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GUN VIOLENCE

Gunshot detection technology effect on gun violence in Kansas City, Missouri: A microsynthetic control evaluation

Eric L. Piza[1] | David N. Hatten[1] | George O. Mohler[2] | Jeremy G. Carter[3] | Jisoo Cho[4]

[1]School of Criminology and Criminal Justice, Northeastern University, Boston, Massachusetts, USA

[2]Department of Computer Science, Boston College, Boston, Massachusetts, USA

[3]Indiana University–Indianapolis, Paul H. O'Neill School of Public and Environmental Affairs, Indianapolis, Indiana, USA

[4]City University of New York Graduate Center, John Jay College of Criminal Justice, New York, New York, USA

Correspondence
Eric L. Piza, School of Criminology and Criminal Justice, Northeastern University, 360 Huntington Ave., Boston, MA 02115, USA.
Email: e.piza@northeastern.edu

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Abstract

Research Summary: We apply the microsynthetic control method to evaluate the gun violence prevention effect of gunshot detection technology (GDT) in Kansas City, MO. We measure the influence of GDT on process measures (ballistic evidence collection and gun recoveries) and outcome measures (shots fired calls for service, non-fatal shootings, fatal shootings, and aggravated assaults and robberies committed with a firearm). The GDT system was associated with higher levels of ballistic evidence collection in the GDT target area and surrounding catchment area, higher levels of gun recoveries in the surrounding catchment area, and lower levels of shots fired calls for service in the GDT target area. The GDT system did not influence any of the gun violence categories involving confirmed victims (non-fatal shootings, fatal shootings, and aggravated assaults and robberies committed with a firearm).

Policy Implications: Agencies that highly prioritize increasing evidence collection and reducing unauthorized firearm discharges may consider dedicating necessary resources to acquire GDT. Agencies that prioritize the reduction of gun violence victimization, however, should consider whether resources are better used for solutions other than GDT. Moving forward, violence prevention scholars should strive to identify contextual factors that facilitate or mitigate the GDT system effect, in an attempt to better understand how to deploy GDT in a manner that maximizes the likelihood of success. This would provide additional guidance to public safety agencies looking to maximize return on investment. Continued adoption of GDT should perhaps be contingent upon the development of such research, given the high cost of the technology.

KEYWORDS
crime prevention, gun violence, gunshot detection technology, microsynthetic control matching, police technology, ShotSpotter

Gunshot detection technology (GDT) has recently emerged as a core entry into the suite of technological gun violence prevention solutions incorporated by police. Despite increased popularity of the technology, the research evidence on GDT is underdeveloped, especially as compared to other police technologies. Given that the first GDT evaluation was published 25 years ago (Mazerolle et al., 1998), it is surprising that relatively few rigorous evaluation studies have been conducted on GDT. The still-developing evidence-based has not slowed the adoption of the technology. SoundThinking—the vendor of the industry-leading ShotSpotter GDT—reports that over 250 public safety agencies worldwide have adopted their platform.[1] These agencies have arguably adopted GDT within a low-information environment, with questions on the technology's efficiency and effectiveness unanswered or underexplored (Lum & Koper, 2017).

Looking more closely at GDT study designs, we note a number of methodological limitations. Some evaluations of GDT did not incorporate a separate control area, measuring pre/post outcomes only within GDT target areas (e.g., Choi et al., 2014). This presents significant threats to internal validity, as the use of a separate control group is widely considered the minimum criteria for interpretable research designs (T. D. Cook & Campbell, 1979; Farrington et al., 2006). While certain studies have taken efforts to select control areas with similar crime and sociodemographic conditions as the target areas (Center for Crime Science and Violence Prevention [CCSVP], 2023; Mares & Blackburn, 2021; Vovak et al., 2021), this is not commonplace in GDT research. Furthermore, such research has used a fuzzy matching approach where control areas are selected based on their general similarity with target areas rather than through quantitative matching techniques that ensure statistical equivalency between treatment and control areas.

The current study aims to contribute to the knowledge on GDT effect on crime occurrence through a rigorous evaluation of the technology in Kansas City, MO. The Kansas City Police Department (KCPD) installed SoundThinking's ShotSpotter GDT system in September 2012, with the target area covering approximately 3.5 mi^2 of the city. We apply the recently developed microsynthetic control method (Robbins & Davenport, 2021; Robbins et al., 2017) in the evaluation, incorporating over 13 years of data. The microsynthetic control method computationally adjusts the synthetic control methodology (Abadie & Gardeazabal, 2003; Abadie et al., 2011) for use with micro-geographic units. The microsynthetic control method improves upon matching techniques used in prior crime-and-justice research—such as propensity score matching (Apel & Sweeten, 2010)—in a number of ways. It allows for both time-variant and time-invariant covariates in the matching algorithm; ensures pre-intervention trends in dependent variables match longitudinally (rather than just cross-sectionally); creates a weighted control group that matches the pre-intervention characteristics of the treatment group, which allows for all treated units to be preserved in the statistical analysis; controls for multiple comparisons by using an omnibus statistic to calculate treatment effect; and incorporates a permutation technique to generate confidence intervals, resulting in conservative effect estimates as compared to alternative quasi-experimental techniques (Robbins & Davenport, 2021).

