ORIGINAL ARTICLE

Don't call it a comeback! Revictimization and the cycle of violence at micro-places

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Abstract

This study presents a new perspective on the influence of time and the reoccurrence of crime problems at micro-places. I examined 342,690 aggravated assault incidents reported to the Chicago Police Department from 2001 to 2020 using a longitudinal repeat and near-repeat research design combined with cumulative incidence graphs across different temporal windows. There are two distinct periods to observe the revictimization of violence at micro-places. There is immediate risk after an incident within a week followed by a longer period with lower risk across 2 to 4 years when crime often routinely circles back to the same locations. Future research should continue to refine understanding of cyclical patterns or the "life course" of crime at micro-places to enhance the efficacy of place-based crime preventions strategies.

Keywords Revictimization · Micro-places · Temporal patterns · Violence · Crime prevention

Introduction

How often does crime reoccur at the same locations over time? This is a foundational question about the temporal relationship between crime and micro-places the criminology of place has frequently investigated (see Weisburd et al. 2012). The study of repeat and near-repeat victimization patterns of crime at micro-places (e.g., street blocks, segments, intersections) is critical to enhancing place-based crime prevention strategies. Specifically, uncovering more about the life course of crime problems at places can further inform how criminal opportunities change over time (see Brantingham and Brantingham 1991) and the most efficient allocation of resources to address crime problems at micro-places (see Braga et al. 2019). Two disparate research designs are often applied to explore the revictimization of crime incidents

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at places. The first research design investigates longitudinal patterns of crime at micro-places over extended periods of time. These studies find stability of temporal patterns and observe between years, most micro-places within cities have similar amounts of crime (Braga et al. 2010; Curman et al. 2015; Andresen et al. 2017). These findings suggest most locations which experience crime events are likely to experience revictimization during the ensuing years.

The second research design examines repeat and near-repeat patterns which describe the distinct spatiotemporal clustering of the reoccurrence of crime incidents (Townsley et al. 2003). These analyses examine varying specifications for these space–time relationships to determine the precise windows which experience an increased risk for revictimization (e.g., shootings are within 1 block and 2 weeks; Ratcliffe and Rengert 2008). Different temporal periods within years such as days, weeks, and months are considered as units of observation for these analyses (see Hatten and Piza 2021). These analyses distinguish between "repeat" victimization or the same location experiencing crime again compared to "near-repeat" victimization which is an adjacent location experiencing a potentially interconnected crime. Collectively, the findings from these two literatures suggest there is often revictimization of crime at micro-places between years but there are pronounced periods within years which experience an elevated risk for repeat and near-repeat victimization immediately after crimes. While previous research from the criminology of place has provided invaluable contributions to addressing this foundational research question on the reoccurrence of crime, there is still much to learn about the revictimization of crime at micro-places.

This study integrates elements from both research designs to provide a more comprehensive assessment of the revictimization of crime across micro-places. The goal of this study is examining the role of time to further develop an understanding of crime problems that prioritizes the importance of their cyclical nature and attempts to define general parameters to understand this crucial period between victimizations. In other words, previous research has not comprehensively addressed some basic issues regarding revictimization such as if a crime occurs what is the underlying expectation for when another crime could happen at the same place? This study contributes a new perspective on the revictimization of crime at micro-places through this integration. I examine the influence of time using a longer time series than previous repeat and near-repeat designs with 20 years of aggravated assault observations in Chicago and conduct a novel application of cumulative incident graphs to observe long-term patterns of revictimization.

Revictimization at micro-places

Longitudinal studies of the developmental patterns of crime at micro-places provide a limited but helpful first step to understanding the revictimization of crime at micro-places. Weisburd et al. (2004) conducted an influential study which provided a framework for research on longitudinal patterns of crime at micro-places. They found around 84% of the total street segments in Seattle were identified as having stable or persistent year-to-year patterns of crime over the observation period

(Weisburd et al. 2004). There have been several replications of this study which have supported the general conclusion that most micro-places experience revictimization or stability of crime patterns over time (Braga et al. 2010; Curman et al. 2015; Hibdon et al. 2017). These studies use observational periods which have ranged up to 50 years (see Wheeler et al. 2021a, b). Most of this research is focused on understanding revictimization of crime at hot spots or micro-places which capture a disproportionate amount of crime incidents based on their distributional representativeness (e.g., Sherman et al. 1989).

Repeat and near-repeat studies provide a more nuanced understanding of revictimization patterns of crime across micro-places. These studies suggest after a place has been victimized there is often an increased risk of future victimization for the same location (i.e., repeat) and nearby locations (i.e., near-repeat) which dissipates over a specific temporal window (Townsley et al. 2003). Observing the victimization of places does present a different set of challenges compared to observing the victimization of people. Specifically, research on individuals can more precisely delineate when one person is repeatedly victimized (e.g., Widom et al. 2008).

Even when one "place" experiences repeat victimization, there is little chance the same person is revictimized since locations are often used by multiple people. For example, single-family housing units are often composed of varying family sizes or numbers of roommates. Large urban areas have dense housing complexes where one central address could be recorded by the police to capture hundreds of units composed of different people. In addition, commercial businesses are frequented by different customers within and between days. This distinction in unit of observation from people to places offers a tradeoff of some precision of observations for more generalizability of patterns across places to inform criminological theories and crime prevention strategies.

A voluminous collection of research has demonstrated repeat and near-repeat victimization patterns across different crime types and locales. These studies have established the spatiotemporal distribution of crime often experiences a "near-repeat phenomenon" or pronounced periods of revictimization risk following crimes (see Townsley et al. 2003; Johnson et al. 2007; Piza and Carter 2018). Burglary was the first and most extensively investigated crime for these studies. For instance, Bernasco (2008) found burglary incidents in Hague, Netherlands clustered within 30 days and 200 m of each other. There is much detailed theoretical consideration of why repeat and near-repeat victimization occurs which provided the groundwork for these analyses (Farrell 1992; Farrell et al. 1995; Farrell and Pease 2001). In general, there are two leading theoretical explanations for repeat and near-repeat victimization patterns (Tseloni and Pease 2003). The first is the boost hypothesis wherein one crime increases the risk for additional crimes because of several short-term, situational opportunity factors arising across a few places (i.e., state dependence). There are several potential explanations for these increases such as offenders engaging in crime sprees, having limited mobility to select targets, or the sharing of information between offenders (Bowers and Johnson 2004). The second is the flag hypothesis wherein additional crimes occur because of the long-term confluence of criminal opportunity across a few places (i.e., risk heterogeneity). Therefore, some crime hot spots constantly provide the opportunities which offenders find attractive to commit

crimes and the clustering of these incidents could be a result of just the underlying high volume of crimes (see Farrell 2015).

These explanations provide an important context to understand the phenomena of repeat and near-repeat victimization and some studies have further tested these explanations (Spelman 1995; Johnson et al. 2009; Wheeler et al. 2021a, b). Most research on repeat and near-repeat victimization relies on just descriptive analyses instead of rigorous tests of these explanations which are difficult to conduct (i.e., Hatten and Piza 2021). In addition, these studies are often unable to differentiate between revictimization as a single incident or the escalation of an area into becoming a crime hot spot. Prior to the use of epidemiological space–time clustering techniques to model repeat and near-repeat victimization (see Townsley et al. 2003), the first wave of research on this topic was more explicitly focused on charting the time course of repeat incidence. For example, Polvi et al. (1991) examined 4 years of burglaries in Saskatoon, Canada finding the elevated risk after an initial victimization usually dissipates between 6 and 36 months (also see Polvi et al. 1990). Johnson et al. (1997) generally replicated these results in Merseyside County in the United Kingdom observing an exponentiated decrease in repeat burglaries within 1 year with 32.5% reoccurring within 1 week. Robinson (1998) found in Tallahassee, Florida using 3 years of observations that 25% of burglary repeat victimizations occurred within 1 week, over 50% occurred within 1 month, and all repeat victimization occurred within 35 weeks after the original incident.

