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From cartridge cases to spatial patterns: Leveraging NIBIN to identify near-repeat shootings in Detroit

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ABSTRACT

This study uses ballistic evidence entered into the National Integrated Ballistic Information Network (NIBIN) to examine near-repeat shooting patterns in Detroit, Michigan, drawing on 5487 incidents involving the discharge of one or more firearms between January 2021 and October 2022. Conducted within the context of the Detroit Crime Gun Intelligence Center, our study captures a broad view of gun violence, integrates NIBIN linkages to advance understanding of the nature of gun violence, and extends analysis beyond dyads to multi-incident shooting chains. To this end, we applied the Knox test to identify near-repeat patterns and then grouped shooting incidents into chains based on their spatiotemporal proximity. We used multinomial and mixed-effects logistic regression to distinguish between the observed patterns. Our results show that gun violence in Detroit clusters tightly in space and time and is linked to high-risk places as well as circulating, multi-use crime guns. We discuss the implications of these findings for guiding law enforcement in developing integrated strategies that combine place-based and network-focused interventions to prevent and reduce gun violence in communities.

1. Introduction

Two dominant perspectives help explain the proliferation of shooting incidents: one emphasizes retaliation and diffusion through social networks, while the other points to enduring structural and environmental conditions that maintain risk. When spatial and temporal clustering is observed in these incidents, it is often unclear which factors are at play. Examining near-repeat patterns using data from the National Integrated Ballistic Information Network (NIBIN) can shed light on these dynamics, while also offering practical guidance for violence prevention efforts. This combination of analytic tool and data advances existing work by capturing incidents that are often overlooked, yet central to the daily reality of violence in many communities.

By systematically linking ballistic evidence from incidents involving the discharge of a firearm, NIBIN provides a more nuanced and complete understanding of how gun violence moves through space and time, advancing both theory and practice. For example, if the same firearms are used in spatially and temporally linked incidents, this lends support to the argument that gun violence spreads through contagion, assuming the firearms are shared within networks or used by the same offenders. If not, it points to place-based features and enduring neighborhood conditions as drivers of violence. In either case, the information gleaned can sharpen strategies used to address local gun violence.

Despite the substantial social and economic toll of gun violence (Cook & Ludwig, 2006; Miller et al., 2024), research on near-repeat shooting patterns remains limited. The present study addresses this gap by analyzing 5847 shooting incidents in Detroit, Michigan, and, in a novel contribution, incorporates NIBIN data to evaluate near-repeat patterns of gun violence. By focusing on incidents involving the discharge of one or more firearms and linking events through ballistic evidence, we gain a more nuanced and comprehensive understanding of gun violence and the patterns it produces. To this end, our study is guided by four research questions: What near-repeat shooting patterns exist? What distinguishes shootings involved in these patterns from those that are not? In addition, what factors distinguish the severity of these patterns? And how often do they involve the same firearms?

In the sections that follow, we introduce the near-repeat phenomenon and its theoretical underpinnings, then turn our attention to how it has been applied to study patterns of gun violence. As part of that discussion, we review the epidemic and endemic perspectives on gun violence and highlight prior research on near-repeat shooting patterns, noting key limitations. We then introduce NIBIN and consider how its

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use can expand both the theoretical and practical dimensions of the study of near-repeat shootings. Building on this foundation, we present the current study, describe our data and analytical approach, and share our findings. We conclude by discussing their implications for both practice and theory and outlining directions for future research.

2. Literature review

2.1. The near-repeat phenomenon

First observed in epidemiological studies of the spread of infectious disease (Pike & Smith, 1968), the near-repeat phenomenon has since been adopted as a framework for understanding the tendency of criminal incidents (hereon referred to as incidents) to cluster across space and time. Townsley, Homel, and Chaseling (2003) were the first to explore this phenomenon among reported burglary incidents, identifying elevated crime risk within 200 m and two months of an initial incident. Since then, research has identified near-repeat patterns across a range of crime types, including robbery, motor vehicle theft, arson, terrorist events, and piracy (e.g., Piza & Carter, 2018; Rieber-Mohn & Tripathi, 2021; Townsley & Oliveira, 2015; Turchan et al., 2019).

Criminological studies of the near-repeat phenomenon have used the Knox Method to calculate the elevated risk of subsequent incidents occurring near the location of an initial event within defined spatial and temporal bandwidths (Knox, 1964; Knox & Bartlett, 1964). By narrowing the spatial bandwidth, the Knox method can also be used to identify evidence of repeat victimization. A closely related phenomenon, repeat victimization refers to incidents that recur at the same location, often within a short timeframe.

Within the near-repeat framework, incidents fall into two *general* categories: those involved in a near-repeat pattern and those that are not. Incidents not linked to any subsequent events are referred to as *isolate incidents*. If an incident is the first in a chain, triggering one or more subsequent events, it is referred to as an *initiator incident*. The subsequent incidents have been broadly referred to as near-repeat incidents. The roles of the initiator and near-repeat are not mutually exclusive, though. A single event may initiate subsequent events while simultaneously serving as a near repeat within other patterns. Further complicating matters, the identification of near-repeat patterns depends heavily on the spatial and temporal bandwidth selected and the underlying method used to detect chains of events (Loeffler & Flaxman, 2018; Ratcliffe, 2009; Wheeler, Riddell, & Haberman, 2021). These decisions influence both interpretation and application, a topic we further develop in our discussion of our analytic plan.

Two primary hypotheses have emerged from the literature on repeat victimization to explain the phenomenon. Both have been extended, to varying degrees, to account for near-repeat patterns. The flag hypothesis (also known as risk heterogeneity) attributes repeat victimization to stable features of targets that make them attractive to offenders. Simply put, certain features act as *flags* that signal to offenders that a target is attractive, a concept developed further in crime pattern theory (Steenbeek & Elffers, 2020). Some studies have suggested that near-repeat patterns may emerge simply due to the clustering of high-risk targets (i.e., targets with many flags) in close proximity (see Johnson, 2008; Pitcher & Johnson, 2011). However, others contend that these patterns should be distinguished from true near-repeat events because the incidents that generated them occurred independently of one another and are not representative of a contagion (Ornstein & Hammond, 2017; Loeffler & Flaxman, 2018; Steenbeek & Elffers, 2020).

By contrast, the boost hypothesis attributes repeat victimization to the increased risk (or boosting) of subsequent crimes following an initial event. Boosting can occur when offenders leverage knowledge gained during the first offense (such as, access points, household routines, or security vulnerabilities) to facilitate future offenses at the same locations. As it relates to near-repeat patterns, offenders may apply what they have learned from their offending to identify other attractive targets in nearby areas. This behavior is well documented, although less explored in the context of near-repeat patterns (Bernasco, 2008; Bowers & Johnson, 2004). In this way, boosting can be interpreted as a specific form of spatio-temporal risk heterogeneity, an elevated crime risk tied to high flag features in nearby targets (Steenbeek & Elffers, 2020).

Much of what is known about the near-repeat phenomenon in crime has been developed from studies on burglary and, more broadly, property crimes. These foundational studies have significantly advanced our understanding of how crime spatially and temporally concentrates. Yet gun violence differs markedly from property crimes in both nature and context. It is shaped by a variety of coalescing factors, including individual (e.g., Kelsay, Silver, & Barnes, 2021; Laqueur et al., 2024), group (e.g., Papachristos, Braga, & Hureau, 2012; Papachristos et al., 2015; Papachristos, Wildeman, & Roberto, 2015), and situational dynamics (e.g., Altheimer et al., 2019), as well as neighborhood conditions (e.g., Gill, Novak, & Patterson, 2024; Semenza et al., 2023) and broader policies (Crifasi et al., 2024; Kagawa et al., 2018). Given this complexity, the mechanisms driving near-repeat shooting patterns may diverge considerably from those observed in property crime research, where the phenomenon has been most extensively studied. In what follows, we offer a focused discussion on the factors driving these patterns, followed by a review of the limited, but growing, body of research on near-repeat shootings.

2.1.1. Patterns of gun violence

There are two dominant explanations of near-repeat shooting patterns. The first emphasizes the role of social dynamics in propagating violence. Following an initial shooting event, retaliation may be carried out by the original parties involved or by individuals within their broader social networks, either alongside them or on their behalf (Carter et al., 2017; Whitehill, Webster, & Vernick, 2013; Wilkinson, 2021). This perspective views violence as an epidemic or contagion, where retaliatory acts transmit risk through social networks and across space and time.

Not all shootings are retaliatory, though. As previously discussed, some places may be particularly attractive for shootings due to the features they possess and the neighborhood conditions in which they are embedded (Gill et al., 2024; Semenza et al., 2023). In this case, space-time clustering does not arise because one event triggers another, but rather because the underlying conditions of these places support violence. This perspective aligns with the endemic model, which contends that violence concentrates in specific locations due to static environmental features and the broader contexts in which they are situated.

How epidemic and endemic mechanisms actually play out in real-world settings is less straightforward, especially in high-crime neighborhoods (Loeffler & Flaxman, 2018). Shootings tend to occur in neighborhoods with distinct structural conditions that contribute to their high crime rates. These environments contain locations that, for a variety of reasons, may consistently make them high-risk for criminal activity. Retaliatory violence may exploit these high-risk places or not. Likewise, offenders may use their knowledge of neighborhood conditions and features of places to perpetuate crime. While residents residing in high-crime neighborhoods have a greater familiarity with violence, salient incidents may have a profound effect. A shooting on one's block or involving a family member, for instance, can resonate more strongly than incidents involving strangers or occurring farther away. Such events may motivate individuals to obtain and carry firearms (Beardslee et al., 2018; Kopf & Gresham, 2025; Schleimer et al., 2021), reinforcing cycles of violence in ways not explained solely by place-based conditions.

Empirical studies reflect this complexity. In Chicago, Illinois, Green et al. (2017) estimated that 63.1 % of incidents between 2006 and 2014 were attributable to social contagion. This finding aligns with extensive evidence that offending and victimization are often concentrated within social networks, providing support for contagion-based explanations

(Papachristos et al., 2012; Papachristos et al., 2015; Papachristos, Wildeman, & Roberto, 2015). In contrast, Loeffler and Flaxman's (2018) assessment of Washington, D.C., characterized gun violence as largely endemic rather than epidemic, echoing earlier observations by Christoffel (2007). Similarly, Brantingham et al. (2021) found that non-contagious events represented the majority of shootings across four U. S. cities during the COVID-19 pandemic.

Certainly, understanding why near-repeat patterns occur is important for optimizing strategic responses to crime. At the same time, simply identifying these patterns and where they occur is of strategic value to law enforcement agencies. By identifying linked incidents, their characteristics, and where they concentrate, these agencies can, at a minimum, develop proactive enforcement strategies to target areas at elevated risk and intervene before patterns escalate. Of course, information about whether a specific group or individual is driving these patterns would help inform the type of enforcement mechanism best suited to respond. However, in real-world settings, such information is often unavailable. What is known, however, is that the pattern exists and that, in itself, is actionable.

2.1.2. Near-repeat shooting analyses

Near-repeat shooting patterns have been observed to varying degrees in cities and municipalities both within the U.S and abroad. We engage with this limited body of research by structuring our review around three key areas of inquiry that inform the study's focus and design. The first involves how shooting incidents are defined. The second concerns the extent to which these incidents cluster in space and time, as well as the spatial and temporal parameters used to detect such clustering. And lastly, the features of the incidents themselves that influence whether or not they are involved in near-repeat patterns. This discussion also includes a summary of the impact of proactive enforcement strategies informed by near-repeat shooting patterns. The overview that follows considers these areas among those studies that adopt the Knox method to identify near-repeat shooting patterns.