The current study found that the GDT system was associated with higher levels of ballistic evidence collection in both the GDT target area and surrounding catchment area, higher levels of gun recoveries in the catchment area, and lower levels of shots fired calls for service (CFS) in the GDT target area. No gun violence crime types involving confirmed victims exhibited significant differences in the GDT target or surrounding catchment area. We conclude this article with a discussion of the implications for public safety agencies. We begin with a discussion of the prior literature on GDT that informed our research.

1 | REVIEW OF THE RELEVANT LITERATURE

1.1 | Overview of GDT

GDT systems deploy networks of acoustic sensors that detect sounds from firearm muzzle blasts or the sonic booms generated by a bullet traveling through the air (Mares, 2022). According to SoundThinking's website, the ShotSpotter system uses acoustic sensors that are strategically placed in an array of approximately 20 sensors per square mile.[2] The sensors triangulate the data and pinpoint the source of gunfire, assigning a precise x,y coordinate to the location (La Vigne et al., 2019). Each GDT alert generated by ShotSpotter is manually reviewed by a team of gunshot acoustic experts at the SoundThinking headquarters. Confirmed gunshots are relayed to the dispatch center of the police department in question, with dispatchers and officers able to access the GDT alert via the computer-aided dispatch system, from patrol car terminal computers, or through the vendor's smartphone app (La Vigne et al., 2019; Mares, 2022).

The prevention of gun violence by GDT rests on some specific (expressed or implied) causal mechanisms being generated by the technology. Given the small and inconspicuous nature of microphones installed in GDT systems, the stand-alone technology likely does not generate any general deterrence effects from visual presence. Any crime reductions would have to result from the continuous monitoring of gunfire and consistent, geographically accurate response by police (Mares & Blackburn, 2021). Police consistently responding to GDT alerts may operate as what

Ratcliffe et al. (2011) refer to as a *certainty-communicating device* that signals increased risk of apprehension within the microspatial contexts police officers occupy. Such causal mechanisms have been observed during prior interventions meant to increase police responses to observed crime. Newark, NJ's, Closed-Circuit Television (CCTV) directed patrol strategy generated an over 10-fold increase in officer responses to crime observed on CCTV and subsequent enforcement actions and significant reductions of violence and social disorder (Piza et al., 2015). Constant police response could further increase visible police presence within target areas, which research has consistently found to be related to crime reduction (Chalfin, 2022; Dau et al., 2023).

Response to GDT alerts may further generate police enforcement actions against gun offenders or the seizure of illegal firearms, which research indicates can reduce the risk for subsequent gun violence (Sherman & Rogan, 1995; Wheeler et al., 2021; Wyant et al., 2012). Increasing firearm recovery also has the potential to prevent gun violence by minimizing the number of firearms in circulation, thus reducing the inventory for potential use in crime (Mares, 2022). The collection of shell casings and recovery of firearms supports the comprehensive analysis of gun crime intelligence, which can facilitate the identification, arrest, and prosecution of gun offenders (Novak & King, 2020; PERF, 2017).

1.2 | GDT evaluations

Much research has focused on GDT's performance in detecting gunfire and identifying the location of gunfire events. Watkins et al. (2002) conducted the first field trial testing the ability of GDT to accurately detect gunfire and identify the location of gunfire events in Redwood City, CA. They found that the GDT system identified nearly 80% of the test shots. GDT evaluations conducted in real-world settings have indicated that GDT can significantly increase the proportion of gunfire events that come to the attention of the police (Carr & Doleac, 2016; Irvin-Erickson et al., 2017). However, other research suggests the possibility that a proportion of GDT alerts may be false positive events. While modern GDT systems often include incident review processes that should reduce false positives (Mares, 2022), some research has highlighted potential negative impacts of inaccurate GDT alerts, specifically the regular deployment of officers to incidents that do not truly necessitate a rapid police response (Litch & Orrison, 2011; Ratcliffe et al., 2019). This can substantially increase officer workloads while reducing officer enthusiasm for responding quickly to the scene of GDT alerts (Ratcliffe et al., 2019).

With respect to temporal effects, previous studies have generally observed that GDT significantly reduces police response time to shots fired incidents. These observed reductions in the response time range from 7% (Mazerolle et al., 1998) to 14% (Choi et al., 2014) and to 42% (Mares & Blackburn, 2012). A multi-jurisdictional evaluation of GDT in Denver, CO, Milwaukee, WI, and Richmond, VA, found mixed effects (Lawrence et al., 2019). Response times to GDT alerts were faster than CFS for shootings and shots fired in both Denver and Richmond. In Milwaukee, GDT alerts were faster than CFS for shots fired but slower for shootings (Lawrence et al., 2019). Mares and Blackburn (2021) observed mixed results across 18 neighborhoods in St. Louis, MO, a finding the authors contend is a function of unique neighborhood-level firearm crime as well as variance in police dispatch procedures for differentiating shooting-involved incidents. Goldenberg et al. (2019) examined 627 shootings in Camden, NJ, to quantify differences of transport to trauma care across GDT and CFS. While their results showed no significant difference in mortality rates between GDT alerts and 9-1-1 calls, events originating from a GDT activation were accompanied by faster response times by both police and emergency medical services (EMS). Most recently, an evaluation conducted by the Center for Crime Science and Violence Prevention (CCSVP, 2023) found that officer response times were approximately 5 min faster to GDT alerts than to citizen calls for service in Winston-Salem, NC.