There is not much of an explicit connection between longitudinal and repeat/near-repeat research designs despite both addressing the underlying issue of revictimization. Longitudinal research designs primarily use latent class analyses and examine years as the predominant unit of temporal observation (Curman et al. 2015). These designs do not offer much insight on temporal patterns outside of identifying groups of developmental trajectories which are often just characterized as either stable or volatile (see Braga et al. 2010). Repeat and near-repeat research designs provide much attention to the specific temporal units within observational periods to examine revictimization, but they are explicitly cross-sectional analyses. There is almost no longitudinal research on repeat and near-repeat patterns across different observational windows. This can help further unpack the role of time by determining the impact of using specific observation periods on results. For example, Hatten and Piza (2021) found general consistency of results when exploring rolling 12-month windows (i.e., January to December) across a 2-year observation period (i.e., 2015–2016) for repeat and near-repeat robberies. In contrast, Hoppe and Gerell (2019) found varying annual periods across a 6-year observational period (i.e., 2009–2014) presented noteworthy variance in results of repeat and near-repeat patterns for burglaries.

Compared to longitudinal research on individuals which can closely adhere to well-understood milestones for human development such as adolescence (e.g., Moffitt, 1993), longitudinal research on places cannot follow this underlying temporal structure. In addition, the increased availability of public criminal justice data today presents more opportunities for researchers to select between a wide range of possible observation periods. Due to these differences, research on this topic should provide increased attention to the specification of time (Schnell and McManus 2022).

In other words, the meaning of time is quite different when comparing the life course of a person to a place and there is not much consideration of how to approach this issue for longitudinal research on places. Therefore, I propose this integration to further investigate the impact of time within the context of research on the revictimization of crime at micro-places. This study proposes an expansion of earlier research which explicitly charted the time course between victimizations (e.g., Polvi et al. 1991). Repeat and near-repeat analyses provide a framework to examine the impact of temporal specification within observation periods and longitudinal studies provide a starting-point to address the issue between observation periods. This study expands upon longitudinal repeat and near-repeat research designs by integrating other methodologies to extend understanding of the role of time on the revictimization of crime at micro-places.

Data and methods

Study setting

This study examines aggravated assault incidents reported to the Chicago Police Department (CPD) from 2001 to 2020. Incident report data were collected through the City of Chicago's open data portal.[1] Despite the well-documented limitations of these data (see Black 1970), incident reports still provide a helpful overview of where crimes occur within jurisdictions and are frequently used within the criminology of place (Weisburd 2015). Aggravated assaults are generally defined as an attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury (e.g., FBI 2019; p. 2). I selected aggravated assaults to focus on a general category of violence or an individual's motivation to cause interpersonal harm. Thus, the aggravated assault variable excludes the instrumental use of violence (i.e., robbery) and does not discern more specific details about the incident such as whether a weapon was used (i.e., firearm violence) or the victim died (i.e., homicide).

The repeat and near-repeat victimization patterns of aggravated assaults at places could be explained by both the boost and flag hypotheses. First, the retaliatory nature of urban violence could provide support for the boost hypothesis (Jacobs and Wright, 2006). Many offenders commit crimes close to where they live and violence is closely transmitted through dense interpersonal social networks across small places (Bernasco 2010; Papachristos et al. 2015). Therefore, a triggering violent incident at a place could result in the spillover of future violence in the immediate area because these places are used by both the victims and offenders. Second, the disproportionate concentration of violence at a small number of hot spots within cities could provide support for the flag hypothesis (Braga et al. 2010). These locations remain stable over extended periods suggesting the underlying criminal opportunities for aggravated assaults also remain stable at these places. For instance, these

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[1] data.cityofchicago.org. Due to CPD's more specific reporting procedures, I combined both "aggravated assault" and "aggravated battery" incident categories from the data portal to approximate the standard definition of an aggravated assault.
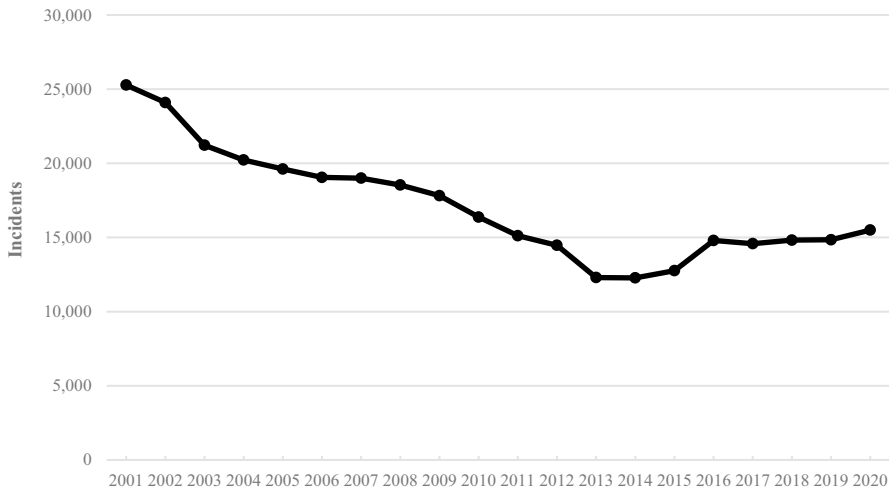
Fig. 1 Aggravated assault incidents in Chicago, 2001–2020

flagged locations are likely places where people interact by design (i.e., parks or markets) and these encounters just routinely escalate into violence (i.e., bars or schools) thus presenting a constant revictimization pattern.

The goal of this study is descriptive, and my focus is just on observing patterns of how often violence returns to places. Most repeat and near-repeat analyses are by design an exploration of the parameters of spatiotemporal clustering. This framework has been used for similar crimes in addition to a wide range of others ranging from arson (Turchan et al. 2019) to economic crimes (Powell et al. 2019). Most of the previous research on aggravated assaults have examined these crimes when committed with firearms. For example, Ratcliffe and Rengert (2008) found the risk of a repeat incident increased by 33% within 2 weeks and one block of a previous incident. Youstin et al. (2011) found risk increased for aggravated gun assaults for four blocks from the initial shooting for up to 14 days, with the most noticeable risk increase occurring within 4 days and three blocks. Finally, Wells et al. (2012) observed a significant risk of gun assault occurring over the next 3 weeks after an initial incident, finding the chance of a second incident taking place within 400 feet and within the next 14 days was 35%.

