime types (burglary, theft from a motor vehicle [TFMV], and common assault) across three Canadian cities (Edmonton, Alberta; Moose Jaw, Saskatchewan; and Saint John, New Brunswick). The results demonstrate significant near repeat space-time clustering for Edmonton burglary, Edmonton TFMV, and Saint John TFMV, with the exact space-time pattern varying from one data file to the next. The implications of these results, as well as some limitations and directions for future research, are discussed.

Keywords: space-time analyses, near repeat crime, repeat victimization, hot spot mapping, Canadian crime

Previous research has shown that prior burglary victimization is a significant predictor of future victimization (i.e., repeat victimization is common; e.g., Budd 1999; Townsley, Homel, and Chaseling 2000). While this research clearly has value in terms of the development of crime prevention strategies (i.e., installing security devices on previously victimized residences), there is also value in determining how burglary victimization impacts the risk of attack for other dwellings that are in close proximity to the targeted site (i.e., near repeats). Several studies have conducted research on the topic of near repeat victimization and found that burglaries do in fact cluster together in time and space (e.g., Townsley, Homel, and Chaseling 2003; Johnson and Bowers 2004).

Interestingly, these studies demonstrate how burglary can be thought of as being transferable. In fact, this transference of burglary appears to be a fairly robust finding, with Johnson and colleagues (2007) obtaining similar results for 10 cities in five different countries. However, the precise pattern of burglary risk varies across samples, which highlights the importance of examining the near repeat phenomenon in different countries and cities. In addition to burglary, further research has examined the space-time patterns of many other types of crimes, such as gun crime (Ratcliffe and Rengert 2008) and theft from motor vehicles (Summers, Johnson, and Pease 2007). These studies found that these crime types also cluster together in space and time, but, again, the precise patterns that were observed varied across crime types.

The near repeat phenomenon has rarely been examined using Canadian crime data.[2] The current study helps address this gap in the research by examining how criminal events cluster together in space and time across several Canadian cities (of various sizes) and across various crime types. A more thorough discussion of the literature pertinent to the current study will now be provided.

Repeat victimization

Although the current study focuses on near repeat crime, repeat victimization is also an important concept to discuss given that the discovery of the "near repeat" phenomenon was the direct result of repeat victimization research. Repeat victimization refers to "the recurrence of crime in the same places and/or against the same people" (Pease 1998: 1). Several studies have shown that repeat victimization is not a rare occurrence; people and places that have been victimized in the past are at an elevated risk for future victimization (e.g., Sherman 1992; Tseloni and Pease 1998; Kleemans 2001). In other words, repeat victimization occurs much more frequently than would be expected by chance.

The 1992 British Crime Survey found that 4% of people in the U.K. experienced 44% of the total crime in that year (Farrell and Pease 1993). Similarly, the Australian Bureau of Statistics found that 50.6% of all property crimes were committed against only 28.7% of households from May 1992 to April 1993 (Mukherjee and Carcach 1998). In fact, prior burglary victimization is one of the most significant predictors of future victimization (e.g., Pease 1998; Budd 1999; Townsley et al. 2000).[3] It is important to note, however, that the risk of repeat burglary victimization is highest during the time period immediately following the initial burglary and that this risk declines over time (e.g., Kleemans 2001; Sagovsky and Johnson 2007).

In one particular study, Morgan (2001) was examining repeat burglary in Perth, Australia, when he observed that dwellings near a previously burglarized home would often be victimized soon after the first offence. Morgan referred to these occurrences as "near repeats," and his observation resulted in other researchers examining near repeat crime more directly.

Near repeat victimization

Burglary

Among the first to examine the near repeat phenomenon were Townsley et al. (2003). These researchers analyzed residential burglary data from Brisbane, Australia, using an epidemiological approach known as the Knox test. This test was developed by Knox (1964) to assess whether childhood leukemia was a contagious disease. In brief, the Knox test is used to determine whether there are more observed pairs of events that occur close together in space and time than would be expected by chance (i.e., whether the pairs of events are independent from one another). The Knox test compares each data point to all other data points, and a contingency table is generated. Using this table, observed cell counts for crime pairs that occurred close together in space and time are compared to expected cell counts; contagion is deemed to be present if the observed counts are significantly greater than expected. Defining near repeats as those crime pairs that occurred within 100–200 metres of one another and within one to two months apart, the results from the Knox test indicated that near repeats were present in Townsley and colleagues' data. Also using the Knox test, Johnson and Bowers (2004) examined near repeat burglaries in Merseyside, U.K., and found that houses within 300–400 metres of an original burglary exhibited an elevated risk of also being burglarized. Importantly, this elevated risk was only temporary and appeared to subside approximately one to two months after the initial event.