Further research has focused on the spatial accuracy of GDT alerts. Aguilar's (2015) review of field tests in both urban and military environments reported gunfire scenes to be between 10 and 25 m from their corresponding GDT-reported location, considered close enough to identify shooting locations in terms of street names and block numbers. Wheeler et al. (2020) found that reported addresses for shooting incidents were between 60 and 90 ft from the related GDT alert on average, depending on the geocoder used to map the data. Piza et al. (2023) found that GDT and CFS locations were a median of 234.91 ft apart in Kansas City, MO. Furthermore, GDT and CFS locations were geocoded to the same street segment in only 46.95% of cases, meaning officers responding to the CFS location would potentially be a meaningful distance from where the gunshot occurred as recorded by the GDT alert. Piza et al. (2023) also found that GDT alerts occurred a median of 93 s before the first call for service reporting the gunfire event in question. The median time is nearly 12% of the summated police response, EMS response, and EMS travel times to the nearest trauma center in Kansas City, which represents a potentially important head start for the victim transport process.

Researchers have increasingly evaluated the potential of GDT to prevent gun violence. Mares and Blackburn (2012) conducted an interrupted time series analysis in the neighborhoods covered by GDT, control neighborhoods without GDT, and the citywide study setting of St. Louis, MO. From January 2006 to October 2009, shots fired 9-1-1 calls significantly reduced in the GDT target areas while no discernable change was observed in the control areas. Relative to GDT influence on criminal investigation processes, Mares and Blackburn (2012) found only approximately 2% of GDT gunfire alerts led to ballistic evidence of a shooting as compared to a citywide rate of 17% for shots fired calls for service.

Mares and Blackburn (2021) incorporated a longitudinal quasi-experimental panel design—selecting as control areas neighborhoods with similar levels of crime and sociodemographic conditions as the GDT target areas—to test the expanded GDT coverage area in St. Louis. The case-control analysis was conducted to test the GDT effect across three temporal phases: the initial GDT implementation in 2008, the expansion of the GDT target area in 2013, and a 4-month period in 2016 during which the GDT system was temporarily suspended. The analysis found consistent and substantial reductions of around 30% in citizen-initiated shots fired calls for service in the GDT target area, compared to the controls. No significant changes were observed for reported violent crime incidents. Using a similar longitudinal difference-in-differences model, Mares (2023) found that GDT led to sizable crime reductions in Cincinnati, OH. Shots fired calls for service and gun assaults significantly reduced by 45% and 46%, respectively, in the GDT target area as compared to the control area. Benefits were also observed in Winston-Salem, NC, with overall violent crime reducing by 24% in the GDT target area during the first year of the program, which was largely driven by a reduction in aggravated assault. No significant changes in violent crime occurred in the comparison area over the same time period (CCSVP, 2023).

The aforementioned study by Lawrence et al. (2019) found that GDT was associated with significant increases in gun crime calls for service with no significant changes in reported gun crimes in Milwaukee and Richmond. However, less restrictive statistical models found some evidence of crime reduction in Richmond. No significant effects were observed for Denver. A marginally significant ($p = 0.10$) increase in the collection of shell casings was observed in the GDT target areas collectively, with the increase achieving statistical significance in Richmond.

Vovak et al. (2021) analyzed GDT in Wilmington, DE. The system was originally deployed in 2013, with a target area expansion and integration with CCTV cameras occurring in 2018.

Potential changes in crime were measured through a series of Bayesian structural time series modes, with data from other, similar jurisdictions incorporated as the control condition. Overall crime levels did not significantly change, while homicides and shootings increased during the post-implementation phase.

Doucette et al. (2021) analyzed the effect of GDT on firearm homicides and arrests through an analysis of 68 large U.S. metropolitan counties from 1999 to 2016. GDT was not associated with any significant changes in firearm homicide, murder arrests, or weapons arrests. Effect heterogeneity was observed across observations for firearm homicide, however. Homicide rates decreased by 15% in counties within states with permit-to-purchase firearms laws and increased by 21% in counties within states with right-to-carry laws. It should be noted, however, that GDT systems rarely cover entire municipalities, let alone entire counties. The inability to operationalize precise areas covered by GDT may have biased the results of the study—making a null result more likely—which Doucette et al. (2021) acknowledge.

Litch and Orrison (2011) faced difficulties in testing the effect of GDT on gun crime in Hampton, VA, and Newport News, VA. Crime data were only available at the district level, meaning the precise GDT coverage area was not operationalized, similar to the issues faced by Doucette et al. (2021). Furthermore, the 5-month intervention period made for a very low baseline of crime events. With these caveats, the findings suggest that neither GDT system had any significant effect on the occurrence of crime or case clearance. However, we recommend caution in interpreting these results given methodological limitations.

1.3 | Literature review summary and scope of the current study

The knowledge base for GDT is not nearly as developed as the literature on other contemporary police technologies. A recent review of body-worn camera (BWC) research, for example, identified 70 empirical studies (Lum et al., 2019) with 30 studies providing sufficient empirical data to be included in a meta-analysis testing BWC effect on pertinent outcomes (Lum et al., 2020). GDT research stands in stark contrast, as our literature review identified only 11 outcome evaluations, eight of which tested the technology's crime prevention capacity. Results of these studies indicate that the GDT effect on crime prevention is mixed, with the magnitude and direction of crime level changes varying across study settings (Doucette et al., 2021; Lawrence et al., 2019; Mares, 2023; Mares & Blackburn, 2012, 2021; Vovak et al., 2021). Given this, it can be difficult for public safety agencies to anticipate the precise return on investment they would experience from deploying GDT. The nature of the quasi-experimental designs typically incorporated in GDT evaluations may provide low levels of internal validity, with studies commonly lacking rigorous comparable control conditions and quantitative matching techniques that balance between treatment and control areas being absent in the GDT literature.