2.1.3. Defining shooting incidents

Prior research has predominantly defined shootings either narrowly, by focusing on incidents involving fatal or nonfatal injuries (Ratcliffe & Rengert, 2008; Youstin, Nobles, Ward, & Cook, 2011), or more broadly, by expanding consideration to violent crimes involving a firearm (Wells & Wu, 2011; Wells et al., 2012; Youstin et al., 2011). There are two limitations of these approaches. First, restricting near-repeat assessments to only those incidents involving injuries or fatalities fails to capture the broader scope of gun violence, if that is indeed the focus. The distinction between fatal and nonfatal shootings often comes down to chance, and arguably the same could be said for incidents in which a shot was fired without injury. Excluding these incidents overlooks a substantial portion of gun violence, limiting what can be learned about its dynamics. Second, including incidents that merely involve a firearm does not necessarily mean the weapon was discharged. It is therefore important not to conflate firearm involvement with firearm use, as these represent distinct though related forms of firearm crimes. Still, in the absence of more precise data, firearm involvement is often the best available proxy for identifying incidents involving the discharge of a firearm.

More recently, Mazeika and Uriarte's (2019) assessment of near-repeat patterns in Trenton, New Jersey, adopted the broadest definition of shootings incidents. In the first study of its kind, Mazeika and Uriarte (2019) integrated data from a gunshot detection system with official police records of firearm-related homicides, assaults with a gun, and shots fired. Importantly, only incidents with verified firearm discharges were included in the analysis, ensuring that all incidents reflected firearm usage. While their study considers the most comprehensive data on shooting incidents to date, there is room for expansion. The gunshot detection system deployed in Trenton only covered 40 % of the city, underscoring the value of a more complete collection of gun-related evidence. Beyond the information generated by this system, the incidents considered could also be broadened to capture a more diverse array of offenses involving the discharge of a firearm.

NIBIN provides a unique opportunity to build on these efforts. As a premier source of crime gun intelligence, NIBIN can generate the most comprehensive record of shooting incidents currently available under ideal conditions.[1] Intelligence gleaned through the NIBIN process can also meaningfully inform discussions about the nature of gun violence. Later, we explore what NIBIN data stands to contribute to the study of the near-repeat phenomenon in shootings in greater detail.

2.1.4. Spatial and temporal thresholds

With few exceptions, studies have found evidence of near-repeat shooting patterns, generally concentrated in short spatial and temporal windows. For example, Wells and Wu (2011) observed the highest risk for near-repeat shootings within one block (400 ft) and 15 to 28 days of an initial incident. Similarly, Wells et al. (2012) found near-repeat patterns within 1 block (400 ft) and 14 days, a pattern with earlier support from Ratcliffe and Rengert (2008). Furthermore, Sturup et al. (2018) identified near-repeat patterns in two of the three observed Swedish cities, with spatial-temporal clustering occurring within 100 m and the first two weeks after an initial incident.

A key takeaway from this body of work is the importance of remaining open to a range of spatial and temporal thresholds. Doing so can improve the accuracy of detection and the potential utility of this information for violence prevention strategies. This practice is observed in prior research. For example, Youstin et al. (2011) used a spatial bandwidth of one block (575 ft) and considered four temporal bandwidths: 1 day (up to 4 days), 4 days (up to 16 days), 7 days (up to 28 days), and 14 days (up to 56 days). They found near-repeat shooting patterns within 4 blocks (2300 ft) and 14 days of an initial incident, with the greatest elevated risk observed within 3 blocks (1725 ft) and 4 days. Mazeika and Uriarte's (2019) study further supported the consideration of broader array of temporal windows, with some of the most pronounced effects occurring within 2 days of the originating event.

2.1.5. Strategic responses

Despite growing interest in near-repeat shooting patterns, we still know relatively little about the characteristics of incidents that drive them. To start, identifying the roles these incidents play is more complex than it may appear. As earlier discussed, this complexity stems from the fact that a single incident can occupy multiple roles across near-repeat chains. With this complexity in mind, research has found that most shooting incidents do not follow a near-repeat pattern. Wells et al. (2012) found that 95 % of shootings showed no signs of near-repeat activity, and only 3 % served as initiator incidents. Wells and Wu (2011) identified slightly greater involvement in near-repeat patterns, with 7.9 % of shootings involved before a proactive enforcement intervention, dropping to 6.8 % during the intervention. Mazeika and Uriarte (2019) reported the highest levels of near-repeat involvement, finding that nearly 20 % of incidents involving a gun-related offense were a part of a near-repeat pattern, rising to almost 31 % when incorporating gunshot detection data. These elevated proportions likely reflect the use of more comprehensive data to capture shooting incidents.

While there is inherent value in identifying incidents involved in near-repeat patterns, evidence on the effectiveness of such efforts remains mixed. Ratcliffe and Rengert (2008) found that near-repeat patterns persisted despite the proactive enforcement strategy adopted in Philadelphia. They offered several possible explanations, most notably the dosage of police available. Despite these findings, Ratcliffe and

[1] A crime gun is a firearm involved or suspected to have been involved in criminal activity. This term is used here and throughout to emphasize the connection between a firearm and its use in crime.

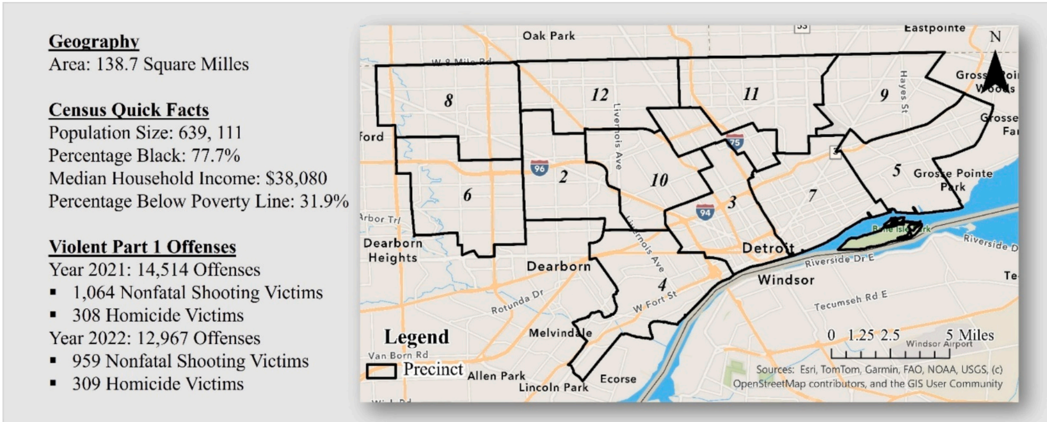

Fig. 1. City of Detroit.
Notes. This figure presents a map of the city of Detroit by precinct boundaries and includes key geographic, demographic, and crime-related characteristics.

Rengert (2008) emphasized the strategic value of focusing on initiator incidents. They observed that such incidents tended to cluster in areas distinct from other shootings, suggesting opportunities for geographically targeted interventions aimed at preventing subsequent violence. In contrast, Wells and Wu (2011) found that near-repeat shooting patterns observed prior to proactive enforcement activity diminished in districts where such activity was the greatest. Unlike Ratcliffe and Rengert's (2008) earlier study, Wells and Wu's (2011) findings support the potential of proactive enforcement strategies to disrupt recurring violence, with consideration given to dosage and context.

These findings notwithstanding, Wells and Wu (2011) identified few differences between near-repeat and isolated shooting incidents overall, suggesting that actually targeting the right incidents to optimize crime prevention may be difficult. Shootings at businesses were slightly more likely to be part of a near-repeat pattern compared to those occurring at residences or in open areas. Additionally, gang-involved shootings exhibited a slightly higher likelihood of near-repeat clustering. Notably, incidents that were part of near-repeat patterns were more likely to involve murders and justifiable homicides than aggravated assaults, suggesting an escalation in the severity of violence within these patterns.

Ultimately, more investigation is needed into the incident, place, and neighborhood features that shape near-repeat shootings. Such understanding can better guide intervention strategies that are both timely and targeted. NIBIN data offers an important contribution on this front, as it offers insights into the criminal histories of crime guns that have yet to be leveraged within a near-repeat framework. When comprehensively collected, this information not only provides a fuller understanding of gun violence patterns but also allows for the direct examination of how incidents are linked to one another through the criminal histories of the firearms involved.

2.2. *NIBIN: a new frontier*

NIBIN represents the systems and processes used to collect and analyze ballistic evidence and disseminate the gained intelligence (U.S. Department of Justice, Bureau of Alcohol, Tobacco, Firearms and Explosives [ATF], 2023). The NIBIN process begins with the collection of cartridge cases from crime scenes, as well as from test-fires of recovered crime guns. High-resolution, 3D, digital images of these cartridge cases are captured using a NIBIN acquisition station, along with associated information about the pieces of evidence (POEs) and the incidents from which they were recovered. On a separate machine, these images are then cross-correlated against existing entries in the system using an automated correlation algorithm. High-confidence correlations, once reviewed and confirmed by a correlation review technician, are referred to as NIBIN leads. A NIBIN lead connects two or more POEs recovered from separate incidents, indicating that the same firearm was likely used in each event. These leads have been predominantly used to serve an investigative purpose and may later be confirmed by a firearms examiner through microscopic analysis for evidentiary use in court.

The tactical and strategic potential of NIBIN is closely tied to the comprehensive collection of ballistic evidence. The more comprehensive the collection efforts, the greater the value NIBIN can offer. While emerging research lends support to its tactical utility (De Biasi, 2024a; Katz et al., 2021; Swatt et al., 2024; Uchida et al., 2020), the strategic value of NIBIN remains underdeveloped. Under ideal conditions, where comprehensive collection is upheld, NIBIN can provide a detailed picture of shooting incidents. For each shooting incident, information stored in the NIBIN system includes the number of firearms discharged, the caliber of the acquired cartridge cases, and, if the firearm is recovered, its make, model, and serial number. Perhaps most importantly, these records include whether a firearm has a known criminal history, a determination made through the cross-correlation reviews previously described. Gunshot detection systems can further bolster this effort by alerting law enforcement to shootings that might otherwise go unreported, increasing the number of recovered cartridge cases and supporting more comprehensive entry into NIBIN.

NIBIN data can also meaningfully advance the theoretical discussion of whether gun violence operates as an epidemic or endemic condition. This contribution lies in its ability to document the criminal histories of firearms, enabling analysts to determine whether incidents that occur close in space and time are linked by the same firearm. For example, if the same firearm is discharged across clustered incidents, this pattern lends support to the epidemic model of violence. There is strong reason to believe that these events were perpetuated by the same offender or group of offenders. In contrast, if different firearms with no known criminal histories are used in incidents that are similarly clustered, this pattern aligns more closely with endemic conditions, where the environment itself drives gun violence. Insights become murkier, however, when different firearms with criminal histories are used in clustered incidents. Such patterns may reflect the diffusion of violence among connected individuals or groups, the transference of knowledge informing offending decisions, or the recurring attractiveness of certain places that draw them back.

3. Current Study

Our study contributes to the existing body of research on the near-repeat phenomenon in gun violence by, for the first time, leveraging ballistic evidence submitted to NIBIN to reveal patterns in incidents involving the discharge of a firearm. Our study is guided by four research questions:

1. What near-repeat shooting patterns exist?
2. What distinguishes shootings involved in these patterns from those that are not?
3. What factors distinguish the severity of these patterns?
4. And how often do they involve the same firearms?

We advance prior work on both practical and theoretical fronts. Practically, by adopting a broad definition of shootings (i.e., not just those involving fatal or nonfatal shooting injuries), we are better positioned to detect patterns that may have gone overlooked, patterns that can inform proactive enforcement strategies. At the same time, by limiting our scope to events where a firearm was actually discharged, we stay focused on incidents that matter most for understanding and addressing firearm use on the ground. Theoretically, NIBIN allows us to determine whether spatially and temporally linked shooting incidents involve the same firearms, enabling us to contribute to ongoing discussions of gun violence as either epidemic or endemic in nature.

Our analysis is based on 5487 shooting incidents that occurred between January 1, 2021, and October 27, 2022, in Detroit during a period when the city's CGIC was operational (see Fig. 1). The city of Detroit is approximately 138.7 mile^2, with a total population of 639,111 (U.S. Census Bureau, 2025a). Its population is predominantly Black, representing 77.7 % of residents (U.S. Census Bureau, 2025b). The median household income is $38,080 (U.S. Census Bureau, 2025c), less than half the state average. And nearly one in three residents (31.9 %) live below the poverty line (U.S. Census Bureau, 2025d), more than double the statewide rate.