Chicago has a population of over 2,700,000 residents and is the third largest city in the United States covering around 234 miles[2] (U.S. Census Bureau 2020). Chicago is an ideal location to conduct this study because of its celebrated history of research on violence and place (see Sampson 2012). In addition, Chicago's rates of aggravated assault per 100,000 residents over the study period were more than twice as high as rates in both Illinois and the United States (FBI 2022).[2] Over the study period, Chicago experienced 341,162 aggravated assault incidents. Figure 1 illustrates the precipitous decrease from the high of 25,278 in 2001 to the low of 12,276

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[2] /crime-data-explorer.app.cloud.gov/pages/explorer/crime/crime-trend.

in 2014. From 2015 onward, there was a modest increase back to 15,502 incidents by 2020. Over the full observation period, this corresponded to a 38.7% decrease in aggravated assaults.

This study examines two measurements of micro-places: *XY* coordinates and street segments. *XY* coordinates were included and matched for 99.6% (341,162 of 342,690) of the incidents from the data portal which are used for the point-pattern analyses (see Andresen et al. 2020).[3] These incidents are aggregated to street segments for the remaining analyses I conduct using ArcGIS 10.8 software. There are 48,310 total street segments in Chicago (mean length = 450.38 ft., SD = 254.14 feet) excluding locations associated with interstates, highways, and non-public access roadways. All the CPD incident reports correspond to street addresses rather than the intersection of two or more streets (see Schnell et al. 2017). Therefore, I did not have to develop street intersections as an additional micro-place unit of analysis (e.g., Braga et al. 2010).

Research design

This study investigates the extent aggravated assaults reoccurred at locations within Chicago over time. These descriptive analyses proceed in two stages. First, I conducted a longitudinal repeat and near-repeat analysis on aggravated assaults. The findings are compared across repeated cross-sections of years within the observation period to determine the consistency of results. These analyses provide a more granular, within-year assessment of the spatiotemporal dimensions of repeat and near-repeat victimization risk. Second, I use cumulative incidence graphs to characterize the shape of repeat victimization patterns at street segments over time. These analyses explore a broader portrait of how all types of locations can experience repeat victimization over much longer temporal periods instead of focusing on just spatiotemporal concentration of risk (e.g., Polvi et al. 1991).

These graphs are commonly associated with survival analyses within criminology or a wide range of other disciplines outside of criminology to observe the exposure of a population to an outcome (see Zunn et al. 2015; Cox and Oakes 2018). The integration of these two divergent analytic techniques combines a short-term assessment through the repeat and near-repeat analyses with a long-term counterpart via the cumulative incidence graphs to offer a more comprehensive portrait of revictimization across micro-places. Each strategy individually provides a partial understanding of revictimization at micro-places, but together they can begin the process of constructing a more complete portrait. Across these stages of analysis, I test two hypotheses:

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[3] These *XY* coordinates are approximations of street addresses. Incident reports included on Chicago's open data portal have a small offset for privacy concerns, but these locations still do capture micro-variation within 100-address blocks and street segments (see Schnell et al. 2017). Due to these offsets, I felt more comfortable using street segments because these differences would be washed away in the traditional aggregation process when going from street addresses to segments (i.e., addresses collapsed into segments). In addition, repeat and near-repeat analyses require spatial buffers which I set based on the average length of a segment which further connects the analysis to street segments. These places should be considered the primary unit of analysis.

Hypothesis 1 There is consistency of repeat and near-repeat patterns of aggravated assault incidents at micro-places between years.

Hypothesis 2 There are more micro-places which experience repeat victimization when observing longer temporal periods across the observation period.

Repeat and near-repeat analysis

The first stage of the analysis uses the Near-Repeat Calculator to test for repeat and near-repeat victimization patterns of aggravated assaults (Ratcliffe 2020).[4] This program conducts a point-pattern analysis to identify clusters in space and time of crime incidents. This open-access software program offers a user-friendly output with Knox ratios which present the primary measure used by repeat and near-repeat studies to identify statistically significant spatiotemporal clusters of crime (see Hoppe and Gerell 2019). In general, this test compares the observed count of events with the expected counts across specified spatiotemporal bands which represent a randomly distributed counterfactual to classify clustering of patterns (Knox 1964). Knox ratios quantify the risk of future offending as repeat and near-repeat pairs linked via these space–time bands with values over 1.00 indicating an observable pattern. Ratcliffe (2009) suggested using ratios of 1.20 or a 20% increased risk to capture more robust spatiotemporal clusters. The software uses a Monte Carlo simulation process where the user specifies the number of iterations which is connected to the resulting p values created (Johnson et al. 2007). Therefore, more iterations offer more precise values with $p < 0.05$ for 20 iterations, $p < 0.01$ for 100, and so on. I use 1000 iterations to observe $p < 0.001$ for each repeat and near-repeat analysis presented in the findings.

Repeat and near-repeat research often uses an exploratory data approach to identify the most appropriate spatial and temporal parameters to observe victimization risk. Studies have used several different ranges with same day, 1 day, 7 days, and 14 days as common building blocks to represent salient units of time within a year. These temporal units are often repeated across multiple bands (e.g., 1 day, 2 days, 3 days, etc.). In addition, studies often examine multiple temporal windows to identify the optimal representation of victimization risk (e.g., 1 day vs. 7 days). Previous research on repeat and near-repeat patterns of aggravated assault in Chicago found revictimization most likely to occur within one block and 1 week of an initial incident (Kennedy et al. 2015). Since this stage of the analysis observes within-year patterns, I wanted to consider longer temporal periods to capture a wider range of temporal windows. I selected 7 days as the base temporal unit of observation and examined three additional temporal bands. Based on the programing of the

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[4] I used this software instead of the R package (see Steenbeek, 2018) because there were no differences in results, the calculator was more user-friendly, and estimation was almost twice as fast using the calculator which was an important concern considering the large number of temporal periods I analyzed.

Near-Repeat Calculator, this presents five total windows: same day, 7 days, 14 days, 21 days, and 28 days.[5]

One of the major innovations of repeat and near-repeat research designs is the examination of both temporal *and* spatial patterns. Thus, these studies can account for if a crime does not happen at the exact same location but in a nearby, interconnected sequence. Spatial bandwidths were based on the average length of a street segment in Chicago which was 450 ft. for the street segment map (see Hatten and Piza 2021). I calculated findings for only two additional spatial bands outside of the same location since the study is primarily focused on the temporal patterns and I wanted to keep the results parsimonious due to the larger number of models estimated. Distances were calculated using Manhattan distance instead of Euclidean distance specifications (i.e., "as the crow flies"). Manhattan distance offers an improved approximation of street grids through calculations via right angles which is how people realistically navigate urban areas (Chainey and Ratcliffe 2013). These three spatial windows are examined: same location, 1 block, and 2 blocks.

Near-repeat models are calculated for 20 total years from 2001 to 2020.[6] I adopted an approach from Hoppe and Grenell (2019) which compares each year of results across all findings and does not filter based on which were statistically significant across the entire observation period. I use simple descriptive statistics such as the range width (i.e., difference between minimum and maximum values) which Hatten and Piza (2021) used to summarize results and provide assessments of the consistency of results across the multiple observation periods. This approach creates a distribution of results: 15 results per year across 20 years to create 300 total observations. The findings from these analyses are used to test the first hypothesis of the study.