With these issues in mind, we conduct what is to our knowledge the first matched quasi-experiment of the crime prevention effects of GDT. Focusing on Kansas City, MO, our analysis applies the microsynthetic control method (Robbins & Davenport, 2021; Robbins et al., 2017) to longitudinally measure process and outcome variables across street segments in the GDT target area and a control area that comprised weighted street segments from other parts of the city. This methodology provides a number of benefits not obtained through traditional quasi-experimental techniques, which increase interval validity and generate comparatively conservative estimates of effect size. In sum, the microsynthetic control method generates the conditions necessary for a rigorous test of program effects than has typically occurred in prior GDT evaluation studies.

2 | STUDY SETTING

Kansas City is the largest city in Missouri with an estimated population of approximately 508,000 and a land area of ~315 mi^2. Racial and ethnic minority residents are approximately 28% Black and 11% Latino according to U.S. Census Bureau figures. Approximately, 15% of residents subsist below the poverty level. The KCPD employed 1,299 sworn officers and 520 civilians in 2019 (the final year of our study period) as per the Federal Bureau of Investigation's Police Employee Data.[3]

As demonstrated by Novak and King (2020), Kansas City experienced increasing gun homicide rates through the early 1990s, with a precipitous decline occurring throughout the 2000s. The 2010s saw steady increases in gun homicides, with the city's third-highest homicide rate on record occurring in 2017 (30.53 per 100,000). Monthly counts of non-fatal shootings were largely correlated with gun homicides throughout the 2010s. In the midst of these ebbs and flows, Kansas City's homicide rate has been substantially higher than the average of similarly sized cities (250,000 to 499,999 population) each year since 1970 (Novak & King, 2020). Gun violence in Kansas City is further challenged by state-level legislative contexts. Missouri's permit-to-purchase handgun law was repealed in 2007. The repeal was associated with a 23% increase the Missouri's annual firearm homicide rate while having no impact on the state's non-firearm homicide rates (Webster et al., 2014). Beginning in 2017, Missouri law allows the permitless carrying of concealed firearms in most public places throughout the state.[4] While we are unaware of any evaluation studies specifically on the effect of Missouri's law, Lundstrom et al. (2023) found that a permitless concealed carry law in West Virginia was associated with a 29% increase in general firearm mortality and a 48% increase in handgun mortality. Doucette et al. (2022) further found that officer-involved shootings increased by 12.9% in the 11 states that enacted permitless concealed carry laws (inclusive of Missouri), which highlights an additional potential harm associated with increased public firearm carrying.

SoundThinking's ShotSpotter GDT system went live on September 14, 2012 in Kansas City. The system detected 11,517 gunfire events through the end of 2019. Upon classification of a GDT alert as gunfire by the SoundThinking acoustic experts, a call of "ShotSpotter Sound of Shots" appears in the KCPD computer-aided dispatch (CAD) system and the patrol car computer terminal. The nearest available patrol car is automatically dispatched to the location of the GDT alert. Officers typically use the point reflecting the location of the GDT alert and an accompanying map displayed on the computer terminal to direct their response. The discovery of a gunshot victim is followed by the response of detectives and crime scene technicians to secure the crime scene, perform an area canvas, and interview relevant witnesses. The discovery of ballistic evidence absent any victims results in officers collecting the evidence and submitting it for analysis in the National Integrated Ballistic Information Network (NIBIN) system.[5]

A target area of approximately 3.5 mi^2 is covered by the GDT system.[6] Initial funding for the GDT system was provided by the Kansas City Area Transportation Authority, with the target area focused on a high-violence area encompassing a busy transit corridor of the city. Kansas City pays between $227,500 and $315,000 per year for their ShotSpotter system based on the advertised annual subscription cost of between $65K and $90K per mi^2.[7] This translates to a total cost of between $1,820,000 and $2,520,000 over the current study's intervention period (September 14, 2012—December 31, 2019). The GDT target area comprises slightly more than 1% of Kansas City's total geography and houses a disproportionate share of violent crime. From September 14, 2012, to December 31, 2019, the GDT zone accounted for approximately 11% of shots fired calls for service (6770 of 60,348), 16% of fatal (123 of 751) and non-fatal (452 of 2689) shootings, and over 15% (2478 of

TABLE 1 Study area characteristics.

Measures	Gunshot detection technology (GDT) target area	Kansas City
Area	3.5 mi^2	314.95 mi^2
Shots fired calls for service	6,770	60,348
Fatal shootings	123	751
Non-fatal shootings	452	2,689
Gun assaults and robberies	2,478	16,158
Non-White population	67.72%	31.91%
Poverty rate	34.33%	15.63%

Note: Crime and shots fired data cover the period September 4, 2012–December 31, 2019. All incidents involving shooting victims are excluded from the gun assault and robbery category so that the crime categories are mutually exclusive. GDT target area demographics measured from the 20 intersecting census tracts. American Community Survey 2019 5-year estimates are reported.

16,158) of assaults and robberies (non-shooting related) committed with a firearm from September 14, 2012, to December 31, 2019. The percentage of residents who are non-White (67.72% vs. 31.91%) and the percentage of households under the poverty rate (34.33% vs. 15.63%) are more than twice as high in the GDT target area than Kansas City as a whole (see Table 1).