In one of the most comprehensive studies to date, Johnson et al. (2007) observed similar space-time patterns of near repeat burglary for 10 cities in five different countries (Australia, the Netherlands, New Zealand, the United Kingdom, and the United States), thus demonstrating the robustness of the transferability of burglary. Across all their samples, houses within at least 200 metres of a previously burglarized home were at an elevated risk of burglary for a minimum of two weeks. However, the precise pattern of burglary risk varied across the samples (from 200 to 1,200 metres and from two to eight weeks), highlighting the importance of examining space-time clustering across different countries and even cities. Similarly, Kikuchi et al. (2010), Moreto, Piza, and Caplan (2014), and Wu et al. (2015) more recently found significant space-time clustering for residential burglaries in Japan, Newark, NJ, and China, respectively.

Although it was not the main focus of their article, Fitterer, Nelson, and Nathoo (2015) did examine the near repeat space-time clustering of commercial and residential break and entries that occurred in Vancouver, BC, between 2001 and 2012. Relying on Ratcliffe's (2009) near repeat calculator, which was also used in the current study, Fitterer and colleagues found a significant near repeat space-time pattern of 500 metres and two days for commercial burglary, and 850 metres and two days for residential burglary. The researchers then integrated this near repeat space-time pattern into a statistical model; they found that this model was able to predict future commercial and residential break and entries. As far as the authors are aware, this is the only published study to date that has examined the near repeat phenomenon using Canadian data.

Other crime types

The ubiquity of the finding that residential burglary is transferable led researchers to examine space-time patterns for other types of crime. Summers et al. (2007), for example, found theft *from* a motor vehicle (TFMV) in Derbeyside and Dorset, U.K., to be transferable, whereas theft *of* a motor vehicle was not. Similar to the findings of Summers and colleagues, Johnson, Summers, and Pease (2009) also found evidence of space-time clustering for TFMV occurring in Bournemouth, U.K. Specifically, TFMV was more likely to occur within 800 metres of an initial theft, and this elevated risk was found to persist for 14 days. More recently, Block and Fujita (2013) examined the near repeat phenomenon in overall, temporary (recovered), and permanent (unrecovered) motor vehicle thefts in Newark, NJ. Significant space-time clustering was found for both overall and temporary vehicle thefts but not for permanent thefts.

In another study, Kikuchi et al. (2010) analyzed Japanese crime data and found the near repeat phenomenon to be present in purse snatching, TFMV, and business burglary. Violent offences were the only crime type examined where significant space-time clustering was not present. Similarly, Youstin et al. (2011) examined the near repeat phenomenon using crime data from Jacksonville, FL, for multiple crime types – auto theft, robberies, and shootings. They observed significant space-time clustering for all three crime types examined, but, as expected, the exact space-time pattern was found to vary from one crime type to the next. In another study, Ratcliffe and Rengert (2008) examined whether near repeat patterns existed for shooting incidents in Philadelphia, PA; they found significant space-time clustering in their data. Specifically, a shooting incident resulted in an elevated risk (33% greater than expected) of another shooting incident occurring within one city block (122 metres) of the original incident; this elevated risk subsided two weeks following the initial shooting.

Wells, Wu, and Ye (2012) examined gun assaults in Houston, TX, and found a significant near repeat space-time pattern very similar to that found by Ratcliffe and Rengert. In addition, Haberman and Ratcliffe (2012) found significant space-time clustering of 1,200 feet and seven days when examining armed street robbery that occurred in Philadelphia.[4]

In another study, Townsley, Johnson, and Ratcliffe (2008) examined insurgent activity in Iraq to identify space-time patterns that would be operationally useful from a security standpoint. They determined that there was evidence of space-time clustering for incidents involving improvised explosive devices (IED) in Iraq, with the highest risk of future IED attacks being at distances up to one kilometre for a period of two days following the initial IED attack. Similarly, Behlendorf, LaFree, and Legault (2012) also found significant space-time clustering when examining terrorist attacks by two terrorist organizations, with the risk of future terrorist attacks for both terrorist groups being highest at distances up to five miles (eight kilometres) for up to two weeks following the initial attack.

Some researchers have recently even begun exploring the space-time patterns of maritime piracy. Townsley and Oliveira (2015), for example, used the Knox test to examine the space-time clustering of pirate attacks that occurred on the high seas around the Horn of Africa from 2006 to 2011. Their results indicate that maritime piracy does indeed cluster together in space and time with the risk of future pirate attacks being highest within 10 nautical miles (18.5 kilometres) of the prior pirate activity for a period of one week following the initial attack. Similarly, Marchione and Johnson (2013) examined all incidents of maritime piracy from May 1978 to January 2012 and consistently found significant space-time clustering from 1997 onward.

The aforementioned studies demonstrate how space-time clustering is consistently found across an array of crime types (with permanent theft of a motor vehicle in Newark, NJ, and violent offences in Japan being the only exceptions thus far) and in a variety of different geographic regions. However, the precise space-time patterns were found to vary across crime types and regions, thus emphasizing the importance for additional research that examines this issue (i.e., specific space-time patterns cannot necessarily be generalized across all crime types and regions).