On the most basic level, this strategy leverages other temporal periods to offer comparison groups which provide additional, transparent parameters to assess the robustness of results. Previous research on repeat and near-repeats relies upon the comparison of results between studies to strengthen inference and within study

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[5] The 1-day temporal band has an explicit limitation which is endemic to most repeat and near-repeat analyses. The data are analyzed based off dates without 24-h time signatures and cannot differentiate between a revictimization as another interrelated event or a standalone event later in the day. CPD's reporting of these incidents is effective at removing almost all duplicates from the data portal which suggests each observation is a unique case. Nevertheless, the data recording cannot differentiate if these incidents are interrelated such as two offenders from one incident (i.e., co-occurrence) or an entirely different incident from later in the day (i.e., new event). The former was not a widespread problem based upon sorting the data by both case numbers, times, and locations. Thus, there are no incidents with identical case numbers, times, and locations included in the dataset. A detailed review of the unredacted case files would be the only true way of addressing this matter. There is a possibility minor reporting differences by officers could obscure these differences—one officer saying 13:00 was the time of incident and another 13:05—but regardless this did not appear to be a major concern with the CPD data. This is a limitation not unique to this analysis and I would just emphasize some caution in the interpretation of the same day results due to this ambiguity in what they are truly representing.

[6] Unfortunately, I could not estimate full results for 2001 and 2002 because there were such a large number of incidents. I conducted supplemental analyses on these 2 years where I split both into 6-month periods and compared results to the main findings from our study. The findings were consistent between both 6-month periods and the full year results across the other years. I randomly selected one of the two 6-month periods for these years and inputted the results in our final analyses.

sensitivity analyses to display the impact of certain temporal specifications. These techniques do not account for how results could change by shifting an entire observation period (e.g., 2023 to 2024). A key innovation of longitudinal repeat and near-repeat research designs is providing an immediate assessment of this context instead of relying on future studies to draw contrasts.

Cumulative incidence

The second stage of analyses presents a series of cumulative incidence graphs to examine the repeat victimization of aggravated assaults at street segments over time. These analyses facilitate the examination of longer temporal periods than the repeat and near-repeat analyses. Repeat and near-repeat analyses only provide insight on periods of elevated risk for revictimization and not an overview of the duration between incidents for all locations. Thus, these studies only examine revictimization through a specific modality. These cumulative incidence analyses present a more restrictive assessment of spatial patterns by focusing on just street segments instead of point patterns which are used for repeat and near-repeat analyses. In other words, removing the spatial component (i.e., "near") from repeat and near-repeat analyses of victimization.[7] These analyses are supplemented with crime maps to examine the spatial mobility of aggravated assaults between street segments over time. These maps help visualize the findings to further illustrate the mobility of aggravated assaults since spatial patterns are not accounted for as directly as the first stage with those analyses.[8]

Each individual graph displays the percentage of street segments which experienced an aggravated assault in subsequent years after a specified temporal window. Table 1 presents each temporal windows examined across the observation period. A wide range of rolling temporal windows are examined to minimize the influence of outlier years to denote generalized patterns over multiple years. The test year presents the specific annual period that is analyzed. I observed test years from 2001 to 2010. Each year has a post-test period which captures a prospective window of 10 additional years. This permits the use of all 20 years of the incident data. This also allows for an assessment of variance between years since I examined multiple test years to determine the consistency of these temporal patterns. Results from each test year are combined to observe a more comprehensive repeat victimization curve which is used to examine the second hypothesis for this study which suggests there is a linear relationship between exposure and time. My specific interest is the shape of the curve and the period where over 50% cumulative incidence or a majority of location's incidence is surpassed since time is expected to increase incidence.

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[7] As previously discussed in the literature review, this is another challenge to observing revictimization at places compared to people. Therefore, repeat victimization at a street segment is possibly from another address found within the street segment. This blurs the line between what is a repeat and near-repeat victimization when using these spatial units of analysis to study revictimization.

[8] The use of street segments aligns with the spatial distances from the repeat and near-repeat analyses. Street segments would capture the spatial band of the same location and within one block. The latter distance is based upon the average length of a street segment in Chicago which approximates the common street grid.

Table 1 Temporal windows for cumulative incidence graphs

Graph	Test year	Post-test period
1	2001	2002–2011
2	2002	2003–2012
3	2003	2004–2013
4	2004	2005–2014
5	2005	2006–2015
6	2006	2007–2016
7	2007	2008–2017
8	2008	2009–2018
9	2009	2010–2019
10	2010	2011–2020

A new incident or event is denoted by when a street segment experiences another aggravated assault over the post-test period. Ultimately, these values capture the percent of street segments that had another aggravated assault incident across the next year, next 2 years, and so on until 10 years after the original incident with values ranging from 0 to 100%. Cumulative incidence graphs present a straightforward output but have important implications for understanding repeat victimization at places. I compare two groups of street segments: locations with one or more aggravated assaults and crime hot spot locations. The latter are identified as the street segments that represent the top 5% of the distribution or the 5% of locations with the most incidents for each individual year. This is a common distributional threshold used to measure crime hot spots (see Levin et al. 2017). The threshold corresponds with the center point of the distributional bandwidth presented by Weisburd's (2015) law of crime concentration (i.e., 4–6%) since the discrete values of crime incidents do not perfectly correspond to precise percentages (e.g., 4.3% for 5+incidents in 2010 or 4.9% for 5+incidents in 2020). All values for cumulative incidence graphs were collected using descriptive statistics in Stata 18.0.

Results

Repeat and near-repeats

Table 2 provides summary descriptive statistics for repeat and near-repeat analyses across the full observation period. "Appendix" includes the results from each individual year. Three of the space–time windows offered consistent and statistically significant findings across the entire period. The same day and same location window (i.e., repeat) had the largest mean Knox ratio of 7.982. This suggests the chance of revictimization is 698.2% greater compared to if there was no pattern in offender behavior (see Ratcliffe 2020). These values are calculated by subtracting one from the Knox ratio. There was a fair amount of variance in the results across years with a range width of 6.916 but each of the annual observations was statistically significant

Table 2 Summary statistics of Knox ratios for repeat and near-repeat spatiotemporal windows across annual periods, 2001–2020

Space–time window	Mean	Min	Max	Range width	$p < 0.05$ (%)	$p < 0.01$ (%)	$p < 0.001$ (%)	Marginal	Robust
Same Location & Same Day	7.982	5.086	12.002	6.916	100.0	100.0	100.0	0	20
Same Location & 7 Days	1.350	1.004	1.949	0.945	90.0	90.0	60.0	0	18
Same Location & 14 Days	1.097	0.942	1.225	0.283	40.0	15.0	10.0	5	3
Same Location & 21 Days	1.058	0.889	1.354	0.465	15.0	15.0	10.0	2	1
Same Location & 28 Days	1.074	0.959	1.280	0.321	25.0	15.0	5.0	4	1
1 Block & Same Day	1.824	1.419	2.144	0.725	100.0	100.0	100.0	0	20
1 Block & 7 Days	1.045	0.988	1.113	0.125	40.0	25.0	15.0	8	0
1 Block & 14 Days	1.029	0.956	1.091	0.135	25.0	10.0	5.0	5	0
1 Block & 21 Days	1.010	0.978	1.045	0.067	5.0	0.0	0.0	1	0
1 Block & 28 Days	1.019	0.959	1.070	0.111	25.0	5.0	0.0	5	0
2 Blocks & Same Day	1.222	1.003	1.571	0.568	70.0	55.0	45.0	5	9
2 Blocks & 7 Days	1.026	0.997	1.057	0.060	40.0	20.0	5.0	8	0
2 Blocks & 14 Days	1.012	0.966	1.051	0.085	20.0	10.0	0.0	4	0
2 Blocks & 21 Days	1.005	0.958	1.054	0.096	10.0	5.0	0.0	2	0
2 Blocks & 28 Days	1.014	0.975	1.059	0.084	10.0	0.0	0.0	2	0