During the study period, violent crime, notably homicide, was at an unprecedent high (De Biasi et al., 2023), as in other major cities in the U. S. following the COVID-19 pandemic (Abrams, 2021; Meyer et al., 2022; Rosenfeld & Lopez, 2020). In 2021, the Detroit Police Department (DPD) reported 14,514 Violent Part I offenses, including 1064 nonfatal shooting and 308 homicide victims (City of Detroit, 2023).[2] By 2022, Violent Part I offenses decreased by 10.7 % (from 14,514 to 12,967). This decline was driven by a 9.9 % reduction (from 1064 to 959) in nonfatal shooting victims, while homicide remained effectively stable at 309 victims (City of Detroit, 2023).

As a designated CGIC site, DPD is required to meet the Minimum Required Operating Standards (MROS) set forth by ATF (2019). These include the comprehensive collection of all suitable ballistic evidence for NIBIN entry. Contributing to the repository of ballistic evidence in this system, our study period overlaps with the rollout of gunshot detection technology (GDT) in Detroit. GDT predominately covered the 8th and 9th precincts, with only limited coverage of the 10th precinct during the final weeks of our study period. Ultimately, coverage in these precincts helped capture a more complete picture of shooting incidents in the city.

DPD maintains a host of proactive enforcement initiatives. One of its most longstanding practices is Compstat, modeled after New York City's system of data-driven management and accountability (Weisburd et al., 2003). On a bi-weekly basis, sworn law enforcement personnel from all precincts and specialized units meet to review crime trend patterns, with a special focus on gun-related and violent crime. A key purpose of this meeting is to direct its patrol response through crime analysis and intelligence of enduring and emerging hot spots. Complementing this approach, DPD deploys Special Operations Units that provide rapid, tactically oriented responses to priority-1 incidents (e.g., shootings, robberies) and conduct targeted enforcement activities in areas with elevated violence.

As an additional resource supporting proactive policing strategies, the Department implemented a Real Time Crime Center in 2016 that monitors surveillance cameras, calls for service, and other sources of intelligence in order to provide timely intelligence to officers and special units. This includes monitoring cameras from businesses and other commercial locations that participate in Project Greenlight, a partnership between city government, DPD, and businesses (see Circo & McGarrell, 2021; Circo et al., 2022).

Beyond real-time intelligence capabilities, DPD's strategy also includes violence-prevention partnerships, such as its participation in Detroit Ceasefire, a pulling-levers focused deterrence approach to reducing gun violence that involves community outreach and intervention (Ceasefire Detroit, n.d.;Circo et al, 2019). In addition to Ceasefire, the department engages in a range city-wide initiatives and grant-funded programs (e.g., Byrne State Crisis Intervention Program) that leverage community stakeholders and organizations in a coordinated response to reduce violent crime (see City of Detroit, n.d..).

4. Methods

4.1. Data sources

Our data are derived from ballistic evidence collected by DPD and entered into NIBIN between January 1, 2021, and October 27, 2022. In accordance with the MROS, participating CGIC sites like DPD are required to submit all eligible POEs into NIBIN.

POEs submitted to NIBIN generally take two forms: cartridge cases and test-fires. Cartridge cases are discharged from a crime gun and recovered from a crime scene. In contrast, test-fires result from the recovery of a firearm by law enforcement that is subsequently test-fired, with the resulting cartridge case submitted to NIBIN. The critical distinction here is that a cartridge case signifies a shooting event, whereas a test-fire alone does not.

In total, our dataset is a record of 5487 shooting incidents, involving 7804 cartridge cases. Importantly, it excludes incidents that *only* involved test-fires, as these are unlikely to capture actual shooting events. Each POE is accompanied by metadata, including the unique ID of the incident it was collected from, the cartridge case caliber, and the location, date, and time of the incident. Furthermore, a Crime Gun ID (CGI) is assigned when a NIBIN lead is identified, signifying with high confidence that the unique firearm markings on a POE from one incident match those left on a POE from another, separate incident. Simply stated, a CGI is evidence of a firearm's criminal history.

4.2. Analytic plan

We addressed our research questions in three phases. First, we conducted an evaluation of near-repeat shooting patterns from NIBIN data. This phase involved identifying shooting incidents that were part of near-repeat shooting pairs and longer shooting chains. This foundational step informed our subsequent analyses and addresses our first research question.

The second phase addresses our second research question. We conducted a multinomial logistic regression to classify incidents from our earlier assessment of near-repeat shooting pairs as isolates, initiators, or near-repeats. Complementing this analysis, we used mixed-effects logistic regression to more precisely identify the factors associated with a shooting incident's involvement in a near-repeat shooting pair.

In the third phase, we used multinomial logistic regression to examine how the characteristics of near-repeat shooting chains varied based on the number of incidents they involved. We also assessed the characteristics of the firearms used in these chains, including whether the same firearms were involved across incidents. This phase addresses our third and fourth research questions. Below, we describe each phase of our analytic plan in greater detail.

4.3. Phase 1: near-repeat shooting patterns

We used the *NearRepeat* package in R, developed by Steenbeek (2018), to explore spatio-temporal associations among shooting

[2] A nonfatal shooting is used to describe incidents involving nonfatal firearm injuries (i.e., penetrating bullet wounds).

incidents. Two critical features are needed to support this analysis: (1) the location of a shooting incident, provided as an XY-coordinate; and (2) the date of the shooting incident.

With this information, we calculated near-repeat and repeat victimization risk using the Knox test. For all recorded incidents, the Knox test considers incident pairs to determine the victimization risk within user-specified spatial and temporal thresholds. Specifically, it examines whether the time between two incidents in a pair is related to the distance between them. Thus, to identify near-repeat victimization, the Knox test assesses whether incident pairs that occur close in time also occur close in space. Repeat victimization is assessed by examining whether incidents occur at the exact same location.

The user-specified spatial and temporal thresholds intersect, forming distinct spatio-temporal windows. For each spatio-temporal window, the number of observed event pairs is recorded and compared to the number expected under a null distribution generated through a Monte Carlo permutation procedure. This information is stored in a contingency table, with the spatial windows organized as rows and temporal windows organized as columns. Each cell in the contingency table captures a distinct spatio-temporal window. For each of these windows, comparisons are expressed as a Knox ratio, the ratio of observed to expected pairs.

We adopt Steenbeek and Elffers' (2020) interpretation of the Knox ratio, which recognizes that some clustering may still occur under the null distribution, however unlikely. Leaving open this possibility, observed clustering should be assessed relative to what could occur by chance. In this context, a Knox ratio of 1 indicates no difference between the observed and expected number of incident pairs; not necessarily no clustering. In cases of near-repeat victimization, a ratio greater than one suggests, "an increase of risk for some limited time period in an area close by a previous victimization, over and above the effect of chance" (p. 3). For repeat victimization, a ratio greater than one suggests that "some targets are victimized at higher rates than other targets, over and above the effect of chance" (p. 3).

To evaluate patterns of near-repeat and repeat victimization, we selected spatial and temporal thresholds that captured variation in proximity across both dimensions. We adopted a spatial threshold of one block, approximately 350 ft. We considered incidents occurring at the same location and within one-block increments up to four blocks, with distances calculated based on Manhattan distance. The final spatial window captured incidents that occurred beyond four blocks. Furthermore, we adopted three temporal thresholds: 4 days, 7 days, and 14 days. For each threshold, we considered five incremental temporal windows. This approach afforded us greater granularity, allowing us to identify the timeframes in which near-repeat and repeat victimization were most prominent. Following Ratcliffe (2009), we considered the risk of near-repeat and repeat victimization to be meaningful when the Knox ratio was 1.2 or greater and the associated *p*-value (derived from 999 Monte Carlo simulations) was less than 0.05.

Informed by these findings, we selected spatial and temporal thresholds to classify incidents as isolates, initiators, or near-repeats. In this framework, an incident can serve as both an initiator and a near-repeat in separate dyads (/pairs). As suggested, this approach is limited to dyadic relationships, identifying links between individual pairs of incidents (e.g., incident A is followed by incident B), without accounting for broader sequences of connected events.

To address this limitation, we created a function in R, following Wheeler et al. (2021), to identify broader near-repeat chains. Our function constructs a network where incidents are connected if they fall within pre-determined spatial and temporal thresholds, informed by our previous near-repeat findings. Thus, our approach enables the detection of multi-incident chains, extending beyond pairs of incidents. To enable this network-based identification of connected incidents, each incident is assigned to a single role within a given chain and cannot simultaneously serve as both an initiator and a near-repeat.

4.4. Phase 2: isolates, initiators, and near-repeat incidents

We conducted multinomial and mixed-effects logistic regressions based on our pairwise comparisons of shooting incidents, with spatial and temporal thresholds informed by our near-repeat analysis findings. The multinomial logistic regression distinguishes among isolates, initiators, and near-repeat incidents. The mixed-effects regression examines the likelihood that a shooting incident was part of a near-repeat pair versus an isolated incident and includes random effects to account for geographic clustering. In both models, we use robust standard errors and present results as relative risk ratios for the multinomial regression and odds ratios for the mixed-effects regression.

To determine the optimal level of clustering for our mixed-effects logistic regression model, we compared models with varying random effects structures, including those that accommodated clustering at the scout car area, precinct, and census tract levels.[3] For each model, we calculated intraclass correlation coefficients to assess the percentage of variation in the outcome explained by clustering. We also evaluated model fit using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). Overall, the mixed-effects logistic regression model that included random effects for both scout car area and census tract provided the best fit ($AIC = 5654.13$; $BIC = 5852.43$).[4] Scout car areas nested within census tracts accounted for 19.1 % of the variance in the outcome, while census tracts alone explained 9.6 %.

Our multinomial and mixed-effects logistic regression models include the same 29 explanatory variables, grouped into five categories (see Table 2 for descriptive statistics). To start, we used ArcGIS Pro (version 3.4) to geocode each shooting incident. We captured proximity to the boundary of scout car areas and major roads using shapefiles obtained from the City of Detroit's Open Data Portal and TIGER/Line shapefile from the U.S. Census Bureau, respectively. To maintain consistency across our analyses, we coded features as present if located within 700 ft (approximately two street blocks) of a shooting incident and absent otherwise.

In the same way as just described, we created seven dichotomous variables to capture the presence of crime generators and attractors within 700 ft of a shooting incident using shapefiles provided by Data Axle, a provider of residential and commercial data. Informed by prior research (Thomas, Harris, & Drawve, 2022; Xu & Griffiths, 2017), these features included ATMs, bus stops, gas stations, liquor license retailers, marijuana dispensaries, pawnshops, and parks.

Furthermore, we represent temporal characteristics captured by six dichotomous variables, including the year ($2021 = 1$; $2022 = 0$) and quarter (with separate variables identifying whether an incident occurred in Quarter 1, Quarter 2, Quarter 3, or Quarter 4) that a shooting incident occurred, as well as whether it occurred on a weekend (1) or weekday (0).

We also captured the characteristics of the incidents themselves using eight dichotomous variables. These variables captured the involvement of semi-automatic rifles, the number of firearms discharged, and whether one or more recovered firearms had a criminal history. To determine a firearm's criminal history, we considered all

[3] We do not consider the 'near-repeat shooting pair' as a random effect for two primary reasons. First, involvement in a near-repeat shooting pair was relatively limited. For this reason, including near-repeat shooting pair as a random effect would yield unstable variance estimates due to insufficient within-chain variation. Second, a primary goal of the model was to examine the incident, place, and structural factors that influenced the likelihood of a shooting incident's involvement in a near-repeat shooting pair. This focus aligned with our broader emphasis on how context shaped the spatial distribution of firearm violence risk.

[4] For comparison, the model with only scout car area random effects yielded an AIC of 5699.89 and a BIC of 5891.59. The model with only census tract random effects had an AIC of 5664.89 and a BIC of 5856.58.

firearms that were discharged during an incident and identified whether they were associated with a NIBIN lead. Firearms with NIBIN leads provide strong evidence that they were previously used in one or more shooting events. In addition, we captured offense type using five dichotomous variables: violent offense, property offense, fatal or nonfatal shooting, weapons offense, and other offense. For a comprehensive list of casing calibers associated with semi-automatic rifles and the offense categorizations, please refer to Appendices A and B, respectively.