Theoretical explanations for repeat and near repeat victimization

Although the "boost" and "flag" accounts are two key theories that were originally proposed to explain the occurrence of repeat burglary victimization (Pease 1998), they can also be applied to near repeat victimization (Bowers and Johnson 2004). According to the boost account, repeat (or near repeat) burglary victimization is the result of the initial burglary "boosting" the likelihood of future victimization (Pease 1998). In other words, repeat (or near repeat) victimization is the result of the same offender, or his/her acquaintances, returning to burglarize a dwelling (or a nearby dwelling) that he/she has successfully burglarized in the past. The offender may return to burglarize the same (or similar) houses for various reasons, such as the fact that known escape routes may lower the perceived risk of offending in a particular area.

In contrast to the boost account, the "flag" account proposes that repeat (or near repeat) burglary victimization occurs as a result of a dwelling's enduring attributes that flag it (or surrounding dwellings) as a suitable target (e.g., easy access, lack of alarm systems, no nearby neighbours) (Pease 1998). Thus, according to the flag account, repeat (or near repeat) victimization is the result of different offenders choosing to burglarize the same (or similar) dwellings as a result of its particular attributes (i.e., houses have an enduring level of risk for burglary).

Previous research has found support for the boost account as an explanation for both repeat and near repeat victimization (e.g., Pease 1998; Bowers and Johnson 2004; Bernasco 2008; Johnson et al. 2009). However, the boost account cannot necessarily explain the occurrence of *all* repeat and near repeat victimization, and existing research does not entirely rule out the flag account. Thus, it seems likely that the boost and flag accounts both play a role in explaining repeat and near repeat victimization. As explained by Johnson (2008), the boost account appears to be the most probable explanation for repeat (or near repeat) crime that occurs soon after the initial offence, whereas the flag account offers a likely explanation for why multiple offenders would all initially select the same (or similar) target. It is important to consider both the flag and boost accounts when examining repeat and near repeat victimization, as they may have different implications for the development of effective crime prevention strategies.

Current study and hypotheses

The current study determined the exact space-time clustering of several crime types (residential burglary, theft from motor vehicle [TFMV], and common assault) across various Canadian cities (Edmonton, Alberta; Saint John, New Brunswick; and Moose Jaw, Saskatchewan). Based on the results obtained in previous studies (e.g., Johnson et al. 2007; Summers et al. 2007; Fitterer et al. 2015), it was expected that burglaries and TFMV would cluster together in space and time across each of the three Canadian cities examined (i.e., space-time clustering exists in a Canadian context). The exact space-time patterns, however, were expected to vary across the two crime types (i.e., burglary and TFMV) and from one city to the next. Given the inconsistent findings in regard to violent offences (e.g., Ratcliffe and Rengert 2008; Kikuchi et al. 2010), it was unknown whether common assaults would show a significant near repeat space-time pattern.

Method

Data

An official request for data was sent out to various police agencies across Canada; three city police forces (from Edmonton, AB, Moose Jaw, SK, and Saint John, NB) agreed to provide data for the current study. Conveniently, these three cities represent Canadian cities of varying populations, areas, and population densities (see Table 1 for a comparison across the three cities).

The data from each region consisted of offence locations and the date of each offence[5] across three different crime types – residential burglary, TFMV, and common assault – that occurred between 1 January and 31 December 2007. The Edmonton Police Service and the Saint John Police Force provided the crime site location data as geocoded x, y coordinates that had been offset by a constant value unknown to the researchers. This did not impact the analyses in any way but did ensure that the x, y coordinate data could not be used to determine an exact address for the offence. The crime data for Moose Jaw was converted from standard address format to projected x, y coordinate format using the GPS Visualizer geocoding tool (Schneider 2013) and *ArcView* (v. 10.1), which is a desktop geographic information system.

Table 1: Demographics for Edmonton, AB, Moose Jaw, SK, and Saint John, NB, from 2006 census

City	Population	Population Change since 2001 Census (%)	Area (km^2)	Population Density (per km^2)
Edmonton, AB	730,372	9.6	684.37	1,067.20
Moose Jaw, SK	32,132	0.0	46.82	686.30
Saint John, NB	68,043	−2.3	315.49	215.70

Source: Statistics Canada (2008).

Table 2: Number of incidents by crime type and geographic region.

	Crime Type		
City	**Burglary**	**TFMV**	**Common Assault**
Edmonton, AB	4,031	12,037	3,394
Moose Jaw, SK	148	137	222
Saint John, NB	221	394	877

TFMV = theft from a motor vehicle.

Also important to note is that the various police agencies only provided data on confirmed offences (i.e., an officer was sent out and an official report was filed).