Full years would not estimate for 2001 and 2002

Marginal either Knox ratio below 1.20 or no statistical significance, *Robust* Knox ratio 1.20+ and statistical significance

at the $p < 0.001$ level. In general, the observations did not have a large range width and across annual observations these values were like results from Hatten and Piza (2021). This finding presents one indication that the annual observation periods did not have a large impact on estimates of repeat and near-repeats patterns. The same day and one block window had the second largest effect across the observation period (i.e., near-repeat). The mean Knox ratio was 1.824 with all observations statistically significant at the $p < 0.001$-level and the minimum value well over 1.20. These observations did not have a large range width suggesting the year-to-year differences were small. The same location and within a 7-day window offered the third consistent result. This window did experience 2 years without demonstrating an effect and the second largest range width but still displayed a mean Knox ratio well over 1.20. The remaining 18 years demonstrated a robust repeat revictimization pattern. This pattern does begin to demonstrate how results can vary over time with only 60% of the observations having statistically significant results at the $p < 0.001$-level.

A few space–time windows showed some evidence of revictimization effects but there were also noteworthy signs of inconsistency. The same day and two block windows had a mean Knox ratio of 1.222. Thus, the same day findings showed statistical significance across all the specified spatial distances. This suggests most of "the action" of aggravated assault revictimization is found on the same day across varying distances. Only 9 of 20 years though demonstrated a robust near-repeat effect and 5 of 20 displayed a marginal effect with either a Knox Ratio below 1.20 or no statistical significance. The remaining three temporal windows at the same location presented some varying repeat victimization effects. Each of these windows experienced robust effects between 1 and 3 years and several additional years had marginal effects. These findings provide another indication that the specific observation period does have a noteworthy effect on findings. All the remaining spatiotemporal windows displayed marginal effects for between 1 and 5 years but did not demonstrate a single robust revictimization relationship. As per Table 2, these windows do not have maximum values over 1.20 and displayed very narrow range width values. Overall, 3 of 15 revictimization results would be classified as consistent with statistical significance, 4 of 15 as inconsistent with statistical significance, and the remaining 8 of 15 as consistent with non-statistically significant patterns.

Cumulative incidence

From 2001 to 2020, 68.4% of street segments in Chicago experienced an aggravated assault incident (33,063 of 48,310). The mean number of aggravated assaults per street segment was 7.05 (SD = 13.74, min. = 0, max. = 413). Of these locations, 49.1% had 1–10 incidents, 9.5% had 11–20, and 9.8% had 20 or more. Only 0.6% (278 of 48,310) had an aggravated assault occur across each of the 20 years. Around half of the street segments (54.5%) experienced one to four total years with incidents and the other half five plus total years (45.5%). The percentage of aggravated assaults per year from a street segment which experienced repeat victimization followed a similar trend to the city-wide number of aggravated assaults displayed in
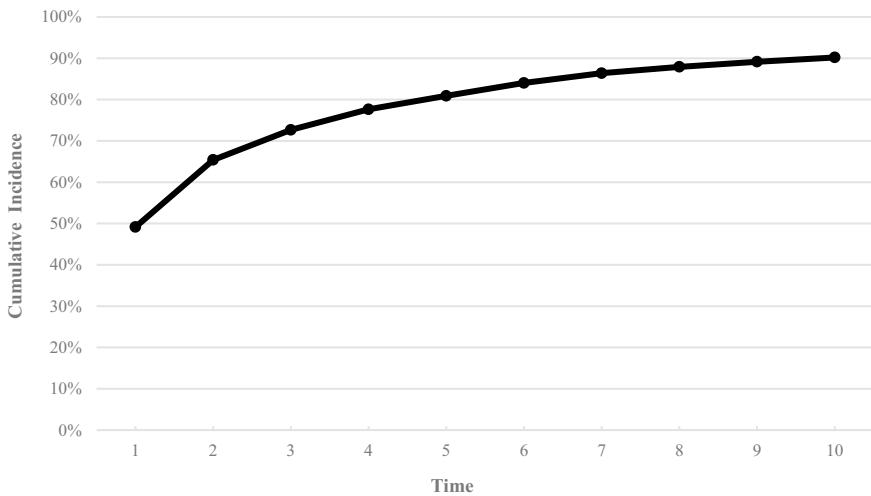
Fig. 2 Cumulative incidence of repeat victimization at street segments, 2010

Fig. 1. The highest value was in 2001 with 71.8% of incidents being from repeat locations and decreased until 2014 to 56.5% before increasing to 63.5% in 2020. Figure 2 displays a cumulative incidence graph from 2010 to demonstrate the temporal window of how all locations experience revictimization. This graph displays street segments which experienced one or more aggravated assault incidents during 2010. This figure demonstrates how most street segments which had an incident in 2010 had repeat victimization over the next 10 years. By the next year (i.e., 2011), 49.2% of street segments experienced another aggravated assault incident. Across the next 5 years (i.e., 2011–2015), up to 80.9% of the original locations had another aggravated assault while across the full 10 years the cumulative incidence increased to 90.2%.[9]

Figure 3 displays the spatial distribution of street segments with aggravated assaults across three cross-sections within a single Chicago community area. The first map shows the street segments which had an aggravated assault in 2010. These locations captured 12.8% of the total street segments in the community area (105 of 823). The second and third maps display only the remaining street segments which experienced incidents 1 year (i.e., 2011) and 5 years (i.e., 2015) later to demonstrate the spatial mobility of these incidents. From 2010 to 2011, only a few additional locations appear to have aggravated assault but by 2015 the spatial mobility of these locations becomes more apparent. From 2010 to 2011, 5.5% of the remaining 87.2% of street segments (45 of 823) without an aggravated assault experienced an incident. By 2015, a larger number of 17.6% of the remaining street segments experienced an

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[9] The findings are comparable to the same retrospective period. Only 51.5% of street segments which had an aggravated assault in 2010 experienced an incident during 2009 with 85.0% from 2005 to 2009, and 92.4% from 2001 to 2009. These retrospective patterns are generally consistent across the other test years.

2010   2011   2015

Fig. 3 The spatial mobility of street segments with aggravated assaults, 2010–2015

aggravated assault (145 of 823). Therefore, from 2010 to 2015, just 35.8% of the street segments in this community area experienced at least one aggravated assault (295 of 823). These maps help visualize how there is a moderate degree of variability between years in which locations experience aggravated assaults and provide a spatial context to findings from the cumulative incidence graph.