3 | DATA AND METHOD

3.1 | Data sources

Data were compiled from several sources for this evaluation. KCPD provided outcome measures including all shots fired calls for service, fatal and non-fatal shootings, and assaults and robberies committed with a firearm for the period January 1, 2007 to December 31, 2019. For the analysis, all incidents involving shooting victims are excluded from the gun assault and robbery category so that the crime categories are mutually exclusive. GDT alerts were removed from the shots fired calls for service to allow for the measurement of citizen—rather than GDT—reporting of gunfire. KCPD also provided data on gun recoveries, NIBIN ballistic evidence, uniform crime report Part-1 crime incidents that did not involve the use of firearms, arrests, CCTV camera locations, and field interviews. To be clear, NIBIN data capture the frequency of ballistic evidence collected and not ballistic matches within the NIBIN system. All incident data were geocoded in ArcGIS Pro 2.7 with a 20-ft offset from street centerlines.[8]

The street file we used to derive the unit of analysis and the property parcel file used to derive the residential parcel percentage were downloaded from the Kansas City Open Data Portal (https://data.kcmo.org/). We used the *tidycensus* R package (https://walker-data.com/tidycensus/) to collect the American Community Survey (2015–2019) 5-year estimates at the census tract level. Our ambient population index was derived from the Land Scan Data generated by the Oak Ridge Laboratory (https://landscan.ornl.gov/).

3.2 | Unit of analysis and intervention areas

Contemporary policing research emphasizes the importance of place in understanding the distribution of crime, evolving from reliance on larger administrative geographies, such as patrol beats, to microlevel geographic units that more accurately reflect the clustered distribution of

TABLE 2 Descriptive statistics.

Process and outcome variables	**Source**	**Sum**	**M**	**SD**	**Min.**	**Max.**
Gun Recovery	Kansas City Police Department	27,194	0.005	0.118	0	42
NIBIN	Kansas City Police Department	3,667	0.001	0.034	0	8
Shots Fired CFS	Kansas City Police Department	71,213	0.013	0.131	0	14
Fatal Shootings	Kansas City Police Department	1,141	0.000	0.014	0	2
Non-fatal Shootings	Kansas City Police Department	4,061	0.001	0.027	0	4
Gun Assaults/Robberies	Kansas City Police Department	20,559	0.004	0.062	0	4
Continuous pre-intervention matching variables		**Sum**	**M**	**SD**	**Min.**	**Max.**
Non-firearm Crime (pre-intervention)	Kansas City Police Department	147,389	0.061	0.371	0	70
Arrests (pre-intervention)	Kansas City Police Department	126,329	0.053	0.424	0	56
Field Interviews (pre-intervention)	Kansas City Police Department	22,205	0.009	0.280	0	78
Street Segment Length (ft)	Kansas City Open Data Portal	–	522.086	590.170	2.456	11,651.300
Residential Parcel Percentage (pre-intervention)	Kansas City Open Data Portal	–	−0.146	0.458	−0.667	0.333
Disadvantage Index (pre-intervention)	Census American Community Survey	–	0.005	2.869	−13.922	8.676
Demographic Index (pre-intervention)	Census American Community Survey	–	116.423	26.180	−1.193	177.311
Population Density: persons per sq. mi. (pre-intervention)	Census American Community Survey	–	−0.133	0.046	−0.133	8.043
Geographic Mobility	Census American Community Survey	–	0.070	0.828	−1.931	2.456
Ambient Population Index	Oak Ridge Land Scan	–	1.160	2.006	−0.380	16.807

(Continues)

TABLE 2 (Continued)

Binary pre-intervention matching variables		Yes	% Yes	No	% No
Principal Roadway	Kansas City Open Data Portal	790,160	14.06	4,828,608	85.94
CCTV Presence	Kansas City Police Department	121,180	2.16	5,497,588	97.84

Note: $N = 5{,}618{,}768$ (pre-intervention $n = 2{,}403{,}208$). M = mean; SD = standard deviation. Measures for residential parcel percentage, disadvantage index, demographic index, population density, geographic mobility, and ambient population index are standardized.

Abbreviations: KCPD, The Kansas City Police Department; NIBIN, National Integrated Ballistic Information Network.

TABLE 3 Balance table for treated and weighted control areas: Main analysis.

Covariates	Targets	Weighted controls
Shots Fired CFS (sum)	2,973.00	2,973.00
Fatal Shootings (sum)	84.00	84.00
Non-fatal Shootings (sum)	273.00	273.00
Gun Assaults/Robberies (sum)	1,091.00	1,091.00
Gun Recovery (sum)	1,542.00	1,542.00
NIBIN (sum)	144	144
Non-firearm Crime (sum)	14,151.00	14,151.02
Arrests (sum)	19,884.00	19,884.04
Field Interviews (sum)	2,708.00	2,708.00
Principal Roadway	350.00	350.00
Street Segment Length	727,138.90	727,139.63
Residential Parcel Percentage	−249.81	−249.82
CCTV Presence	88.00	88.00
Disadvantage Index	5317.32	5317.32
Demographic Index	239,162.59	239,162.96
Population Density	−211.91	−211.91
Geographic Mobility	409.82	409.82
Ambient Population Index	2818.02	2818.03

Note: For time variant measures, the *microsynth* output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation. Control group street segment weight summary statistics: mean = 0.41, median = 0.32, standard deviation = 0.35, minimum = 0, maximum = 2.48.