For the purpose of this study, residential burglary is defined as a crime that occurs when an offender enters a residential dwelling with the intent to burglarize the home. TFMV is similar to burglary, except that the offender enters a motor vehicle instead of a residential dwelling to take something that he/she is not the owner of. Common assault is considered the least serious type of assault and includes behaviours such as slapping, punching, pushing, and face-to-face threats. Aggravated assaults, assaults with a weapon, and assaults causing bodily harm are not included in common assaults. Prior to the analyses, the Edmonton, Moose Jaw, and Saint John data files were screened in their entirety, and any offences with missing x, y coordinates or missing date information were excluded from the analyses. Table 2 provides the final number of incidents included in each data file.

Procedure

To determine the precise space-time patterns of Canadian crime, Ratcliffe's (2009) near repeat calculator (v. 1.3) was used. In total, nine data files were used in the analyses; each data point within each file had x, y coordinates denoting the crime site location and the date on which the crime occurred, with each row representing a different crime. Once a particular data file was loaded into the near repeat calculator, the following program parameters had to be specified: spatial bandwidth, number of spatial bands, temporal bandwidth, number of temporal bands, and significance level. Following the same methodology as Johnson and Bowers (2004), the current study used a spatial bandwidth of 100 metres, a temporal bandwidth of seven days, and a significance level of 0.01. The number of spatial bands was set to 14, and the number of temporal bands was set to 10. Note that the number of spatial and temporal bands depends on how far and how long the near repeat pattern is expected to extend (Ratcliffe 2009). In Johnson et al.'s (2007) study, in which space-time patterns of burglary across 10 different cities were examined, the authors found the farthest near repeat effect to be 1,200 metres (Canberra, Australia) and the longest near repeat effect to be eight weeks (Philadelphia, PA). Thus, 10 temporal bands (at one week per band) and 14 spatial bands (at 100 metres per band) were selected in the current study because it was expected that the near repeat effects would not extend beyond 1,400 metres and 10 weeks.

Next, the use of either Manhattan distance or Euclidean distance for the calculations had to be specified. The Euclidean (direct) distance represents the straight-line distance between two points; the Manhattan (indirect) distance adds the difference between the x coordinates of the two points to the difference between the y coordinates of the two points. Manhattan distances are useful if the data originated from a geographic area that consists of road networks based on grid-like patterns and if the travel routes of offenders are known. Given that offender travel routes were unknown and not all streets within the three cities followed a grid-like pattern, the current study used Euclidean distances.

The final step in the procedure involved running the near repeat calculator. Briefly, this program compares the actual space-time pattern observed in the data to that which would be expected based on chance. The expected pattern is generated by randomly redistributing the date values across the various spatial points. Each reallocation of the date values is referred to as a Monte Carlo iteration. The number of iterations that run depends on the significance value selected. In the current study, a p-value of 0.01 was selected, which means that 100 Monte Carlo iterations were run. At a p-value of 0.01, the observed space-time pattern was expected to occur by chance in only 1 out of 100 iterations.

Once the near repeat calculator completed all of its iterations, the program produced two tables as output: (1) an observed over mean expected frequencies table, and (2) a statistical significance table. The observed over mean expected frequency is a ratio that represents the difference between the average expected cell values and the values actually observed for each cell. The observed over mean expected frequencies table also indicates which values are significant both at the user specified p-value and at $p < 0.05$. The statistical significance table is simply a table that indicates the exact p-value for the finding at each spatial and temporal band (i.e., within each cell).

Results

As outlined by Ratcliffe (2009), the observed over mean frequencies (i.e., Knox ratios) tables produced by the near repeat calculator can be used to determine whether significant space-time clustering is present in the data (i.e., whether there is an increased risk that another crime will occur within close space-time proximity to the initial crime). Specifically, a significant and meaningful near repeat victimization pattern is present when the Knox ratios close in space and time to the initial crime incident (i.e., cells near the upper left of the matrix) are (1) equal to or greater than 1.20 and (2) significant at the p-level specified by the user (recall that a p-level of 0.01 was specified in the current study) (Ratcliffe, 2009). When examining the tables, significant cells only represent a meaningful victimization pattern when there are other significant cells nearby and a risk decay pattern is evident (i.e., a gradual reduction in Knox ratios and p-values over several nearby cells). Following Ratcliffe's approach, the tables produced by the near repeat calculator in the current study were examined for significant near repeat space-time clustering and the results for each data file are summarized in Table 3.[6] The near repeat space-time pattern results will now be discussed in more detail for each crime type across all three cities.

Table 3: Summary of near repeat space-time pattern results.

		Risk	
City	**Crime Type**	**Space**	**Time**
Edmonton, AB	Burglary	500 m	1 week
	TFMV	200 m	1 week
	Common assault	n.s.	n.s.
Moose Jaw, SK	Burglary	n.s.	n.s.
	TFMV	n.s.	n.s.
	Common assault	n.s.	n.s.
Saint John, NB	Burglary	n.s.	n.s.
	TFMV	100 m	1 week
	Common assault	n.s.	n.s.

TFMV = theft from a motor vehicle; n.s. = not significant.