Figure 4 summarizes results from the entire observation period using 10 temporal windows with test years from 2001 to 2010. This figure examines all locations which experienced one or more aggravated assault incidents. The figure displays the minimum and maximum values identified across these periods to present the full distribution of results. There is a striking degree of consistency across all observations. Between 49.2 and 54.8% of street segments which experienced an aggravated assault report another one within the next year. After 5 years, 79.9% to 85.5% of locations experienced at least one more incident and after 10 years 87.8% to 92.2% experienced another incident. The increase of incidence stagnates after the fifth year with most additional locations being added in the first few years. Overall, these findings suggest aggravated assaults are likely to reoccur at the same street segments in Chicago over a relatively short period. A small number of street segments still do not experience revictimization from an aggravated assault incident after 10 years.[10]

Figure 5 examines hot spot street segments (i.e., top 5%) from the entire observation period using the same temporal windows and test years as Fig. 4.[11] This

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[10] Even when using the longest possible temporal window within the observation period, which is 2001 across the next 19 years, the cumulative incidence only rose to 92.7%. This reinforces there are some locations where crime is truly a rare event. In addition, I explored incidence curves for locations which experienced no aggravated assaults. After 1 year between 11.2 and 13.5% of street segments experienced an incident, after 5 years 31.1–35.6% of segments, and after 10 years only 44.6–47.2% of segments which suggests locations which do not have crimes experience more of a steady, linear increase in victimization risk over time.

[11] From 2001 to 2020, only 6.7% of street segments in Chicago were identified as aggravated assault hot spots (3,263 of 48,310). Depending on the year, the 5% threshold began around 4–6 incidents. The mean number of incidents at these places across all years was 44.7 (SD = 26.22, min. = 6, max. = 413). Of
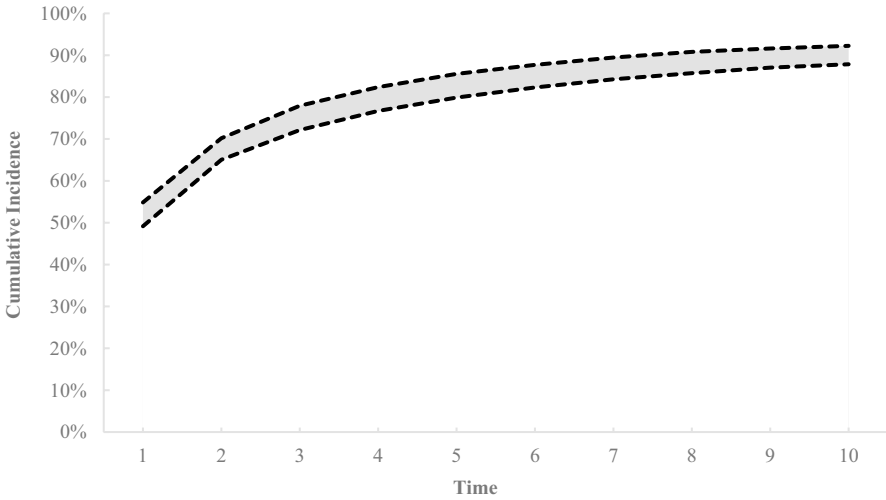
Fig. 4 Minimum and maximum cumulative incidence for repeat victimization of any segment with aggravated assaults, 2001–2010
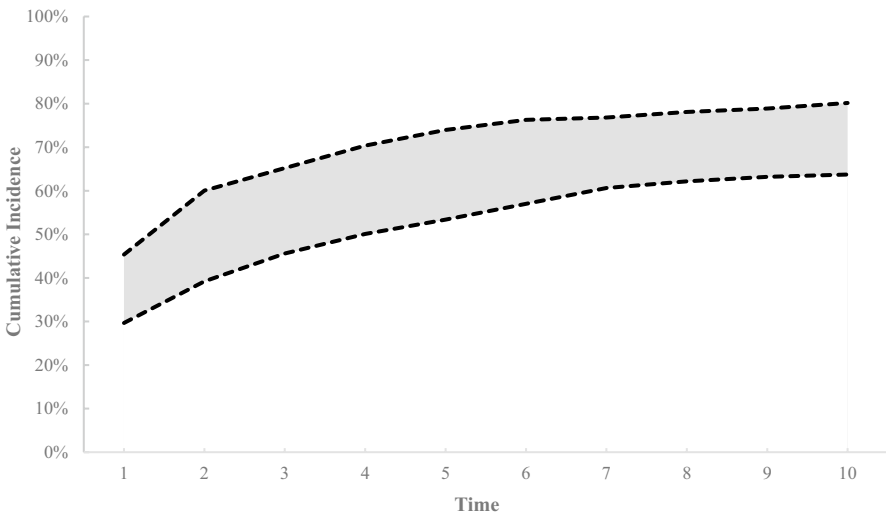

Fig. 5 Minimum and maximum cumulative incidence for repeat victimization of aggravated assault crime hot spots, 2001–2010

cumulative incidence graph defines incidence as when a crime hot spot in a certain year becomes a crime hot spot again in a subsequent year. The hot spot values

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Footnote 11 (continued)

these locations, 47.1% were hot spots for 1 year, 36.5% for 2–4 years, 12.3% for 5–9 years, and 4.1% for 10+ years. Only two street segments were aggravated assault hot spots for each of the 20 years.

are calculated independently for each year. The range of results is noticeably larger compared to Fig. 4 which indicates there is more variance in patterns of repeat victimization for crime hot spots. These values are also much lower compared to the comparable temporal periods displayed in Fig. 4 suggesting these locations are less likely to be revictimized. Between 29.7 and 45.4% of street segments which experienced an aggravated assault hot spot report another one within 1 year. After 5 years, 53.4% to 74.0% of locations experienced another hot spot year and 63.7% to 80.2% after 10 years. These findings suggest aggravated assault hot spots are less likely to reoccur at the same street segments in Chicago over a short period compared to just locations which experienced one or more incidents. The minimum value for 5 years after being a hot spot barely exceeds 50% incidence, while this threshold is surpassed within 2 years for locations with one more incident displayed in Fig. 4.[12]

Discussion

This study examined the revictimization of aggravated assaults across micro-places in Chicago by integrating elements from disparate research designs. This approach provided a new perspective on one of the foundational questions of the criminology of place: how often does crime reoccur at the same locations over time? Overall, this study demonstrated the answer to how often crime returns to locations is not simple. I found distinct patterns of spatiotemporal risk for revictimization within 1 week of an aggravated assault incident across multiple micro-spatial distances. These findings provided mixed support to the first hypothesis of there being consistency in repeat and near-repeat patterns over time. On one hand, I classified 11 of the 15 repeat and near-repeat spatiotemporal windows assessed as having consistent results across the observation period which supports the hypothesis. In addition, the range width of results over time was small which suggests general consistency in estimates.

On the other hand, only three of these 11 windows had consistent results which demonstrated a statistically significant repeat or near-repeat effect. The remaining eight windows were not statistically significant and did still present some evidence of a marginal effect across at least 1 year over the observation period. Comparing only the patterns which displayed evidence of statistically significant repeat and near-repeat effects, only 3 of the 7 displayed consistent results. This indicates there is some noteworthy variation in repeat and near-repeat patterns over different observation periods for the most categorically meaningful patterns I detected. These patterns reinforced the most consistent evidence of revictimization risk was found as

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[12] I conduced a supplemental analysis which explored incidence curves of locations with at least one aggravated assault into becoming a hot spot in subsequent years. Only 2.2% to 5.5% of segments became hot spots in after 1 year and just 13.3% to 19.0% after 10 years. There are important methodological caveats to these analyses with the largest being the number of hot spot locations was truncated by the distribution (i.e., top 5%) which limited the number of possible locations. The number which experienced aggravated assaults ranged from 8000 to 12,000 per year and the number which were hot spots between 400 and 600. Therefore, these results are an interesting first step to capturing escalation of patterns, but they are quite limited.

close to the same day and location as possible and the more inconsistent results were on the outer limits of the specified space–time boundaries.