Lastly, we captured the characteristics of census tracts (a proxy for neighborhoods) in which incidents occurred using five continuous variables created from ACS 5-year estimates. These variables included population density (per square-mile), percentage of Black residents, percentage of individuals who changed residences in the past year, and two factor scores generated from a principal components factor (PCF) analysis with oblique (promax) rotation.

Our PCF analysis included five census tract-level measures reflecting concentrated disadvantage (Sampson, Raudenbush, & Earls, 1997): the percentage of female-headed households, the percentage of residents living below the poverty line, the unemployment rate, the percentage of households receiving public assistance, and the percentage of residents under the age of 18. We identified a three-factor solution. Factor 1 accounted for 29.7 % of the variance and loaded strongly on the percentage of female-headed households (loading = 0.88) and the percentage of residents under 18 (loading = 0.82), suggesting a concentration of female-headed households and a high proportion of youth. Factor 2 accounted for 27.2 % of the variance and loaded strongly on poverty (loading = 0.76) and unemployment (loading = 0.87), representing broad economic hardship within the census tracts. While a third factor emerged, it was defined predominately by public assistance (loading = 0.95), with all other loadings falling below 0.3. Consequently, we retained the first two factor scores for use as covariates in our models: 1) female-headed households and youth; and 2) economic disadvantage.

4.5. Phase 3: shooting chains

We used multinomial logistic regression to distinguish more persistent shooting chains from those that involved only two shooting incidents, the bare minimum. For this assessment, our unit of analysis shifted from an individual shooting incident to a shooting chain, with incidents nested within these chains. We classified chains into three categories based on the number of incidents they involved. Importantly, unlike the pairwise comparisons used to identify isolates, initiators, and near-repeat incidents, these chains were derived from a broader network-based approach that captured more extensive spatial and temporal linkages among incidents (see Wheeler et al., 2021). We use robust standard errors, report relative risk ratios, and conduct post-estimation tests to directly compare variables across the two non-reference outcome categories.[5]

Our final model includes 28 explanatory variables, grouped into five categories (see Table 6 for descriptive statistics). These variables are the same as those previously described, with three distinctions. First, we constructed our variables based on their occurrence across incidents *within* shooting chains. By definition, a shooting chain consists of *at least* two shooting incidents. For dichotomous variables, a chain was coded as meeting a condition if any incident within the chain satisfied that condition. For example, if a chain involved three incidents and any of them occurred near a bus stop, the 'near bus stop' variable for that chain was coded as present. For continuous variables, we calculated the average value across all incidents involved in the chain. Second, we excluded the property offense variable and the variable capturing proximity to marijuana dispensaries due to limited variation across our shooting chain classifications. Lastly, we added a variable to indicate whether the same firearms were used in two or more shooting incidents within shooting chains. This variable is distinct from our criminal history variable, which captures whether a crime gun used in a shooting event was involved in other shootings. For ease, we refer to firearms meeting this criterion as repeat crime guns.

5. Results

5.1. Near-repeat shooting patterns

Table 1 presents the Knox Ratios for the four-day, seven-day, and fourteen-day thresholds. For the four-day threshold, shooting incidents were most concentrated within the first 4 days and two blocks of an initiating incident. Between 0 and 4 days, shooting incidents were 9.14 times more likely to occur at the same location, 2.38 times more likely within one block, and 1.38 times more likely between 1 and 2 blocks.

Over time, both the likelihood and spatial reach of these patterns diminished. For example, between 5 and 8 days, a similar pattern was observed for the previous period, but at a lower likelihood. Shooting incidents were 4.87 times more likely to occur at the same location, 1.49 times more likely to occur within one block, and 1.26 times more likely to occur between 1 and 2 blocks.

From 9 to 12 days, the pattern weakened further: shooting incidents were 3.32 times more likely to occur at the same location and 1.41 times more likely within one block. Beyond 12 days, shooting patterns were more inconsistent. Between 13 and 16 days, for the first time, shooting incidents were no more likely than expected to occur at the same location. However, they remained 1.32 times more likely within one block and 1.25 times more likely between 1 and 2 blocks. By 17 to 20 days, the highest elevated risk reemerged at the same location, where shooting incidents were 1.90 times more likely.

For the seven-day threshold, shooting incidents were most concentrated within the first 7 days and within 2 blocks of an initiating incident. Between 0 and 7 days, shootings were 6.82 times more likely to occur at the same location, 1.92 times more likely within one block, and 1.31 times more likely between 1 and 2 blocks. Compared to the four-day window, near-repeat shooting patterns declined much more rapidly. Between 8 and 14 days, shooting incidents were 3.10 times more likely to occur at the same location and 1.47 times more likely within one block. Beyond 14 days, there was only evidence of repeat victimization between 15 and 21 days and 22 to 28 days.

Compared to the shorter temporal thresholds, there was less evidence of near-repeat shooting patterns for the 14-day threshold. Statistically significant findings were limited to the first 14 days following an initiating event. During this period, shootings were 4.90 times more likely to occur at the same location, 1.69 times more likely within one block, and 1.24 times more likely between 1 and 2 blocks. Beyond 14 days, the only remaining spatiotemporal clustering was observed at the same location between 15 and 28 days, where shooting incidents were 2.09 times more likely to occur.

Informed by these findings, we conducted pairwise comparisons of shooting incidents to classify them as isolates, initiators, or near-repeats, considering shooting incidents that occurred within 14 days and two blocks of one another. We also identified near-repeat shooting chains using the same spatial and temporal thresholds.

5.2. Isolates, initiators, & near-repeat incidents

Of the 5487 shooting incidents, 72.2 % (3959) were not linked to any other event, 11.4 % (627) were initiators, 11.8 % (645) near-repeats, and 4.7 % (256) were classified as both initiators and near-repeats. To facilitate our multinomial and mixed-effects logistic regressions, we classified shooting incidents identified as both initiators and near-

[5] As an exception, we do not conduct post-estimation tests for our neighborhood measures, as the estimated associations were statistically significant but not substantively meaningful.

repeats as initiators only.

Table 2 presents descriptive statistics for isolate, initiator, and near-repeat incidents. Unlike isolates, the majority of initiators and near-repeats occurred in the 8th and 9th precincts. Furthermore, most shooting incidents did not occur near major roads or scout car area boundaries, and more than half occurred in 2021. Isolates were most likely to occur in the first quarter of the year, while initiators and near-repeats were more likely to occur in the second quarter. Less than half of all shooting incidents occurred on the weekend.

The majority of isolates, initiators, and near-repeat incidents did not involve semi-automatic rifles or more than two firearms. However, over half of initiators and near-repeats involved firearms with criminal histories. In addition, property and violent crimes were the most frequent offense types, separately accounting for less than a third of all isolates, and more than half of all incidents occurred near bus stops.

Regarding neighborhood characteristics, isolate incidents were more likely to occur in less densely populated areas than initiator or near-repeat incidents. They were also more likely to occur in neighborhoods with a lower proportion of Black residents, although still dominantly represented. On average, these neighborhoods scored higher on a factor score measuring economic disadvantage and lower on a factor score measuring female-headed households and youth.

5.2.1. Multinomial logistic regression

Table 3 presents the results of the multinomial logistic regression analysis. Several variables differentiated initiator incidents from isolate and near-repeat incidents. To start, initiators were more likely to occur in the 8th and 9th precincts and were less likely to occur near major roads and scout car area boundaries. In these precincts, shooting incidents were 71 % ($RRR = 0.29$) less likely to be isolates and 24 % ($RRR = 0.76$) less likely to be near-repeats. Meanwhile, isolates and near-repeats were 1.40 and 1.28 times more likely to occur near patrol boundaries, respectively, while isolates were 1.52 times more likely to occur near major roads.

Isolate and near-repeat incidents followed different temporal patterns than initiator incidents. Compared to initiators, isolates were 23 % ($RRR = 0.77$) less likely to occur in 2021 and 25 % ($RRR = 0.75$) less likely to occur during the second quarter of the year. In comparison, near-repeats were 20 % ($RRR = 0.80$) less likely than initiators to occur in the first quarter and 16 % ($RRR = 0.84$) less likely to happen on weekends.

There were also notable differences in the incidents themselves. Isolates and near-repeats were less likely than initiators to involve crime guns with a prior history, with isolates 31 % less likely ($RRR = 0.69$) and near-repeats 22 % less likely ($RRR = 0.78$). Put simply, initiators were more likely to involve crime guns tied to other shootings, hinting at possible differences in the individuals or networks connected to these incidents. Interestingly, isolates were 1.49 times more likely to involve violent offenses and 1.65 times more likely to involve fatal or nonfatal shootings compared to initiators.

Differences across the remaining incident characteristics were limited. In terms of proximity to crime generators and attractors, there were no meaningful differences between near-repeats and initiators. However, isolates were 20 % (RRR = 0.80) less likely to occur near bus stops and 21 % (RRR = 0.79) less likely to occur near liquor license retailers compared to initiators. In comparison, isolates were 4.38 times more likely to occur near marijuana dispensaries. These differences further affirm that context shapes where shootings occur, with initiators more connected to routine activity nodes.

Overall, neighborhood factors were largely similar across incident types. While population density and percentage Black were statistically significant in comparisons between isolates and initiators, the relative risk ratios were close to one, indicating a small, negligible effect. As such, these findings do not reflect substantively meaningful differences.[6]

5.2.2. Mixed effects logistic regression

Table 4 presents the results of the mixed-effects logistic regression analysis. Several factors were associated with a shooting incident's involvement in a near-repeat shooting pair (also referred to as paired shooting incidents). To start, the location of a shooting incident mattered. Paired shooting incidents were 2.20 times more likely to occur in the 8th or 9th precincts, 1.40 times more likely to occur near ATMs, and 1.25 times more likely to occur near bus stops. However, they were less likely to be located near major roads ($OR = 0.80$) or the boundary of scout areas ($OR = 0.77$).

Temporal and firearm-related characteristics also influenced involvement in near-repeat shooting pairs. Paired shooting incidents were 1.18 times more likely to occur in 2021 and 1.51 times to occur during the second quarter of the year. In terms of firearm characteristics, they were 1.29 times more likely to involve firearms that were used in other shootings, reinforcing the value of considering the criminal histories of crime guns. Paired shooting incidents were also 27 % ($OR = 0.73$) less likely to involve fatal or nonfatal shootings compared to property-related offenses.

Finally, the social and economic conditions of the neighborhoods where shooting incidents occurred did not play a meaningful role in terms of whether they were involved in a near-repeat shooting pair. While paired shooting incidents tended to occur in neighborhoods with a higher percentage of Black residents, this finding does not reflect a substantively meaningful difference.[7]

5.3. Shooting Chains

We identified 606 shooting chains involving 1561 shooting incidents. Table 5 presents the breakdown of shooting incidents, revealing that the majority, nearly 71.6 % (3926 of 5487), were not part of a shooting chain. Shooting chains ranged in size from the minimum of 2 shooting incidents, representing 15.9 % (874 of 5487) of all incidents, to chains involving up to 18 shooting incidents, representing less than 1 % (18 of 5487) of all incidents.

To support our multinomial logistic regression analysis, we grouped shooting chains into three categories based upon their frequency. Low-frequency shooting chains, involving only two shooting incidents, were the most common and accounted for 72.1 % (437 of 606) of all shooting chains. This category served as the reference group in our multinomial logistic regression. Furthermore, medium-frequency shooting chains involved three shooting incidents and comprised 16.1 % (98 of 606) of all shooting chains. Lastly, high-frequency shooting chains involved four or more shooting incidents, representing only 11.7 % (71 of 606) of all shooting chains.

Table 6 presents descriptive statistics for low-, medium-, and high-frequency shooting chains. Shooting chains predominantly involved incidents that occurred in the 8th or 9th precincts, with high-frequency shooting chains disproportionally represented. Furthermore, low-frequency shooting chains were more likely than medium- and high-frequency shooting chains to involve incidents near major roads. They were also more likely to involve incidents near scout car area borders, representing over half of all low-frequency shooting chains.