Edmonton, Alberta

The results of the near repeat analysis for the Edmonton burglary data indicate that significant space-time clustering is present: Houses within 500 metres of a burglarized house are at an increased risk of also being burglarized for a period of seven days. Specifically, houses within 100, 101–200, 201–300, 301–400, and 401–500 metres of the original burglary are at a 164%, 79%, 39%, 29%, and 27% increased risk of also being burglarized, respectively, within the week following the original incident. The results indicate that there was also a significant repeat victimization pattern found: The risk of previously burglarized houses being burglarized again was 315% greater than chance for one week following the initial crime. This risk drops to 97% and 90% during one–two weeks and two–three weeks following the initial burglary, respectively.

The results from the analyses for the Edmonton TFMV data file indicate that significant near repeat space-time clustering is also present: Vehicles within 200 metres of an initial TFMV are at an increased risk of also being victimized for a period of seven days. Specifically, vehicles within 100 and 101–200 metres of the original TFMV are at a 30% and 20% increased risk of also being victimized, respectively, within the week following the initial incident. The results indicate that there was also a significant repeat victimization pattern found: The risk of a vehicle in the same location being targeted again was 67% greater than chance for one week following the initial TFMV.[7]

In contrast to Edmonton burglary and TFMV, a significant near repeat space-time pattern was not found for the Edmonton common assault data file. This indicates that people in close space-time proximity to a previous common assault incident were not at an increased risk of also being victimized. However, a significant repeat pattern was found with individuals at the same location as a previous common assault being at a 38% increased risk of also becoming a victim of common assault for one week following the original crime.[8]

Moose Jaw, Saskatchewan

The results from the near repeat analyses indicate that none of the three Moose Jaw data files (i.e., burglary, TFMV, or common assault) demonstrate significant near repeat space-time clustering; nor were there any indications of a significant repeat victimization pattern across the Moose Jaw data files.

Saint John, New Brunswick

Similar to those for Moose Jaw, the analyses show no indication of a significant near repeat space-time pattern for the Saint John burglary or common assault data files. The Saint John burglary data file, however, did demonstrate a significant repeat victimization pattern, with previously burglarized houses being at a 636% increased risk of being burglarized again for seven days following the initial burglary. The results indicate that there is also a significant repeat victimization pattern present in the Saint John common assault data file: Individuals at the same location as a previous common assault were at a 93% greater risk of also becoming the victim of common assault for one week following the initial incident.

In contrast to the other two crime types, the results from the analyses for the Saint John TFMV data file indicate that significant near repeat space-time clustering is present: Vehicles within 100 metres of an initial TFMV are at an increased risk of also being targeted for a period of seven days. Specifically, vehicles within 100 metres of the original TFMV are at a 67% increased risk of also being the target of TFMV within the week following the initial incident. The results also indicate a significant repeat victimization pattern, with the risk of a vehicle being targeted at the same location as the initial TFMV being 214% and 130% greater for one week and two weeks following the original crime, respectively.[9]

Adjustment of temporal bands

As previously mentioned, significant near repeat space-time clustering was found for three of the nine data files: Edmonton burglary, Edmonton TFMV, and Saint John TFMV. The exact pattern was found to vary in terms of distance, but the time remained consistent at one week across all three data files. Given that all three significant patterns were limited to the first temporal band (i.e., one week), it is impossible to determine whether the patterns are actually driven by even shorter temporal increases in risk. To further investigate this issue, the analyses were run again using two shorter temporal bands. Following Youstin et al.'s (2011) methodology, the two shorter temporal bands were set at one day and four days.

The results using the one-day and four-day temporal bandwidths, as well as the results for the initial seven-day temporal bandwidths, are presented in Table 4.[10] Only one previously non-significant near repeat

Table 4: Near repeat space-time patterns using one-day, four-day, and seven-day temporal bandwidths.

		Risk (Space, Time)		
City	**Crime Type**	**One-day**	**Four-day**	**Seven-day**
Edmonton, AB	Burglary	500 m, 2 days	500 m, 4 days	500 m, 1 week
	TFMV	400 m, 2 days	300 m, 4 days	200 m, 1 week
	Common assault	n.s.	n.s.	n.s.
Moose Jaw, SK	Burglary	n.s.	n.s.	n.s.
	TFMV	n.s.	n.s.	n.s.
	Common assault	n.s.	n.s.	n.s.
Saint John, NB	Burglary	100 m, 1 day	100 m, 4 days	n.s.
	TFMV	100 m, 1 day	100 m, 4 days	100 m, 1 week
	Common assault	n.s.	n.s.	n.s.

TFMV = theft from a motor vehicle; n.s. = not significant.

space-time pattern became significant through the use of shorter temporal bandwidths. Specifically, the Saint John burglary data file demonstrated significant space-time clustering of 100 metres and one day and 100 metres and four days at the one-day and four-day temporal bandwidths, respectively. A significant near repeat space-time pattern was again found for Saint John TFMV with the one-day and four-day temporal bands. The Saint John TFMV data file demonstrated significant space-time clustering of 100 metres and one day and 100 metres and four days at the one-day and four-day temporal bandwidths, respectively.