The examination of cumulative incidence graphs facilitated a different perspective on the revictimization of crime at micro-places. I also found mixed support for the second hypothesis observing a non-linear relationship between repeat victimization and time based on the cumulative incidence graphs. After 2 years more than half of all locations which experienced an aggravated assault had a repeat victimization based on the observation period. While an increase in incidence was anticipated, the speed at which over 50% incidence was surpassed is the key finding. The minimum value for the range of cumulative incidence exceeded 75% after 4 years. Therefore, a 2-to-4-year window captures when most locations experienced repeat victimization. There was not much variance in results based upon using different rolling temporal windows within the broader observation period. In comparison, repeat victimization of crime hot spots was less likely and there was more variance of results between temporal periods. The minimum value for the range of cumulative incidence surpassed 50% after 4 years and did not exceed 75% after 10 years. These alternate cumulative incidence graphs suggest micro-places experience revictimization in varying ways based upon the underlying crime pattern at the place.

There are several implications of this study for the criminology of place. The results reinforce there are important underlying rhythms or mobility to crime patterns within cities (see Brantingham and Brantingham 1991). These rhythms are critical to enhance understanding of criminal opportunity theories by pinpointing the appropriate temporal periods to investigate crime emergence (McGloin et al. 2012). While crime patterns are stable over extended periods of time this stability manifests as more volatile, cyclical patterns over shorter periods (see Deckard and Schnell 2022). For example, crime moves around over days or weeks but across months and years circles back to the same locations. Violent crimes are often rare events at micro-places and the duration between the "on" and "off" periods of when crimes occur is critical to document and helps capture the life cycle of crime patterns at micro-places. These findings suggest locations with lower levels of incidents, see more consistent patterns of revictimization between years compared to crime hot spots.

The results suggest the generalized life cycle of risk for revictimization is divided into a few critical periods. First, micro-places experience an immediate risk of revictimization. I found within the period of 1 week and within one block demonstrated the most robust effects. Second, if locations did not experience an incident during the first period, the risk window for revictimization safely extends to the next several years. I observed most aggravated assaults incidents cycle back to places during this intermediate period of 2 to 4 years. Third, if a location does not experience revictimization during this second period, the risk it will over the subsequent years is very low. This suggests a micro-place has escaped the two most risky periods for revictimization and the crime occurring was more anomalous.

These space–time rhythms are essential for police agencies to understand for the efficient allocation of resources for both preventative patrols but also targeted enforcements efforts. The "whack-a-mole problem" (WAMP) is a persistent concern for place-based crime prevention strategies. While there is much spatial

concentration of crime at places, the WAMP arises because there is an underlying spatiotemporal mobility of these events. In the simplest words, crime often moves around between locations over time. The distinction between what is routine mobility and influenced by crime prevention (i.e., displacement) remains unknown. There could be a natural cycle of how crime moves between locations over time connected to the situational nature of criminal opportunities (Felson and Eckert 2019). These temporal rhythms of opportunity could suggest there is just an ebb and flow of crime patterns at places. In general, the police have been encouraged to be proactive to deal with crime problems instead of using reactive responses (National Academy of Sciences, 2018).

Policing interventions focused on hot spots can result in significant reductions in crime and disorder (Braga et al. 2019). One reoccurring concern for these interventions is crime displacement. This suggests there could be either spatial or temporal mobility of crime as the result of the deployment of place-based crime prevention strategies (Reppetto 1976), although this been found to be uncommon (Guerette and Bowers 2009). Predictive policing is one solution which does not solely rely on previous crime data but instead integrates other spatial correlates to attempt a more proactive response to crime problems at places (see Haberman and Ratcliffe 2012; Moreto et al. 2014). The precise calibration of spatiotemporal dosage for hot spots policing has received much attention (see Connealy and Hart 2023). For instance, Telep et al. (2014) expanded upon the "Koper curve" to illustrate around 15 min per street segment every 2 h is the optimal response.

Repeat and near-repeat policing strategies (see Groff and Taniguichi 2019) present a primarily short-term crime prevention strategy at places since the risk for revictimization dissipates over time. These strategies are not necessarily equipped to address revictimization as an escalation in the level of crime to a hot spot instead of just more routine cyclical, low to moderate-level patterns. Nevertheless, these strategies have demonstrated some promising results at crime reduction and reinforce the importance of focusing on revictimization (Farrell et al 2012). This is a rich literature which has developed around the targeting of revictimization at places to drive long-term crime reductions (Farrell and Pease 1993; Farrell 1995; Pease 1998). Since crime concentrates at hot spots and these locations are driven by repeat and near-repeat incidents, this allows for synergy between these strategies with hot spots interventions (Farrell and Sousa 2001). Future research needs to help distinguish between the revictimization risk profiles for specific places to help deploy the most appropriate interventions for short-term revictimization risk (i.e., increased patrol) and long-term risk (i.e., problem-oriented policing). Overall, this study provides a modest contribution to further documenting and considering these space–time patterns to improve the calibration of place-based crime prevention strategies to crime problems.

There are limitations to the study I could not address by using the integrated research design strategy. Despite using a two-decade observation period and exploring temporal specifications, the results are of course grounded to this specific sample. Two decades is a long period in the lifespan of a person but not as much for the life course of a city like Chicago. The formulation of an integrated revictimization strategy at places could use further refinement by other scholars to strengthen

the broader methodology and presentation of the strategy. I recommend future research continues to explore the specific cycles or natural rhythms of crime patterns between micro-places. This study was descriptive and not able to address questions of explaining differences between patterns of revictimization across micro-places. Future research could explore what differentiates locations which experience routine revictimization within the short-term window of 2 to 4 years with locations which do over longer periods or are not revictimized. This study only examined one category of violent crime. There are still several distinct sub-categories of violence included within aggravated assaults (i.e., domestic, gang, etc.) which could have unique revictimization patterns. In addition, results could vary across different categories of violence or if extended to other categories such as property crimes. Finally, the results of these analyses define the two critical bookends of the life course of repeat crime problems as meaningful but much more refined description needs to occur to better understand the dynamics of the periods in-between (e.g., days and weeks).

In conclusion, this study provided a unique contribution to the crime and place literature by considering a new methodological strategy to study revictimization. This strategy facilitated the integration of interconnected approaches to address a foundational question from crime and place research. This study presents a new conceptualization which emphasizes the interconnected nature of crime events and proposes a longitudinal framework which explicitly addresses revictimization risk is critical to understanding crime problems. In other words, crime events do not happen in isolation, the duration between the event which proceeds or follows crime events matters. These findings suggest the risk for revictimization of aggravated assault at micro-places in Chicago is defined by distinct periods demarcated immediately after an incident and over the next few years. I find there are short-term repeat and near-repeat windows that have some degree of inconsistencies over time and there are long-term windows across several years when most micro-places are revictimized. Both analyses are essential to understanding the full cycle of revictimization which can produce more efficient place-based crime prevention strategies.