Low-frequency shooting chains were the least likely to involve incidents near crime generators and attractors. Across all shooting chains, bus stops were the most prevalent feature and were most commonly

[6] Further illustrating this point, the average marginal effects for both population density and percentage Black were extremely small, at less than 0.001 % and 0.1 %, respectively.

[7] The average marginal effect for percentage Black was less than 0.1 %.

associated with incidents involved in high-frequency shooting chains. Furthermore, high-frequency shooting chains were the most likely to involve incidents near ATMs, liquor license retailers, and parks. In contrast, medium-frequency shooting chains were the most likely to involve incidents near gas stations and pawn stores.

Firearm characteristics and offense types further distinguished high-frequency shooting chains from lower-frequency shooting chains, with most measures consistently higher for high-frequency shooting chains. To start, more than half of high-frequency shooting chains involved incidents with semi-automatic rifles. Furthermore, nearly all high-frequency shooting chains involved crime guns with known criminal histories. Over one-third involved repeat crime guns, compared to 28 % of medium-frequency shooting chains and 10 % of low-frequency shooting chains. High-frequency shooting chains were also more likely to involve incidents with multiple crime guns and fatal or nonfatal shootings.

There were no substantive differences in neighborhood characteristics across near-repeat shooting chains. These chains typically involved incidents that occurred in neighborhoods with an average population density of 6027 residents per square mile. Overall, 90.5 % of residents in these neighborhoods identified as Black, and 12.5 % had moved within the previous year. The neighborhoods also had above-average levels of female-headed households, with high-frequency shooting chains scoring the highest. In addition, levels of economic disadvantage were below average across all chains, with medium-frequency shooting chains scoring the lowest.

5.3.1. Multinomial logistic regression

Table 7 presents the results of the multinomial logistic regression analysis. Several variables differentiate medium- and high-frequency shooting chains from low-frequency shooting chains and one another. Once again, location emerged as an important factor. Medium- and high-frequency shooting chains were 2.72 and 15.95 times more likely, respectively, to involve incidents in the 8th or 9th precincts compared to low-frequency shooting chains. When comparing high- to medium-frequency shooting chains, high-frequency shooting chains were 5.87 times more likely to occur in these precincts (*RRR* = 5.87, *SE* = 3.30, *p-value* = 0.08, *95 % CI* [−0.60, 12.35]).

Shooting chains varied by proximity to major roads and patrol boundaries, with higher-frequency shooting chains more likely to involve incidents that occurred within the interior of neighborhoods rather than along major roads or patrol boundaries. Medium- and high-frequency shooting chains were 62 % (*RRR* = 0.38) and 54 % (*RRR* = 0.46) less likely, respectively, to involve incidents near major roads compared to low-frequency shooting chains, and high-frequency shooting chains were also 62 % (*RRR* = 0.38) less likely to involve incidents near scout car area boundaries. When compared to medium-frequency shooting chains, high-frequency shooting chains were 17 % less likely to involve incidents that occurred near major roads (*RRR* = 0.83, *SE* = 0.44, *p-value* = 0.67, *95 % CI* [−0.03, 1.69]), and 44 % less likely to involve incidents that occurred near scout car area boundaries (*RRR* = 0.56; 1*SE* = 0.23, *p-value* = 0.01, *95 % CI* [0.12, 1.01]).

High-frequency shooting chains showed the strongest ties to crime generators and attractors. They were 3.18 times more likely to involve incidents near bus stops, 1.93 times more likely near liquor license retailers, and 2.24 times more likely near parks than low-frequency shooting chains. Compared to medium-frequency shooting chains, high-frequency shooting chains were 27 % more likely to involve incidents near ATMs (*RRR* = 1.27, *SE* = 0.65, *p-value* = 0.05, *95 % CI* [−0.003, 2.54]), 204 % more likely near bus stops (*RRR* = 3.03, *SE* = 1.49, *p-value* = 0.04, *95 % CI* [0.12, 5.96]), 126 % more likely near liquor license retailers (*RRR* = 2.26, *SE* = 0.91, *p-value p* = 0.01, *95 % CI* [0.48, 4.04]), and 110 % more likely near parks (*RRR* = 2.10, *SE* = 0.77, *p-value* = 0.01, *95 % CI* [0.55, 3.57]).

Temporal patterns further distinguished shooting chain frequency. Higher-frequency shooting chains were especially likely to involve incidents that occurred on weekends. Compared to low-frequency shooting chains, medium- and high-frequency shooting chains were 2.77 times and 9.43 times more likely, respectively, to involve incidents that occurred on weekends. Relative to medium-frequency shooting chains, high-frequency shooting chains were 3.41 times more likely to involve incidents that occurred on weekends (*RRR* = 3.41, *SE* = 2.00, *p-value* = 0.09, *95 % CI* [−0.51, 7.32]).

Relatedly, high-frequency shooting chains showed distinct seasonal and yearly patterns compared to lower-frequency shooting chains. Specifically, they were more likely to involve incidents that occurred in the first three quarters of the year, being 2.25 times more likely in the first quarter, 2.47 times more likely in the second quarter, and 4.17 times more likely in the third quarter relative to low-frequency shooting chains. Compared to medium-frequency shooting chains, high-frequency shooting chains were somewhat less likely to involve incidents that occurred in 2021 but were more likely to involve incidents that occurred in the first three quarters of the year, with elevated risks ranging from 80 % to 155 %.

In addition, higher-frequency shooting chains were more likely to involve semi-automatic rifles, crime guns with criminal histories, and repeat crime guns. Compared to low-frequency shooting chains, high- and medium-frequency shooting chains were 3.62 and 1.66 times more likely, respectively, to involve semi-automatic rifles, and high-frequency shooting chains were over twice as likely as medium-frequency shootings chains (*RRR* = 2.18, *SE* = 0.82, *p-value* = 0.01, *95 % CI* [0.58, 3.78]). High-frequency shooting chains also stood out for their stronger association with crime guns that had criminal histories and repeat crime guns, being 4.54 times and 10.80 times more likely, respectively, than low-frequency shooting chains. When compared to medium-frequency shooting chains, high-frequency shooting chains were 2.30 times more likely to involve repeat crime guns (*RRR* = 2.30, *SE* = 0.92, *p-value* = 0.01, *95 % CI* [0.49, 4.11]).

In respect to offense types, high-frequency shooting chains were associated with a broader range of serious offenses compared to lower-frequency shooting chains. High-frequency shooting chains were 2.75 times more likely to involve fatal or nonfatal offenses, 4.29 times more likely to involve property offenses, and 2.08 times more likely to involve weapons offenses compared to low-frequency shooting chains, while medium-frequency shooting chains showed no significant differences. Both high- (*RRR* = 3.62) and medium-frequency (*RRR* = 1.66) shooting chains were more likely to involve other offenses. Compared to one another, high-frequency shooting chains were 1.51 times more likely to involve fatal or nonfatal shootings (*RRR* = 1.78, *SE* = 083, *p-value* = 0.03, *95 % CI* [0.13, 3.42]).

Lastly, there was limited meaningful differences across low-, medium-, and high-frequency shooting chains with respect to socioeconomic characteristics. There was some evidence suggesting that medium-frequency shooting chains were less likely to involve incidents in neighborhoods characterized by residential mobility. In addition, high-frequency shooting chains were more likely to involve incidents in areas with a higher population of Black residents. But given the small magnitude of this association, this finding was not substantively meaningful.[8] Overall, our results suggest that neighborhood-level factors may play a lesser role in shaping shooting chain frequency, while local context and the characteristics of the incidents themselves may instead have a greater influence.

6. Discussion

Our study is the first to use NIBIN data to examine near-repeat shooting patterns. This dataset provides a uniquely comprehensive record of the criminal histories of crime guns, which can be used to gain

[8] At less than 0.1 %, the average marginal effects for percentage Black were again extremely small.

Table 1b
Offenses by offense type

Offense Type	Offense
Fatal/Nonfatal Shooting	Homicide - Justifiable
	Murder / Non-Negligent Manslaughter (Voluntary)
	Nonfatal Shooting
Other	Abandoned Vehicle
	Accident, Other Shooting
	Accident, PDA- Non-Traffic Area
	Accident, PDA-Traffic Area
	Animal Complaint- Bite
	Animal Complaint- Other
	Animal Cruelty
	Area Check
	Death Investigation
	Entry Without Permission (No Intent)
	Family - Abuse / Neglect Nonviolent
	Family - Other
	General Assistance
	General Non-criminal
	Intimidation / Stalking
	Mental Commitment - Voluntary/Involuntary
	Miscellaneous Criminal Offense
	Missing Persons
	Obstructing Justice
	Obstructing Police
	Open Alcohol in a Motor Vehicle
	Operating Under the Influence of Liquor or Drugs
	Report Pulled in Error
	Suicide
	Suspicious Fires
	Suspicious Situation
	Suspicious Vehicle
	Threats - General
	Tow Impounded Vehicle
	Traffic Violations
	Undetermined Fires
	Violation Of Controlled Substance Act - (VCSA)
	Warrant Arrest Civil
	Warrant Arrest Criminal
Property	Arson
	Burglary - Entry Without Force (Intent to Commit)
	Burglary - Forced Entry
	Damage To Property
	Larceny - Other
	Larceny - Personal Property from Motor Vehicle
	Larceny - Pocket picking
	Larceny - Theft from Building
	Larceny - Theft of Motor Vehicle Parts / Accessories
	Motor Vehicle as Stolen Property (Recovered Only)
	Motor Vehicle Theft
	Property- Confiscated
	Property- Found
	Property- Lost
	Property- Narcotics Found
	Stolen Property
Violent	Aggravated / Felonious Assault
	Assault And Battery/Simple Assault
	Carjacking
	Csc 1st Degree - Penis / Vagina
	Csc 3rd Degree - Oral / Anal
	Kidnapping / Abduction
	Robbery
Weapon	Weapons Offense - Concealed
	Weapons Offense - Other

Table 1
Near Repeat Analysis Knox Ratios

4 DAYS						
Distance	0 to 4 Days	5 to 8 Days	9 to 12 Days	13 to 16 Days	17 to 20 Days	21 or More Days
Same Location	9.14**	4.87**	3.32**	1.62	1.90*	0.80
1 to 350 ft	2.38**	1.49**	1.41**	1.32**	1.17	0.97
351 to 700 ft	1.38**	1.26**	1.10	1.25*	1.06	0.99
701 to 1050 ft	1.06	0.93	1.13	1.20	1.06	1.00
1051 to 1400 ft	1.05	1.05	0.95	1.18	1.02	1.00
More than 1400 ft	1.00	1.00	1.00	1.00	1.00	1.00
7 DAYS						
Distance	**0 to 7 Days**	**8 to 14 Days**	**15 to 21 Days**	**22 to 28 Days**	**29 to 35 Days**	**More than 35 Days**
Same Location	6.82**	3.10**	2.30**	1.87*	0.63	0.77
1 to 350 ft	1.92**	1.47**	1.19	1.08	0.82	0.97
351 to 700 ft	1.31**	1.18	1.14	0.97	1.05	0.98
701 to 1050 ft	1.01	1.07	1.12	0.93	1.04	1.00
1051 to 1400 ft	1.09	0.99	1.10	1.07	1.19	0.99
More than 1400 ft	1.00	1.00	1.00	1.00	1.00	1.00
14 DAYS						
Distance	**0 to 14 Days**	**15 to 28 Days**	**29 to 42 Days**	**43 to 56 Days**	**57 to 70 Days**	**More than 70 Days**
Same Location	4.90**	2.09**	1.00	1.10	0.80	0.74
1 to 350 ft	1.69**	1.14	0.96	1.14	1.02	0.95
351 to 700 ft	1.24**	1.05	1.01	1.08	1.01	0.98
701 to 1050 ft	1.04	1.02	1.01	1.08	1.02	0.99
1051 to 1400 ft	1.04	1.08	1.07	1.02	1.08	0.98
More than 1400 ft	1.00	1.00	1.00	1.00	1.00	1.00

Notes. p-value<0.05*; p-value <0.01**.

insight into whether gun violence is driven by epidemic or endemic processes. Our examination of 5487 shooting incidents between January 1, 2021, and October 27, 2022, identified near-repeat patterns, the characteristics that distinguish incidents involved in these patterns and the severity of shooting chains, as well as the extent to which the same crime guns were used in linked shooting events. Taken together, our study highlights the value of NIBIN data, informs theory and future research, and offers practical guidance for violence reduction and prevention strategies.