Abbreviation: NIBIN, National Integrated Ballistic Information Network.

crime in urban environments (Weisburd, 2015, 2018). In following this perspective, we use the 33,848 individual street segments—the two block faces on both sides of a street between two intersections—in Kansas City as the unit of analysis. Data were measured at 166 28-day intervals, resulting in a panel database that included 5,618,768 cases (33,848 street segments × 166 time periods). A total of 1,597 street segments fall within the GDT target area, and 1,419 fall within the catchment zone used in the test of spatial displacement.[9]

The use of street segments improves upon the units of analysis incorporated in prior GDT evaluation studies, which have largely aggregated point-level data to larger geographic units, such as police districts (Carr & Doleac, 2016; Litch & Orrison, 2011) or counties (Doucette et al., 2021). While such an approach facilitates the integration of multiple large-scale data sets, large geographic units of analysis are unable to properly capture heterogeneity across the micro places that comprise these units (Schnell et al., 2017; Steenbeek & Weisburd, 2016). Street segments

TABLE 4 Crime change estimates: Main analysis.

Crime category	Target	Control	Difference	95% confidence interval Lower	Upper
Gun recoveries	1,939	1,744	11.2%	−0.3%	26.3%
NIBIN evidence*	476	365	30.4%	9.2%	54.8%
Shots fired*	5,665	7,286	−22.2%	−29.2%	−14.3%
Fatal shootings	107	108	−1.2%	−23.2%	30.0%
Non-fatal shootings	389	395	−1.4%	−26.3%	15.1%
Gun assaults & robberies	1,768	1,783	−0.9%	−10.4%	8.4%

Note: N = 5,383,214; 95% confidence interval based on 500 permutation tests. Time period set to three 28-day intervals (i.e., approximately a quarter year) for plots and results. Aggregation to three temporal periods resulted in 164 of 166 28-day periods being used for the analysis. Omnibus test controls for multiple outcome measures. The control counts reported by the *microsynth* R script were rounded to the nearest whole number.

Abbreviation: NIBIN, National Integrated Ballistic Information Network.

* = statistically significant.

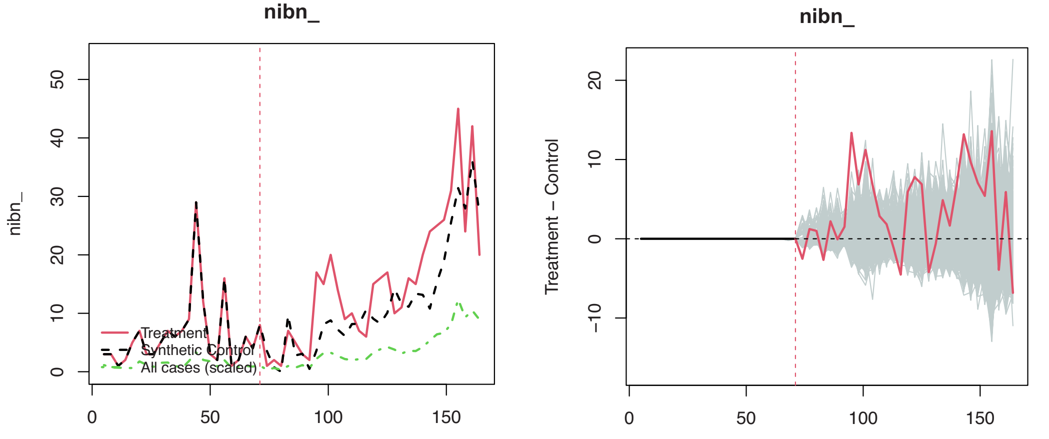

FIGURE 1 National Integrated Ballistic Information Network (NIBIN) ballistic evidence collection synthetic control estimates, main analysis. [Color figure can be viewed at wileyonlinelibrary.com]

are simultaneously small enough to avoid aggregation errors such as the ecological fallacy and large enough to avoid coding errors associated with small units such as street addresses (Braga et al., 2010; Weisburd, 2015; Weisburd et al., 2012).[10] Street segments are best positioned to capture both crime-promoting and crime-mitigating processes within microlevel behavior settings (Groff et al., 2023; Linning & Eck, 2021). From a practical perspective, street segments are most appropriate for the current study as Kansas City's GDT system was not installed within the confines of any administrative boundaries, such as police districts, neighborhoods, or census tracts. Using such administrative areas as the unit of analysis would have overestimated GDT coverage, which has complicated the interpretation of prior GDT study results (e.g., Doucette et al., 2021; Litch & Orrison, 2011).

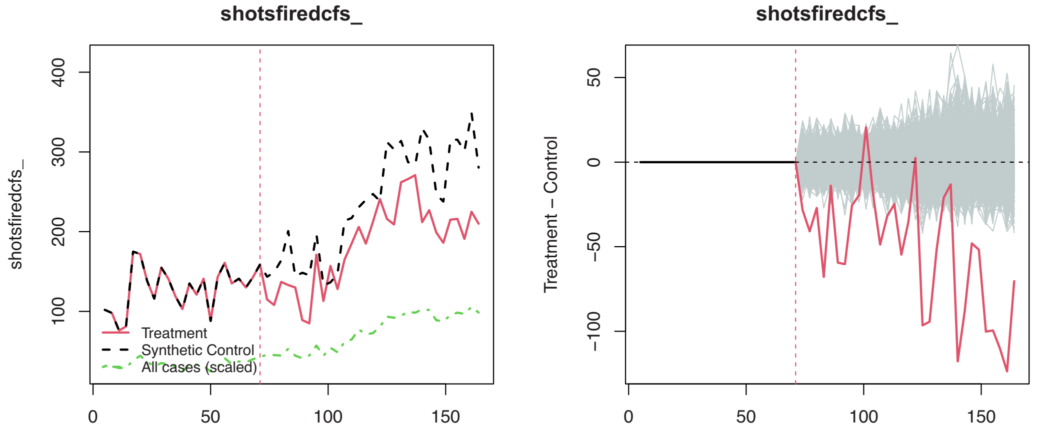

FIGURE 2 Shots fired CFS synthetic control estimates, main analysis. [Color figure can be viewed at wileyonlinelibrary.com]