In addition, significant near repeat space-time patterns were again found for the Edmonton burglary and Edmonton TFMV data files when these two new temporal bandwidths were used. Specifically, the Edmonton burglary data file demonstrated significant space-time clustering of 500 metres and two days and 500 metres and four days at the one-day and four-day temporal bandwidths, respectively. The Edmonton TFMV data file demonstrated significant space-time clustering of 400 metres and two days and 300 metres and four days at the one-day and four-day temporal bandwidths, respectively.

Discussion

To summarize, the results from the current study indicate that significant near repeat space-time clustering is present in just three of the nine data files examined: (1) Edmonton burglary, (2) Edmonton TFMV, and (3) Saint John TFMV. As hypothesized, the exact space-time pattern was found to vary from one data file to the next. The results also indicate that significant repeat victimization was present in all of the Edmonton and Saint John data files but not in the three Moose Jaw data files.

The finding that none of the common assault data files exhibited significant near repeat space-time clustering is not surprising given that previous studies have had mixed results in regard to violent offences (e.g., Ratcliffe and Rengert 2008; Kikuchi et al. 2010). Of the studies that have found significant space-time patterns for violent offences, all have focused on a specific type of violent crime: gun violence (i.e., Ratcliffe and Rengert 2008; Youstin et al. 2011; Haberman and Ratcliffe 2012; Wells et al. 2012). This, of course, was not the case in the present study (gun violence is less common in Canada, which limited the availability of sufficient crime data of that nature). Gun violence is arguably a more serious violent crime than common assault. Thus, crime severity and homogeneity of the crime type are two factors that may impact the significance of near repeat space-time patterns for violent offences. In addition, there is research to suggest that near repeat crime is primarily committed by the same offender (e.g., Bowers and Johnson 2004; Bernasco 2008; Johnson et al. 2009). The results could therefore suggest that common assault is less likely to be the result of repeat offending (i.e., by the same offender), which might explain the lack of significant near repeat space-time clustering. It is important to note, however, that two of the three common assault data files – those from Edmonton and Saint John – did demonstrate significant repeat space-time patterns. This could reflect the commission of multiple common assaults either by the same offender (boost theory) or different offenders at the same location (flag theory).

Contrary to what was expected, significant near repeat space-time clustering was not found for the Moose Jaw burglary, Moose Jaw TFMV, and Saint John burglary data files. The burglary findings are particularly surprising, given that every space-time pattern study to date has found significant near repeat space-time clustering when examining burglary data, including the Canadian study by Fitterer et al. (2015), in which the authors found significant near repeat space-time clustering for both residential and commercial burglary in Vancouver, BC. Insufficient sample size offers one potential explanation for the non-significant findings. Recall that Johnson et al. (2007) found significant space-time patterns of near repeat burglary for 10 cities in five different countries. The smallest sample used in that study consisted of 951 incidents. In contrast, the sample sizes for the Saint John burglary, Moose Jaw burglary, and Moose Jaw TFMV data files were substantially lower at 221, 148, and 137 incidents, respectively.

Level of risk in the social and physical environment offers another potential explanation for the lack of near repeat space-time clustering across six of the nine data files. More specifically, a near repeat offence would be less likely to occur if the areas around a previous target were not conducive to future crime – for example, if guardianship in the surrounding area was particularly high because of the presence of some sort of surveillance, such as closed-circuit television. Police actions or effectiveness would influence the occurrence of near repeat victimization, as well. For example, if the police were to increase patrols in a particular area after an initial offence, the occurrence of near repeat crime may be deterred or reduced. In addition, community actions following an initial offence could deter near repeat crime. For example, individuals could keep a closer watch on houses in their neighbourhood after a nearby burglary, or perhaps individuals near the site of an initial burglary could take action to protect their own homes against burglary (e.g., invest in security alarms, ensure windows and doors are locked whenever no one is home).

As previously mentioned, significant near repeat space-time clustering was found for just three of the nine data files – Edmonton burglary, Edmonton TFMV, and Saint John TFMV. The exact pattern was found to vary in terms of distance, which was expected, but the time remained consistent at one week across all three data files. Given that all three significant patterns were limited to the first temporal band (i.e., one week), it was impossible to determine whether the patterns were actually driven by even shorter temporal increases in risk. To investigate this issue, the analyses were run again following Youstin et al.'s (2011) methodology of using two shorter temporal bandwidths – one-day and four-day.[11] Based on the results from the additional temporal band analyses, only one previously non-significant near repeat space-time pattern became significant through the use of shorter temporal bands (i.e., Saint John burglary). This finding suggests that this particular space-time clustering may be driven primarily by spree offending. Given that significant near repeat space-time clustering was again found for Edmonton burglary, Edmonton TFMV, and Saint John TFMV at the shorter temporal bands, evidence of potential spree offending existed in these three data files as well.