First, our study demonstrates the value of NIBIN data and the role of CGICs in conducting research on gun crime. By adhering to strict standards for ballistic evidence collection, CGICs enable NIBIN to provide a more complete data source on gun crime than was previously available. This more comprehensive data source translates into substantive insight. We found evidence of near-repeat shooting patterns, with the highest risk concentrated within the first two weeks and within two blocks of an initial incident. This finding complements prior research, which has found evidence of near-repeat patterns within similar spatial and temporal windows (e.g., Ratcliffe & Rengert, 2008; Wells et al., 2012; Sturup et al., 2018). In comparison, the proportion of isolate incidents in our study is lower and the corresponding estimates of initiators and near-repeats are higher than in most prior near-repeat shooting studies (Wells & Wu, 2011; Wells et al., 2012), with the exception of Mazeika and Uriarte (2019), which likewise relied on more comprehensive sources of shooting data.

Our findings also offer insights into the ongoing debate between epidemic and endemic perspectives of gun violence. On the one hand, the relationship between near-repeat incidents and crime generators and attractors (e.g., ATMs, bus stops, gas stations, liquor license retailers, marijuana dispensaries, pawn shops, and parks), suggest the role of endemic features of high-risk neighborhoods and micro-places. On the other, the finding that over half of initiator and near-repeat incidents involved a firearm with a prior criminal history could suggest a

Table 2
Isolate, Initiator, and Near-repeat Incidents: Descriptive Statistics.

	Isolates (n = 3959)				Initiators (n = 883)				Near-repeat (n = 645)			
	Mean	S.D.	Min.	Max	Mean	S.D.	Min.	Max	Mean	S.D.	Min.	Max
Precinct												
8th or 9th Precinct	0.40	0.49	0	1	0.75	0.44	0	1	0.70	0.46	0	1
Geographic Edges												
Major Roads	0.20	0.40	0	1	0.13	0.34	0	1	0.15	0.36	0	1
Scout Car Area	0.48	0.50	0	1	0.40	0.50	0	1	0.44	0.50	0	1
Time												
Year of 2021	0.56	0.50	0	1	0.60	0.49	0	1	0.57	0.49	0	1
Quarter 1 (Jan-Mar)	0.32	0.47	0	1	0.34	0.47	0	1	0.29	0.46	0	1
Quarter 2 (Apr-Jun)	0.29	0.45	0	1	0.36	0.48	0	1	0.39	0.49	0	1
Quarter 3 (Jul-Sep)	0.31	0.46	0	1	0.27	0.45	0	1	0.28	0.45	0	1
Quarter 4 (Oct-Dec)	0.17	0.38	0	1	0.16	0.37	0	1	0.18	0.38	0	1
Weekend	0.47	0.50	0	1	0.48	0.50	0	1	0.44	0.50	0	1
Incident												
Semi-automatic Rifles	0.21	0.41	0	1	0.17	0.37	0	1	0.17	0.38	0	1
Criminal History	0.49	0.50	0	1	0.59	0.49	0	1	0.52	0.50	0	1
Total Firearms	0.26	0.44	0	1	0.24	0.43	0	1	0.21	0.41	0	1
Violent Offense	0.31	0.46	0	1	0.19	0.40	0	1	0.20	0.40	0	1
Fatal/Nonfatal Shooting	0.21	0.41	0	1	0.12	0.32	0	1	0.11	0.32	0	1
Weapons Offense	0.06	0.23	0	1	0.09	0.29	0	1	0.08	0.27	0	1
Other Offense	0.10	0.29	0	1	0.09	0.28	0	1	0.09	0.30	0	1
Property Offense	0.32	0.47	0	1	0.51	0.50	0	1	0.51	0.50	0	1
Crime Generators & Attractors												
ATM	0.06	0.24	0	1	0.08	0.27	0	1	0.08	0.27	0	1
Bus Stop	0.60	0.49	0	1	0.55	0.50	0	1	0.55	0.50	0	1
Gas Station	0.09	0.28	0	1	0.08	0.26	0	1	0.07	0.25	0	1
Liquor License Retailer	0.29	0.46	0	1	0.29	0.46	0	1	0.27	0.45	0	1
Marijuana Dispensary	0.01	0.10	0	1	0.002	0.05	0	1	0.005	0.07	0	1
Pawn Store	0.09	0.29	0	1	0.08	0.26	0	1	0.08	0.27	0	1
Park	0.24	0.42	0	1	0.20	0.40	0	1	0.20	0.40	0	1
Neighborhood												
Population Density	5688.20	2391.05	0	20,697.32	6151.97	2299.79	0	15,028.41	6121.22	2251.09	0	10,962
Percentage Different House	12.36 %	7.61 %	0 %	77.70 %	12.45 %	6.96 %	0 %	32.82 %	12.35 %	6.76 %	0 %	33.52 %
Percentage Black	84.31 %	24.03 %	0 %	100.00 %	91.50 %	14.27 %	0 %	100.00 %	90.60 %	16.24 %	0 %	100.00 %
Factor Score: Female-headed Households & Youth	−0.06	1.01	−3.47	3.33	0.17	0.94	−2.54	1.92	0.13	0.95	−3.30	3.33
Factor Score: Economic Disadvantage	0.04	1.02	−3.03	4.31	−0.12	0.93	−2.83	3.34	−0.09	0.96	−2.93	3.35

contagion effect.

Our examination of shooting chains, including the factors that influence their severity and the role of repeat crime guns, further informs this debate. Similarly, the patterns observed in high-frequency shooting chains point to a confluence of epidemic and endemic features of gun violence. The greater prevalence of both repeat crime guns and semi-automatic rifles in higher-frequency shooting chains is suggestive of a contagion model. Yet local contextual forces appear to shape these patterns as well. To this point, high-frequency shooting chains were concentrated in Detroit's two precincts that have historically had the highest rates of gun crime. Within these precincts, they tended to occur near crime generators and attractors; were tied to weekends and certain seasons; involved repeat crime guns and semi-automatic rifles; and were associated with more serious offenses. Although these precincts demonstrate persistent patterns of economic disadvantage, our neighborhood measures were not meaningfully associated with shooting chain frequencies, suggesting the greater influence of local context and firearm- and incident-related factors shaping patterns of high-frequency gun violence.

That the findings appear to be supportive of both the endemic and contagion models should, perhaps, not be surprising. The relationship between concentrated disadvantage and violent crime is well established (Land, McCall, & Cohen, 1990; Sampson et al., 1997; Rosenfeld, Fornango, & Baumer, 2005). At the same time, the relationship between gun crime and situational factors, such as interpersonal disputes and retaliation, is also robust (Felson & Tedeschi, 1993; Griffiths, Yule, & Gartner, 2011; Kubrin & Weitzer, 2003; Pizarro, 2008). Further, more recent research on the crucial role of network relationships in elevating the risk of involvement in gun crime (Papachristos et al., 2012; Papachristos et al., 2015; Papachristos, Wildeman, & Roberto, 2015) is also consistent with the contagion model.

Beyond their theoretical contribution, our findings have practical implications for violence reduction and prevention efforts in Detroit and beyond. They reflect a shared prevention principle across criminal justice and public health approaches: namely, that early identification of risk and rapid intervention can disrupt escalating cycles of violence. Within a criminal justice context, this means deploying precision enforcement and intelligence-led prevention strategies that interrupt near-repeat shooting patterns before additional incidents occur.

Historically, NIBIN has been leveraged primarily as a tactical tool. Indeed, its central role within the CGIC model is to enhance shooting investigations and support the incapacitation of violent gun offenders. In Detroit, the contributions of the CGIC model are evident: fatal and nonfatal shooting cases that occurred during the Detroit CGIC were 4.8 times more likely to be cleared compared to similar cases before CGIC implementation (De Biasi, 2024a). With few exceptions (e.g., De Biasi, 2024b; Dierenfeldt et al., 2024; Stripling et al., 2025), the strategic use of NIBIN data and its application to the study of gun crime remain underdeveloped. The Detroit CGIC is seeking to expand work in this area through extension funds received from the Bureau of Justice Assistance's Local Law Enforcement Crime Gun Intelligence Center Integration Initiative. A core focus of these funds is developing strategies to proactively leverage NIBIN to identify shooting patterns and deploy resources to prevent future violence. Our study demonstrates the value of NIBIN in advancing this objective and highlights its potential to inform both short-term violence reduction and longer-term violence

Table 3
Multinomial Regression: Isolate, Initiator, and Near-repeat Incidents

	Isolates						Near-repeats					
Variable	RRR	S.E.	*z*	*p.*	95 % CI Lower	95 % CI Upper	RRR	S.E.	*z*	*p.*	95 % CI Lower	95 % CI Upper
Precinct												
8th or 9th Precinct	0.29	0.03	−12.64	0.00	0.24	0.35	0.76	0.10	−2.11	0.04	0.59	0.98
Geographic Edges												
Major Roads	1.52	0.20	3.17	0.00	1.17	1.96	1.17	0.20	0.92	0.36	0.84	1.63
Scout Car Area	1.40	0.14	3.37	0.00	1.15	1.71	1.28	0.17	1.83	0.07	0.98	1.67
Time												
Year of 2021	0.77	0.06	−3.28	0.00	0.65	0.90	0.84	0.09	−1.60	0.11	0.68	1.04
Quarter 1 (Jan-Mar)	0.94	0.09	−0.65	0.52	0.78	1.13	0.80	0.10	−1.76	0.08	0.62	1.03
Quarter 2 (Apr-Jun)	0.75	0.07	−3.12	0.00	0.62	0.90	1.15	0.15	1.10	0.27	0.90	1.48
Quarter 3 (Jul-Sep)	0.95	0.11	−0.51	0.61	0.76	1.18	0.99	0.15	−0.07	0.94	0.74	1.33
Weekend	0.92	0.07	−1.00	0.32	0.79	1.08	0.84	0.09	−1.68	0.09	0.68	1.03
Incident												
Semi-automatic Rifles	1.15	0.12	1.26	0.21	0.93	1.42	1.08	0.16	0.51	0.61	0.81	1.08
Criminal History	0.69	0.06	−4.45	0.00	0.59	0.82	0.78	0.09	−2.22	0.03	0.63	0.78
Total Firearms	0.93	0.09	−0.70	0.48	0.76	1.14	0.86	0.12	−1.05	0.30	0.66	0.86
Violent Offense	1.49	0.16	3.81	0.00	1.21	1.84	0.97	0.14	−0.21	0.83	0.74	0.97
Fatal/Nonfatal Shooting Offense	1.65	0.21	3.91	0.00	1.29	2.13	0.92	0.16	−0.45	0.65	0.65	0.92
Weapons Offense	0.96	0.14	−0.27	0.78	0.72	1.29	0.88	0.17	−0.66	0.51	0.60	0.88
Other Offense	1.24	0.18	1.48	0.14	0.93	1.64	1.06	0.20	0.29	0.77	0.73	1.06
Crime Generators & Attractors							0.78	0.09	−2.22	0.03	0.63	0.78
ATM	0.80	0.13	−1.41	0.16	0.59	1.09	1.05	0.22	0.22	0.83	0.69	1.58
Bus Stop	0.79	0.08	−2.19	0.03	0.65	0.98	0.90	0.13	−0.75	0.45	0.68	1.19
	0.95	0.15	−0.30	0.76	0.71	1.29	0.81	0.18	−0.95	0.34	0.53	1.24
Gas Station	0.79	0.08	−2.43	0.02	0.65	0.95	0.82	0.11	−1.51	0.13	0.63	1.06
Liquor License Retailer	4.38	3.15	2.05	0.04	1.07	17.95	2.30	2.13	0.90	0.37	0.38	14.13
Pawn Store	1.12	0.17	0.74	0.46	0.83	1.50	0.98	0.20	−0.08	0.94	0.65	1.48
Park	1.15	0.11	1.41	0.16	0.95	1.39	0.94	0.12	−0.44	0.66	0.73	1.22
Neighborhood												
Population Density	1.00	0.00	−2.25	0.03	1.00	1.00	1.00	0.00	0.18	0.86	1.00	1.00
Percentage Different House	1.00	0.01	−0.38	0.71	0.99	1.01	1.00	0.01	−0.46	0.65	0.98	1.01
Percentage Black	0.99	0.00	−3.01	0.00	0.99	1.00	1.00	0.00	−0.52	0.60	0.99	1.01
Factor Score: Female-headed Households & Youth	0.95	0.04	−1.31	0.19	0.87	1.03	1.00	0.05	−0.01	0.99	0.90	1.11
Factor Score: Economic Disadvantage	1.07	0.05	1.50	0.13	0.98	1.17	1.02	0.06	0.39	0.70	0.91	1.15
Constant	34.06	10.95	10.98	0.00	18.14	63.95	1.61	0.69	1.12	0.26	0.70	3.72

Notes. The unit of analysis is shooting incident. Comparisons are made relative to initiator incidents, the reference category. Quarter 4 (Oct-Dec) is the reference category for the Quarter variables. Property offense is the reference category for the offense variables. Estimates are reported as relative risk ratios (RRR) with robust standard errors. Wald $\chi^2(54) = 575.58$, $p < 0.001$; Prob $> \chi^2 = 0.00$.

prevention strategies.