3.3 | Microsynthetic control matching

The microsynthetic control method modifies the synthetic control method (Abadie & Gardeazabal, 2003; Abadie et al., 2011) for application to micro-geographic units of analysis. Crime researchers have recently used this method to explore the effect of drug market intervention strategies (Robbins & Davenport, 2021; Robbins et al., 2017), anti-drunk driving legislation (Davenport et al., 2021), directed police patrols (Lawrence, 2023; Rydberg et al., 2018), community policing substations (Piza et al., 2020), recreational marijuana dispensaries (Connealy et al., 2020), and neighborhood-level de-policing policies (Piza & Connealy, 2022). The microsynthetic control method is particularly useful in situations where treated units are clustered in a contiguous area. The microsynthetic control approach generates effect estimates by comparing cumulative crime changes in the treated and weighted control areas rather than measuring effect through unit-level averages as is done in alternate matching approaches such as propensity score matching (Piza et al., 2020).

The control group is created through a weighted vector of individual control street segments, with pre-intervention trends and time-variant and time-invariant covariates matched as closely as possible to the treatment group. The weighting process allows for the construction of an approximately equivalent control group even when there are few appropriate matches between individual treatment and control units. This helps ensure unique cases are not dropped from the analysis (Robbins et al., 2017). More computationally intensive backup models can be used to calculate weights (Robbins & Davenport, 2021) when the primary model is not feasible. The microsynthetic control approach meets the parallel trends assumption required for difference-in-differences analysis by construction (Levin et al., 2002).

The analysis was conducted through the *microsynth* R package (Robbins & Davenport, 2021). Data were available from 2007 through 2019. Incident data were aggregated into 28-day temporal periods. Matching was conducted across three matching blocks (i.e., 84 days, approximately a quarter-year) to maximize matching efficiency, translating to 23 pre-intervention periods. This pre-intervention period is longer than all microsynthetic crime-and-place studies cited in this article, with the exceptions of Lawrence (2023; $n = 23$), Davenport et al. (2021; $n = 36$), and Piza and Connealy (2022; $n = 62$).[11]

TABLE 5 Balance table for treated and weighted control areas: Displacement analysis.

Covariates	Targets	Weighted controls
Shots Fired CFS (sum)	1,849.00	1,849.00
Fatal Shootings (sum)	65.00	65.00
Non-fatal Shootings (sum)	203.00	203.00
Gun Assaults/Robberies (sum)	772.00	772.00
Gun Recovery (sum)	1,136.00	1,136.00
NIBIN (sum)	121.00	121.00
Non-firearm Crime (sum)	12,991.00	12,991.01
Arrests (sum)	14,007.00	14,007.00
Field Interviews (sum)	1,930.00	1,930.00
Principal Roadway	214.00	214.00
Street Segment Length	622,022.20	622,024.18
Residential Parcel Percentage	−249.59	−249.59
CCTV Presence	68.00	68.00
Disadvantage Index	2945.03	2945.03
Demographic Index	191,724.38	191,724.73
Population Density	−188.34	−188.34
Geographic Mobility	971.88	971.86
Ambient Population Index	3862.11	3862.11

Note: For time variant measures, the *microsynth* output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation. Control group street segment weight summary statistics: mean = 0.13, median = 0.10, standard deviation = 0.13, minimum = 0, maximum = 2.52.
Abbreviation: NIBIN, National Integrated Ballistic Information Network.

The microsynthetic control model accounted for the pre-intervention presence of 18 covariates. The covariates are listed below, with descriptive statistics presented in Table 2.

1–4. Outcome measure incident counts (time-variant): shots fired calls for service, non-fatal shootings, fatal shootings, and gun assaults and robberies committed with a firearm.
5–6. Process measure incident counts (time-variant): gun recoveries and NIBIN ballistic evidence collection.
7. Non-firearm related crime counts (time-variant): Part-1 crime incidents that did not involve the use of a firearm.
8–9. Enforcement incident counts (time-variant): arrests and field interviews.
10. Principal roadway (time-invariant): whether the street segment was classified as a principal or arterial roadway (coded as 1) or as another roadway classification (coded as 0).
11. Street segment length (time-invariant): measured in ft.
12. Residential parcel percentage (time-invariant): standardized percentage of the parcels zoned for residential properties.
13. CCTV presence (time-invariant): whether any KCPD CCTV cameras were present on the street segment (coded as 1) or not (coded as 0).
14. Disadvantage index (time-invariant): summed standardized percentages of households receiving public assistance, households below the poverty line, persons unemployed, households with a single female head and child under the age of 18, and

TABLE 6 Crime change estimates: Displacement analysis.