Because our data did not include any offender information, it is difficult to establish the reasons why we found evidence for near repeat victimization in some of our data files. To determine whether the boost or flag theories provide a better account for these findings, it is necessary to know who the individuals responsible for the crimes in our data files were; unfortunately, we did not have access to such data. That being said, Johnson (2008) has suggested that repeat crime, when it occurs swiftly, is more likely to be explained by the boost account (i.e., the same offender committing the crimes). Many of the near repeat crimes did occur swiftly (i.e., within one week for the initial analyses), and this finding may provide indirect support for the boost account, at least for these crimes.

Implications of findings

The findings from the current study have important implications for the police with respect to crime prevention strategies. Evidence-based policing, which is the application of research findings to policing practices, has been on the rise since the early twenty-first century (Sherman 2013). The space-time patterns identified and presented in this study have the potential to inform evidence-based policing in that police can implement them in very practical ways to help combat crime (i.e., use them as a crime prevention tool). For example, the space-time clusters could be used by the police to determine high-risk areas to target in their poster campaigns (warning residents that offenders are currently active). They could also be used to inform the public via online bulletins, warning residents that they may reside in a temporary high-risk area. The results could even be used to determine the most effective means to distribute police resources in space and time (e.g., where to assign patrol cars and in what quantity). Based on previous research, initiatives such as targeted publicity in high-risk areas are expected to be an effective crime prevention strategy (e.g., Johnson and Bowers 2003; Sidebottom, Thorpe, and Johnson 2009).

Limitations

There are several limitations associated with this study that deserve further discussion. First, recent research suggests that near repeat space-time patterns may be more precise (or complex) than the patterns uncovered in the present research; however, our relatively small sample sizes precluded us from examining these potential complexities. For example, Glasner and Leitner (2017) found that the space-time clustering of street robberies in Vienna, Austria, varied by the day of the week and time of day. Further dividing our data by day of week and time of day would have been problematic from a sample size standpoint, thus preventing us from uncovering these potential patterns in our data.

Second, while the current study employed the same methodology used by Johnson and Bowers (2004) when specifying the spatial and temporal bandwidth parameters for the Knox test analysis, this approach is somewhat arbitrary. A more objective approach to setting the various parameters could be adopted in future research. For example, Kalantari, Yaghmaei, and Ghezelbash (2016) have begun to examine the possibility of detecting critical distances for the Knox test instead of using an arbitrary spatial parameter. The use of Kalantari and colleagues' proposed method of detecting critical distances may have allowed us to identify more meaningful near repeat space-time patterns in the Canadian crime data we examined.

Third, the x, y coordinates associated with our data may not have been precise enough to distinguish near repeat crimes from repeat crimes. For example, in the case of burglary, if two different apartment units in the same building were burglarized a few days apart, it is possible that they were coded with the same x, y coordinates, thus suggesting repeat crimes when the crimes were in reality near repeats. This potential coding issue could have increased our chances of finding a significant repeat victimization pattern in the current data while under-estimating near repeat patterns of crime (recall that the analyses revealed significant repeat victimization patterns in all of the Edmonton and Saint John data files). It is also important to note that the accuracy of space-time analyses is dependent on geocoding quality, which could vary from one police agency to the next, as well as from one police officer to the next (Hart and Zandbergen 2012).

Fourth, our analyses were limited by the fact that it is not always possible to determine an exact occurrence date for a crime, which might affect the accuracy of our results. Of course, inaccurate occurrence dates are more of a concern for offences where the victim would likely not have been present during the offence (e.g., burglary and TFMV versus common assault). As indicated previously (see note 5), there were also differences in terms of how the occurrence date was represented across the three police agencies, which could limit the extent to which direct comparisons of space-time patterns can be made across geographic regions.

Finally, and as also previously mentioned, none of the data files we analyzed contained offender information. This prevented us from determining with certainty whether the near repeats observed in our analyses were the work of the same offender or different offenders, making it difficult to test *why* we found the space-time clustering patterns that we did.

Future directions

The significant near repeat space-time clustering found in the current study for some of our data sets suggests that additional Canadian research on this topic would be useful, particularly since the exact space-time patterns observed in the literature (and in the current study) consistently vary across geographic locations and specific crime types. Similar research to that reported here should be conducted in additional Canadian cities and across other crime types to determine whether effective crime prevention strategies can be developed for various jurisdictions. In addition, given that research regarding the near repeat space-time clustering of violent crime is so mixed, future research should continue to examine different types of violent offences to identify the conditions under which significant space-time patterns emerge. Future research should also examine whether near repeat crime in Canada is more likely the result of the boost account (i.e., same offender or acquaintances), the flag account (i.e., different offenders), or both, as these results would have different implications for law enforcement and allow for the development of more effective crime prevention strategies. Of course, all future research should also attempt to deal with the limitations that were raised to the extent possible.