Short-term violence reduction strategies that combine a focus on micro-places and social networks are suggested based on both indicators of contagion (e.g., repeat crime guns) and endemic features (e.g., crime generators and attractors) that were found to drive near-repeat shooting patterns. Promising prevention strategies include the "place network investigations" (PNI) model employed by the Cincinnati and Las Vegas Police Departments (Herold & Eck, 2020; Herold et al., 2020; Madensen et al., 2017). Sometimes referred to as Place Investigations of Violent Offender Territories, this is a problem-solving policing strategy that involves systematic problem analysis of both the environmental features and social network connections of violent crime micro-places (see also Koper, Egge, and Lum, 2015). Evaluations of the PNI strategy in both cities found evidence of violent crime reduction (Hammer, 2020; Hammer, Christenson, & Madensen, 2017; Herold et al., 2020; Herold & Eck, 2020; Madensen et al., 2017).

The addition of crime gun intelligence in the form of NIBIN data to a PNI strategy could help both identify priority locations and incidents to launch a PNI analysis. For example, near-repeat shooting patterns identified from NIBIN data could enable law enforcement to take preemptive action to disrupt emerging cycles of gun violence by focusing on the locations and times of highest risk. In conjunction, the criminal histories of the crime guns involved could be examined to reveal offender networks that warrant targeted enforcement and disruption. Applied to Detroit, this suggests focusing interventions within two blocks and two weeks of a shooting incident, with particular attention to known crime generators and attractors, as well as the 8th and 9th precincts where high-frequency shooting chains are concentrated. Overall, this approach recognizes the immediate operational value of near-repeat patterns for precision enforcement, while also acknowledging the underlying offender networks that may be simultaneously sustaining these patterns.

It is worth mentioning that although our NIBIN data revealed meaningful near-repeat patterns, the criminal histories of most crime guns did not follow these patterns. To this point, a little over one-third of high-frequency shooting chains involved repeat crime guns, compared to 28 % of medium-frequency shooting chains and only 10 % of low-frequency shooting chains. Therefore, while strategies informed by near-repeat shooting patterns have clear value, understanding the broader criminal histories of crime guns outside of these patterns as afforded by NIBIN data warrants further consideration. This perspective underscores the importance of complementing near-repeat–focused interventions with approaches that address the broader trajectories and networks through which crime guns circulate.

Longer-term violence prevention strategies focused on the endemic features driving near-repeat shooting patterns are also warranted, a focus highlighted in several recent research reviews. Our findings underscored the influence of local context in facilitating near-repeat patterns, especially the role of crime generators and attractors and the concentration of these patterns in Detroit's 8th and 9th precincts. Shader et al. (2024) reviewed forty-four studies of non-police strategies to reduce crime hot spots, including efforts to increase guardianship, implement environmental changes, and support community-based problem solving. Thirty-three of the forty-four studies included a focus

Table 4
Mixed-effects Logistic Regression: Isolate, Initiator, and Near-repeat Incidents

Variable	Odds Ratio	S.E.	z	p.	95 % CI Lower	95 % CI Upper
Precinct						
8th or 9th Precinct	2.20	0.38	4.60	0.00	1.57	3.07
Geographic Edges						
Major Roads	0.80	0.09	−2.00	0.05	0.65	1.00
Scout Car Area	0.77	0.07	−2.94	0.00	0.65	0.92
Time						
Year of 2021	1.18	0.08	2.30	0.02	1.02	1.35
Quarter 1 (Jan-Mar)	1.00	0.08	−0.06	0.96	0.84	1.17
Quarter 2 (Apr-Jun)	1.51	0.13	4.91	0.00	1.28	1.78
Quarter 3 (Jul-Sep)	1.11	0.11	1.06	0.29	0.92	1.34
Weekend	1.01	0.07	0.13	0.90	0.88	1.15
Incident						
Semi-automatic Rifles	0.96	0.09	−0.41	0.68	0.80	1.16
Criminal History	1.29	0.09	3.53	0.00	1.12	1.48
Total Firearms	1.12	0.10	1.22	0.22	0.94	1.33
Violent Offense	0.85	0.08	−1.74	0.08	0.70	1.02
Fatal/Nonfatal Shooting	0.73	0.08	−2.79	0.01	0.58	0.91
Weapons Offense	0.93	0.13	−0.52	0.61	0.71	1.22
Other Offense	1.00	0.13	0.00	1.00	0.78	1.28
Crime Generators & Attractors						
ATM	1.40	0.21	2.27	0.02	1.05	1.88
Bus Stop	1.25	0.12	2.35	0.02	1.04	1.51
Gas Station	0.98	0.14	−0.14	0.89	0.74	1.30
Liquor License Retailer	1.10	0.10	1.08	0.28	0.92	1.32
Marijuana Dispensary	0.42	0.22	−1.65	0.10	0.15	1.18
Pawn Store	0.90	0.12	−0.77	0.44	0.69	1.17
Park	0.88	0.08	−1.38	0.17	0.74	1.05
Neighborhood						
Population Density	1.00	0.00	1.09	0.27	1.00	1.00
Percentage Different House	1.00	0.01	−0.40	0.69	0.98	1.02
Percentage Black	1.01	0.00	2.22	0.03	1.00	1.01
Factor Score: Female-headed Households & Youth	1.11	0.09	1.34	0.18	0.95	1.29
Factor Score: Economic Disadvantage	0.94	0.07	−0.89	0.37	0.81	1.08
Constant	0.05	0.02	−8.03	0.00	0.02	0.10
Random Effects						
Census Tract	0.39	0.20	–	–	0.14	1.05
Scout Car Area	0.39	0.19	–	–	0.15	1.01
Model						
LR test vs. logistic model: χ^2 (2) = 218.01; Prob > chi2 = 0.0000						
Wald χ^2(27) = 126.33; Prob > χ^2 = 0.0000						

Notes. The unit of analysis is shooting incident. Quarter 4 (Oct-Dec) is the reference category for the Quarter variables. Property offense is the reference category for the offense variables.

on violent crime, with the majority found to be effective or promising. MacDonald et al. (2024) reviewed several evaluations of place-based interventions focused specifically on violent crime hot spots. These included social interventions, such as violence interrupters and security guards, along with physical remediation efforts and technological measures, including improved lighting and surveillance cameras. Remediation of abandoned properties and vacant lots in violent crime hot spots received the strongest research support. Although these studies did not examine how proactive policing strategies in violent crime hot spots might be linked with longer-term environmental and social interventions, they point to the potential benefits of coupling short-term proactive enforcement with broader strategies for sustainable change. Ideally, such an approach would address both the contagion dynamics and the endemic features that contribute to persistent gun crime hot spots.

Table 5
Near-repeat Shooting Chains: Shooting Incident Sequences

Incident Sequence	Number of Chains	Number of Incidents	Percentage of Incidents
1	0	3926	71.6 %
2	437	874	15.9 %
3	98	294	5.4 %
4	34	136	2.5 %
5	16	80	1.5 %
6	5	30	0.5 %
7	8	56	1.0 %
8	2	16	0.3 %
9	2	18	0.3 %
10	1	10	0.2%
12	1	12	0.2%
17	1	17	0.3 %
18	1	18	0.3 %
Total	606	5487	100.0 %

Notes. This table differentiates isolated shooting incidents from near-repeat shooting incidents. For near-repeat shooting incidents, it records the number of incidents within each near-repeat shooting chain. The column labeled “Incident Sequence” captures the number of shooting incidents within a near-repeat shooting chain, while the “Number of Chains” column captures the total number of near-repeat shooting chains for each incident sequence. Isolated shooting incidents, by definition, are not part of any near-repeat shooting chain, so their number of near-repeat shooting chains is recorded as zero and incident sequence recorded as one. The “Percentage of Incidents” column captures the percentage of all shooting incidents that occurred within incident sequences of each size.

7. Limitations

We highlight three considerations that are important for interpreting our findings and for guiding future research. The first concerns the broader comprehensiveness of NIBIN data, while the second and third involve the role of neighborhood context in shaping violence and informing longer-term violence prevention strategies. Despite its value, NIBIN data is only as strong as the evidence entered into it. Comprehensive collection is the backbone of NIBIN, supported by CGICs and reinforced by gunshot detection systems. Beyond this, an external factor also limits its utility: a significant proportion of crime guns are single-use, meaning they lack prior criminal histories, a pattern that may be driven by offenders’ preference for newer firearms (Braga, 2017; Collins, Parker, Scott, & Wellford, 2017; Hureau & Braga, 2018; Pierce, Braga, Hyatt Jr., & Koper, 2004; Wintemute, Romero, Wright, & Grassel, 2004). Under these circumstances, NIBIN’s ability to generate firearm linkages and support theoretical discussions of gun violence as epidemic or endemic is naturally constrained. State and local firearm laws may also shape this dynamic; in jurisdictions with permissive firearm laws, single-use firearms may be more common, whereas more restrictive laws may encourage their reuse. With this caveat in mind, when firearm linkages can be made, NIBIN remains a powerful source of intelligence on near-repeat shooting patterns and can contribute meaningfully to the theoretical understanding of gun violence.

In contrast to prior research that demonstrates a connection between neighborhood context and gun violence (e.g., Gill et al., 2024; Semenza et al., 2023), our study did not find compelling evidence supporting this association. Among our neighborhood measures, statistically significant effects were most often found for population density and percentage Black, though this pattern was not consistent across models and the corresponding coefficients were close to 1.00. Descriptive statistics help contextualize these results, generally revealing small mean differences across outcome categories and substantial within-group variability. This combination, combined with a large overall population size, can contribute to small standard errors and statistically detectable but substantively trivial effects, as we observed. Marginal effects further confirm that even large changes in these neighborhood measures only translated into minimal changes in the predicted probabilities (see footnotes 6–8). Accordingly, we urge caution in the interpretation of

Table 6
Multinomial Regression: Descriptive Statistics.