Appendix: Repeat and near-repeat spatiotemporal windows results per year, 2001–2020

Part I: Knox ratios

Space–time window	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Same Location & Same Day	6.106	5.086	7.307	5.998	5.352	7.865	9.03	5.824	7.863	8.519
Same Location & 7 Days	1.290	1.004	1.949	1.482	1.231	1.410	1.336	1.383	1.256	1.362
Same Location & 14 Days	1.196	0.942	0.942	1.191	1.098	1.077	1.211	1.006	1.016	0.964
Same Location & 21 Days	1.040	0.951	0.941	1.197	0.951	1.072	0.984	1.195	0.889	1.069
Same Location & 28 Days	0.973	1.093	1.095	1.089	0.959	1.037	1.015	1.067	1.140	1.148
1 Block & Same Day	1.684	1.626	1.767	1.892	1.798	1.893	2.029	1.666	1.811	1.871
1 Block & 7 Days	1.039	1.028	1.052	1.033	1.032	0.991	1.072	1.078	1.021	1.031
1 Block & 14 Days	1.063	0.956	1.007	1.031	1.049	1.007	1.091	1.055	1.007	0.984
1 Block & 21 Days	1.008	1.021	1.012	1.044	1.011	1.031	1.012	0.986	0.991	0.989
1 Block & 28 Days	1.003	0.981	0.987	1.018	1.002	0.986	1.011	1.049	1.033	1.070
2 Blocks & Same Day	1.091	1.095	1.194	1.311	1.178	1.268	1.359	1.251	1.133	1.263
2 Blocks & 7 Days	1.029	1.045	1.051	1.029	1.049	0.997	1.011	1.040	1.045	1.025
2 Blocks & 14 Days	1.030	0.994	1.036	1.039	0.970	1.004	1.026	1.026	1.003	0.991
2 Blocks & 21 Days	1.007	0.992	1.003	1.017	1.002	0.992	1.030	1.021	0.994	1.017
2 Blocks & 28 Days	0.975	1.016	1.002	1.023	0.989	1.003	1.007	1.025	1.013	1.003

Part I: Knox ratios

Space–time window	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Same Location & Same Day	9.898	12.002	11.185	7.941	7.502	9.436	9.240	6.289	7.842	9.355
Same Location & 7 Days	1.442	1.399	1.187	1.427	1.290	1.416	1.253	1.260	1.329	1.284
Same Location & 14 Days	1.031	1.138	1.117	1.020	1.225	1.202	1.194	1.190	1.112	1.077
Same Location & 21 Days	1.129	1.005	1.354	1.059	1.097	1.055	1.041	0.979	1.098	1.050
Same Location & 28 Days	1.036	0.980	0.985	1.071	1.092	1.091	1.023	1.280	1.261	1.052
1 Block & Same Day	2.112	2.144	2.126	1.858	1.721	1.850	1.450	1.698	1.419	2.063
1 Block & 7 Days	1.113	1.102	1.036	1.064	1.028	1.040	1.072	1.072	0.988	1.012
1 Block & 14 Days	1.014	1.038	1.050	1.070	1.048	1.020	1.024	1.026	1.013	1.022
1 Block & 21 Days	1.031	1.045	0.982	1.005	1.023	0.995	1.022	0.978	1.017	0.991
1 Block & 28 Days	0.978	0.969	0.959	1.045	1.028	1.046	1.052	1.050	1.059	1.047
2 Blocks & Same Day	1.284	1.437	1.288	1.199	1.141	1.117	1.003	1.157	1.095	1.571
2 Blocks & 7 Days	1.001	1.017	1.027	1.036	1.016	1.011	1.004	1.057	1.022	1.017
2 Blocks & 14 Days	1.023	1.051	1.008	1.025	1.013	0.966	1.010	1.021	0.982	1.013
2 Blocks & 21 Days	0.985	0.958	1.030	1.010	0.992	0.990	1.054	1.004	0.993	0.999
2 Blocks & 28 Days	1.029	0.987	1.041	1.059	1.000	1.036	1.005	1.004	1.033	1.020

Part II: *p* values

Space–time window	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Same Location & Same Day	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Same Location & 7 Days	0.001	0.485	0.001	0.001	0.003	0.001	0.001	0.002	0.002	0.001
Same Location & 14 Days	0.003	0.833	0.913	0.001	0.039	0.141	0.001	0.435	0.340	0.687
Same Location & 21 Days	0.267	0.776	0.921	0.001	0.838	0.152	0.604	0.001	0.995	0.218
Same Location & 28 Days	0.659	0.105	0.023	0.059	0.794	0.293	0.414	0.138	0.004	0.039
1 Block & Same Day	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
1 Block & 7 Days	0.057	0.143	0.013	0.089	0.093	0.633	0.001	0.001	0.207	0.146
1 Block & 14 Days	0.006	0.947	0.390	0.078	0.019	0.392	0.001	0.015	0.414	0.704
1 Block & 21 Days	0.393	0.247	0.304	0.033	0.333	0.112	0.324	0.704	0.638	0.657
1 Block & 28 Days	0.487	0.720	0.725	0.211	0.487	0.723	0.322	0.022	0.104	0.010
2 Blocks & Same Day	0.090	0.099	0.001	0.001	0.001	0.001	0.001	0.001	0.021	0.001
2 Blocks & 7 Days	0.035	0.013	0.001	0.044	0.002	0.555	0.253	0.010	0.005	0.086
2 Blocks & 14 Days	0.039	0.632	0.005	0.004	0.978	0.424	0.055	0.067	0.418	0.681
2 Blocks & 21 Days	0.334	0.660	0.401	0.154	0.446	0.697	0.036	0.114	0.622	0.188
2 Blocks & 28 Days	0.929	0.214	0.450	0.067	0.767	0.427	0.315	0.079	0.230	0.471

Part II: *p* values

Space–time window	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Same Location & Same Day	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Same Location & 7 Days	0.001	0.001	0.068	0.001	0.004	0.001	0.003	0.003	0.001	0.001
Same Location & 14 Days	0.389	0.087	0.160	0.456	0.022	0.032	0.028	0.011	0.096	0.185
Same Location & 21 Days	0.089	0.499	0.002	0.307	0.188	0.300	0.338	0.619	0.134	0.287
Same Location & 28 Days	0.370	0.602	0.571	0.276	0.192	0.188	0.391	0.001	0.005	0.273
1 Block & Same Day	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
1 Block & 7 Days	0.001	0.004	0.176	0.032	0.221	0.091	0.010	0.013	0.661	0.338
1 Block & 14 Days	0.335	0.107	0.093	0.027	0.109	0.259	0.222	0.190	0.345	0.220
1 Block & 21 Days	0.149	0.075	0.685	0.433	0.265	0.546	0.241	0.787	0.285	0.646
1 Block & 28 Days	0.766	0.844	0.864	0.122	0.231	0.083	0.056	0.037	0.029	0.050
2 Blocks & Same Day	0.003	0.001	0.006	0.019	0.069	0.081	0.495	0.025	0.116	0.001
2 Blocks & 7 Days	0.485	0.224	0.151	0.082	0.259	0.303	0.423	0.004	0.149	0.195
2 Blocks & 14 Days	0.138	0.013	0.384	0.153	0.304	0.956	0.322	0.165	0.798	0.234
2 Blocks & 21 Days	0.765	0.977	0.132	0.337	0.623	0.679	0.006	0.428	0.620	0.536
2 Blocks & 28 Days	0.084	0.724	0.050	0.020	0.508	0.051	0.421	0.415	0.062	0.162

Data availability All data used in this study is publicly available through the Chicago Data Portal (data. cityofchicago.org).

Declarations

Conflict of interest The authors report there are no competing interests to declare.

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