Conclusion

This study determined the exact space-time clustering of several crime types (burglary, TFMV, and common assault) across three Canadian cities (Edmonton, AB, Moose Jaw, SK, and Saint John, NB). Although significant near repeat space-time clustering was present in the Edmonton burglary, Edmonton TFMV, and Saint John TFMV data files, the exact space-time clustering pattern was found to vary from one data file to the next. This is in line with previous near repeat space-time research (e.g., Johnson et al. 2007; Behlendorf et al. 2012; Chen, Yuan, and Li 2013; Townsley and Oliveira 2015), which has highlighted the importance for police agencies to examine near repeat space-time patterns with data that are specific to their jurisdiction and to crime type. Interestingly, none of the common assault data files demonstrated significant near repeat space-time clustering. Thus, when combined with the inconsistent findings found in previous research in regard to violent offences (e.g., Ratcliffe and Rengert 2008; Kikuchi et al. 2010), these results suggest that the near repeat phenomenon may apply to some, but not all, violent offence types. The continued examination of near repeat space-time patterns in Canada could prove useful by potentially informing crime prevention strategies and determining the most effective way to allocate police resources.

Notes

1 Special thanks go to the Edmonton Police Service, Moose Jaw Police Service, and Saint John Police Force for providing the data necessary to carry out this study. Additional thanks go to the reviewers of an initial draft of this article for their valuable feedback.

2 See Fitterer, Nelson, and Nathoo (2015) for an exception.

3 Although repeat victimization can and does occur for many types of crime, most research has focused on repeat burglaries.

4 It is unclear why the study by Kikuchi et al. (2010) is the only study that did not find significant space-time clustering when examining violent offences. The difference may lie in the nature of the violent acts being studied. For example, the shootings in Ratcliffe and Rengert's (2008) study occurred in areas where other illegal activities, such as drug trade, were also occurring, and many of the shootings may have been retaliatory in nature. This does not appear to be the case for the violent offences examined by Kikuchi and colleagues. Indeed, Wells et al. (2012) found gang-related shootings to be slightly more likely to result in follow-up gun assaults than those not related to gang activity. In addition, the violent offences examined in Kikuchi and colleagues' study were much more heterogeneous in nature than those examined in the other four studies, which could potentially explain the lack of significant space-time clustering. Specifically, the other studies focused exclusively on either shootings or armed street robbery, whereas Kikuchi and colleagues included various types of assault in their sample of violent offences rather than focusing on one particular type.

5 Note that the Edmonton Police Service provided both an "occurrence from" date (i.e., start date) and an "occurrence to" date (i.e., end date) for each offence. In cases where those dates differed (e.g., resident was away for several days so could not determine exactly when their house had been burglarized), the start date was used as the occurrence date; this is an

approach adopted in other near repeat research (e.g., Block and Fujita 2013). The Moose Jaw Police Service provided the date the offence was reported in place of an occurrence date. Although the report date will not always be the same as the occurrence date (particularly for TFMV and burglary where the victim would likely not have been present for the offence), the report date was used to represent the occurrence date for all the Moose Jaw analyses in the current study. Finally, the Saint John Police Force provided occurrence dates that were a combination of report dates and actual occurrence dates (i.e., the report date was used for offences where the exact occurrence date was unknown). It is acknowledged that these differences in the crime data may impact comparisons that can be made across the three police forces.

6 The complete set of tables produced as output by the near repeat calculator is available from the corresponding author upon request.

7 Note that the near repeat calculator determines repeat patterns based on offences that occur at the same location (i.e., same x, y coordinates) as the initial offence. Thus, in the case of TFMV, it is possible that the significant repeat pattern represents the same vehicle being targeted in the exact same location as the initial TFMV. However, the significant repeat pattern may also represent a *different* vehicle being targeted in the same location as the initial offence.

8 Similar to TFMV, the significant repeat pattern could represent the *same* person being victimized a second time at the same location. It could also represent a *different* person being victimized at the same x, y coordinates as the initial assault.

9 As previously mentioned, these analyses were run using Euclidean (direct) distances. However, the analyses were also rerun using Manhattan distances to examine if different results emerged. The near repeat space-time pattern results remained unchanged, except that significant near repeat space-time clustering was no longer found for the Saint John TFMV data file. In addition, the exact percentage of increased risk at the various space-time intervals varied slightly between these analyses, which was not unexpected given the somewhat different distances used.

10 The complete set of tables produced as output by the near repeat calculator is available from the corresponding author upon request.

11 The use of a one-day temporal bandwidth also helps identify whether the significant near repeat patterns are likely the result of spree offending by repeat offenders (Youstin et al. 2011). Spree offending occurs when the same offender commits a high number of crimes during a relatively short time frame – typically hours or days (Boba Santos 2013).

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