	Low-frequency Shooting Chains ($n = 437$)				Medium-frequency Shooting Chains ($n = 98$)				High-frequency Shooting Chains ($n = 71$)			
Precinct	Mean	S.D.	Min.	Max	Mean	S.D.	Min.	Max	Mean	S.D.	Min.	Max
8th or 9th Precinct	0.64	0.48	0	1	0.73	0.44	0	1	0.93	0.26	0	1
Geographic Edges												
Major Roads	0.24	0.43	0	1	0.13	0.34	0	1	0.17	0.38	0	1
Scout Car Area	0.54	0.50	0	1	0.45	0.50	0	1	0.44	0.50	0	1
Time												
Year of 2021	0.56	0.50	0	1	0.61	0.49	0	1	0.66	0.48	0	1
Quarter 1 (Jan-Mar)	0.32	0.47	0	1	0.29	0.45	0	1	0.44	0.50	0	1
Quarter 2 (Apr-Jun)	0.35	0.48	0	1	0.41	0.49	0	1	0.45	0.50	0	1
Quarter 3 (Jul-Sep)	0.29	0.46	0	1	0.33	0.47	0	1	0.32	0.47	0	1
Quarter 4 (Oct-Dec)	0.22	0.41	0	1	0.20	0.41	0	1	0.20	0.40	0	1
Weekend	0.74	0.44	0	1	0.85	0.36	0	1	0.93	0.26	0	1
Incident												
Semi-automatic Rifles	0.31	0.46	0	1	0.39	0.49	0	1	0.56	0.50	0	1
Criminal History	0.76	0.42	0	1	0.88	0.33	0	1	0.97	0.17	0	1
Total Firearms	0.41	0.49	0	1	0.53	0.50	0	1	0.63	0.49	0	1
Repeat Crime Gun	0.10	0.30	0	1	0.28	0.45			0.34	0.48	0	1
Violent Offense	0.40	0.49	0	1	0.44	0.50	0	1	0.38	0.48	0	1
Fatal/Nonfatal Shooting	0.24	0.43	0	1	0.23	0.43	0	1	0.30	0.46	0	1
Property Offense	0.32	0.47	0	1	0.51	0.50	0	1	0.51	0.50	0	1
Weapons Offense	0.06	0.23	0	1	0.08	0.28	0	1	0.08	0.28	0	1
Other Offense	0.09	0.29	0	1	0.09	0.29	0	1	0.09	0.29	0	1
Crime Generators & Attractors												
ATM	0.10	0.30	0	1	0.13	0.34	0	1	0.21	0.41	0	1
Bus Stop	0.66	0.47	0	1	0.58	0.50	0	1	0.70	0.46	0	1
Gas Station	0.08	0.27	0	1	0.15	0.36	0	1	0.13	0.34	0	1
Liquor License Retailer	0.34	0.47	0	1	0.32	0.47	0	1	0.44	0.50	0	1
Pawn Store	0.11	0.31	0	1	0.18	0.39	0	1	0.07	0.26	0	1
Park	0.25	0.43	0	1	0.27	0.44	0	1	0.41	0.50	0	1
Neighborhood												
Population Density	5964.22	2284.08	0.00	15,028.41	6146.36	2123.68	1723.26	10,273.04	6250.07	2166.24	2694.97	10,273.04
Percentage Different House	12.78	6.60	0.00	61.41	11.27	6.42	0.78	26.29	12.20	6.07	1.05	26.29
Percentage Black	89.95	16.62	0.00	100.00	90.03	16.43	0.00	99.84	94.47	4.32	72.32	99.67
Factor Score: Female-head Household & Youth	0.10	0.95	−2.72	1.92	0.10	0.91	−2.24	1.92	0.20	0.85	−1.00	1.92
Factor Score: Economic Disadvantage	−0.07	0.94	−3.03	2.71	−0.21	0.91	−1.93	3.35	−0.18	0.74	−1.70	1.53

these neighborhood effects. Future research on gun violence patterns may benefit from more focused examinations of the role of neighborhood context in influencing the diffusion of such violence, with consideration given to spatial scale and zoning effects (Openshaw & Taylor, 1979). Indeed, prior research documents the sensitivity of the neighborhood-crime relationship to these issues, referred to as the modifiable areal unit problem (Andresen & Malleson, 2013; Bader & Ailshire, 2014; Hipp, 2007). Better understanding how these dynamics capture (or obscure) contextual influences remains important for advancing research on the diffusion of gun violence.

Relatedly, our study could be expanded to account for a broader scope of neighborhood processes, such as social capital and collective efficacy, including social cohesion and informal social control, that prior research has found to influence violent crime (Browning, Feinberg, & Dietz, 2004; Sampson et al., 1997;Rosenfeld et al., 2001; Weisburd et al., 2021). These processes may have shaped the patterns we observed and, in turn, the recommendations we made for longer-term violence prevention strategies. Prior research clearly demonstrates that collective efficacy is associated with violent crime, even at the micro-place level (Weisburd, Hinkle, Famega, & Ready, 2012), though more work is needed to understand the impact of intentional policing efforts to build collective efficacy. Nevertheless, this observed relationship has inspired innovative efforts to strengthen connections between police and community groups, and among residents themselves (Uchida & Swatt, 2013; Weisburd, 2018). Such strategies have included training officers in procedural justice and supporting the use of unallocated patrol time for neighborhood engagement, relationship building, and problem-solving alongside traditional hotspot patrol. Future research should examine how these neighborhood processes intersect with near-repeat patterns to guide more comprehensive and community-centered violence prevention strategies.

8. Conclusion

Our study is distinguished by its novel application of NIBIN data to examine near-repeat shooting patterns. Drawing on 5847 shooting incidents during a period when the Detroit CGIC was operational, we analyzed a uniquely comprehensive dataset, bolstered by the MROS requirement of comprehensive collection and gunshot detection technology. Our findings demonstrate that near-repeat patterns tend to occur within short spatial and temporal windows and provide evidence supporting both the epidemic and endemic perspectives of gun violence.

From a policy and practice perspective, our findings reinforce the critical role of the CGIC, and more broadly, the value of collaboration between law enforcement and academic partners to explore the strategic potential of NIBIN. CGICs represent a highly valuable resource for both investigative and preventive efforts. While NIBIN itself is not new, its potential within the supportive framework of the CGIC has been largely untapped for understanding near-repeat patterns and other strategic applications. Through such partnerships, NIBIN data opens a new frontier in crime gun intelligence.

Future research should build on NIBIN's unique ability to link the criminal histories of crime guns by expanding place- and network-based approaches and testing intervention impacts informed by learned patterns. Examining these dynamics across diverse contexts will provide deeper insight into the broader forces that sustain or disrupt patterns of gun violence.

Table 7
Multinomial Regression: Frequency of Near-repeat Shooting Chain

	Medium-frequency						High-frequency					
Variable	RRR	S.E.	*z*	*p.*	95 % CI Lower	95 % CI Upper	RRR	S.E.	*z*	*p.*	95 % CI Lower	95 % CI Upper
Precinct												
8th or 9th Precinct	2.72	0.90	3.03	0.00	1.42	5.19	15.95	8.12	5.44	0.00	5.88	43.29
Geographic Edges												
Major Roads	0.38	0.16	−2.34	0.02	0.17	0.85	0.46	0.20	−1.76	0.08	0.19	1.09
Scout Car Area	0.68	0.19	−1.35	0.18	0.39	1.19	0.38	0.15	−2.52	0.01	0.18	0.81
Time												
Year of 2021	1.33	0.34	1.09	0.28	0.80	2.20	1.16	0.43	0.40	0.69	0.56	2.40
Quarter 1 (Jan-Mar)	0.93	0.33	−0.21	0.83	0.46	1.88	2.25	0.98	1.86	0.06	0.96	5.30
Quarter 2 (Apr-Jun)	1.37	0.54	0.81	0.42	0.64	2.96	2.47	1.17	1.91	0.06	0.98	6.26
Quarter 3 (Jul-Sep)	1.64	0.71	1.13	0.26	0.70	3.83	4.17	2.38	2.50	0.01	1.36	12.78
Quarter 4 (Oct-Dec)	1.00	0.44	0.00	1.00	0.42	2.37	2.21	1.26	1.40	0.16	0.73	6.74
Weekend	2.77	0.99	2.86	0.00	1.38	5.56	9.43	5.32	3.98	0.00	3.12	28.51
Incident												
Semi-automatic Rifles	1.66	0.46	1.84	0.07	0.97	2.85	3.62	1.31	3.55	0.00	1.78	7.38
Criminal History	1.43	0.54	0.96	0.34	0.69	2.98	4.54	3.64	1.89	0.06	0.94	21.89
Total Firearms	1.28	0.35	0.91	0.36	0.75	2.18	1.35	0.51	0.78	0.44	0.64	2.84
Repeat Crime Gun	4.69	1.58	4.60	0.00	2.43	9.07	10.80	4.63	5.55	0.00	4.66	25.03
Violent Offense	1.33	0.37	1.01	0.31	0.77	2.30	1.50	0.52	1.16	0.25	0.76	2.97
Fatal/Nonfatal Shooting	1.40	0.45	1.05	0.29	0.74	2.65	2.75	1.23	2.26	0.02	1.14	6.60
Property	1.41	0.49	0.97	0.33	0.71	2.80	4.29	1.74	3.59	0.00	1.94	9.52
Weapons	1.17	0.39	0.47	0.64	0.61	2.26	2.08	0.85	1.79	0.07	0.93	4.65
Other	1.66	0.46	1.84	0.07	0.97	2.85	3.62	1.31	3.55	0.00	1.78	7.38
Crime Generators & Attractors												
ATM	1.43	0.59	0.85	0.40	0.63	3.23	1.80	0.89	1.20	0.23	0.69	4.74
Bus Stop	1.05	0.33	0.15	0.88	0.57	1.94	3.18	1.52	2.42	0.02	1.25	8.13
Gas Station	2.64	1.11	2.31	0.02	1.16	6.03	1.85	1.11	1.02	0.31	0.57	6.01
Liquor License Retailer	0.86	0.26	−0.51	0.61	0.47	1.56	1.93	0.69	1.84	0.07	0.96	3.90
Pawn Store	3.34	1.30	3.08	0.00	1.55	7.18	0.61	0.43	−0.70	0.49	0.15	2.44
Park	1.09	0.31	0.29	0.77	0.62	1.90	2.24	0.79	2.30	0.02	1.13	4.45
Neighborhood												
Population Density	1.00	0.00	0.40	0.69	1.00	1.00	1.00	0.00	−0.17	0.87	1.00	1.00
Percentage Different House	0.96	0.02	−1.70	0.09	0.92	1.01	0.99	0.03	−0.40	0.69	0.94	1.04
Percentage Black	1.00	0.01	−0.20	0.84	0.98	1.01	1.04	0.02	2.12	0.03	1.00	1.08
Factor Score: Female-headed Households & Youth	0.88	0.14	−0.77	0.44	0.64	1.21	0.79	0.16	−1.16	0.24	0.54	1.17
Factor Score: Economic Disadvantage	0.92	0.12	−0.65	0.52	0.71	1.19	1.20	0.22	1.00	0.32	0.84	1.72
Constant	0.02	0.02	−3.77	0.00	0.00	0.14	0.00	0.00	−6.71	0.00	0.00	0.00

Notes. The unit of analysis is near-repeat shooting chain. Wald $\chi^2(56) = 156.38$, Prob > Chi-squared = 0.00. Estimates are reported as relative risk ratios (RRR) with robust standard error.

CRediT authorship contribution statement

Alaina De Biasi: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Jeff Rojek:** Writing – review & editing, Writing – original draft, Conceptualization. **Edmund McGarrell:** Writing – review & editing, Writing – original draft, Conceptualization.

Appendix A. Appendix

Table 1a summarizes the calibers most frequently associated with semi-automatic rifles among cartridge cases collected in Detroit and entered into NIBIN between January 1, 2021, and October 27, 2022.

Table 1a
Semi-automatic Rifles: Caliber Types

7.62 × 51 mm NATO	7.62 × 33 mm Carbine
7.62 × 51 mm	5.45 × 39 mm
7.62 × 39 mm Soviet M43 / 7.62 × 39 mm	0.450 Bushmaster
	0.308 Winchester
0.308 Norma	0.30–06 Springfield
0.30 Remington	0.223 Remington
0.30 M1 Carbine	0.22 Short Rimfire
0.30–30 Winchester	0.22 Magnum Rimfire
0.22 Long Rifle Rimfire	

Appendix B. Appendix

Table 1b summarizes the offenses by type associated with incidents where cartridge cases were collected in Detroit and entered into NIBIN between January 1, 2021, and October 27, 2022.

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