Crime category	Target	Control	Difference	95% confidence interval Lower	Upper
Gun recoveries*	1,668	1,477	12.9%	0.1%	29.1%
NIBIN evidence*	351	271	29.7%	6.2%	55.5%
Shots fired	4,623	4,489	3.0%	−5.3%	11.9%
Fatal shootings	77	65	18.5%	−13.3%	56.7%
Non-fatal shootings	328	299	9.5%	−18.6%	30.4%
Gun assaults & robberies	1,386	1,323	4.7%	−3.9%	15.5%

Note: $N = 5{,}353{,}666$; 95% confidence interval based on 500 permutation tests. Time period set to three 28-day intervals (i.e., approximately a quarter year) for plots and results. Aggregation to three temporal periods resulted in 164 of 166 28-day periods being used for the analysis. Omnibus test controls for multiple outcome measures. The control counts reported by the *microsynth* R script were rounded to the nearest whole number.

Abbreviation: NIBIN, National Integrated Ballistic Information Network.

* = statistically significant.

persons without a high-school diploma or equivalent in the encompassing census tract.[12]

15. Demographic index (time-invariant): summed standardized percentages of non-White residents, residents aged 15–29, vacant properties, and renter-occupied properties in the encompassing census tract.
16. Population density (time-invariant): standardized average of the number of residents per square mile in the encompassing census tract.
17. Geographic mobility (time-invariant): standardized percentage of residents of the encompassing census tract who lived at a different address 1 year prior.
18. Ambient population (time-invariant): standardized ambient population in the encompassing 1.5km x 1.5km grid as measured in the annual Oak Ridge Laboratory Land Scan data.

3.4 | Treatment effect estimation

Both process and outcome measures were tested in the analysis. Process measures included gun recoveries and NIBIN ballistic evidence collection to reflect the enforcement-related causal mechanisms of GDT.[13] Outcome measures included shots fired calls for service, non-fatal shootings, fatal shootings, and gun assaults and robberies. All process and outcome measures were incorporated in this portion of the analysis.

The treatment effect is calculated through the formula:

$$\text{Treatment Effect} = \left(\sum_{jt=1}^{\text{Target}} Y_{jt} \right) - \left(\sum_{jt\ =\ 1}^{\text{Control}} w_j \cdot Y_{jt} \right),$$

with Y indicating the outcome, j depicting the units in the intervention area, and t denoting the time specification. The weighted control group outcome sum is subtracted from the sum of the aggregate treatment units (GDT target area) to calculate the treatment effect. The statistical significance of the treatment effect is determined through the use of iterative permutation-based placebo tests. Five hundred permutations are used in the current analysis.[14] The statistical analysis incorporates various outcome measures to provide a holistic assessment of the GDT system effect. The effect estimates incorporate an omnibus statistic that jointly tests for the presence of an intervention effect across the multiple outcome measures and postintervention time periods, allowing for a control of the multiple comparisons (Robbins et al., 2017).

4 | RESULTS

The balance achieved across the treated and weighted control areas is displayed in Table 3. The matching algorithm succeeded in creating a weighted control area that nearly perfectly matched the aggregate characteristics of the GDT target area.

Table 4 presents the results of the crime change estimates in the GDT target area. The table presents 95% confidence intervals in lieu of the calculated *p* values. Given that permutation tests use approximation techniques for statistical inference, the *microsynth* R outputs may occasionally list contradictory *p* values and confidence intervals (Robbins & Davenport, 2021). This mirrors observations from the general synthetic control literature that *p* values calculated through random placebo tests lack a clear statistical interpretation (Ferman et al., 2020). Therefore, we consider only the crime change estimates where the lower and upper bounds of the confidence interval do not cross 0 as statistically significant.

The collection of NIBIN ballistic evidence was significantly higher in the GDT target area than the weighted control area by approximately 30% (476 vs. 365) during the intervention period. Shots fired calls for service was the lone outcome measure to experience a statistically significant change with incident levels approximately 22% lower in the GDT target area than the weighted control area (5665 vs. 7285). Importantly, none of the three crime types involving confirmed victims (fatal shootings, non-fatal shootings, gun assaults and robbery) exhibited any significant changes following the installation of GDT.

Figure 1 (NIBIN ballistic evidence collection) and Figure 2 (shots fired calls for service) graphically display the synthetic control estimates for the measures that achieved statistical significance.[15] NIBIN counts were similar in the treated and control areas early in the intervention period. NIBIN evidence collection in the GDT target area began an upward trajectory in mid-2013 that outpaced what occurred in the control area. While shots fired progressively increased in both treated and control areas following the introduction of GDT, counts were lower in the GDT target area for the entirety of the intervention period.

We repeated the microsynthetic control approach to test for the presence of spatial displacement. As observed in the main analysis, near perfect balance was observed between the catchment zone and the weighted control area (see Table 5).

Table 6 displays the results of the displacement analysis. Gun recoveries were nearly 13% higher in the catchment zone than the weighted control area (1668 vs. 1477). NIBIN evidence collection was nearly 30% higher in the catchment zone than the weighted control area (351 vs. 271). These findings indicate a diffusion of benefits for the process measures (Clarke & Weisburd, 1994). Gun recoveries were somewhat volatile in both the catchment zone and control area throughout the intervention period, though counts were higher in the catchment zone in most time periods (see Figure 3). NIBIN evidence collection counts were similar in the catchment zone and control area through early 2015. From that point forward, NIBIN counts were consistently higher in the

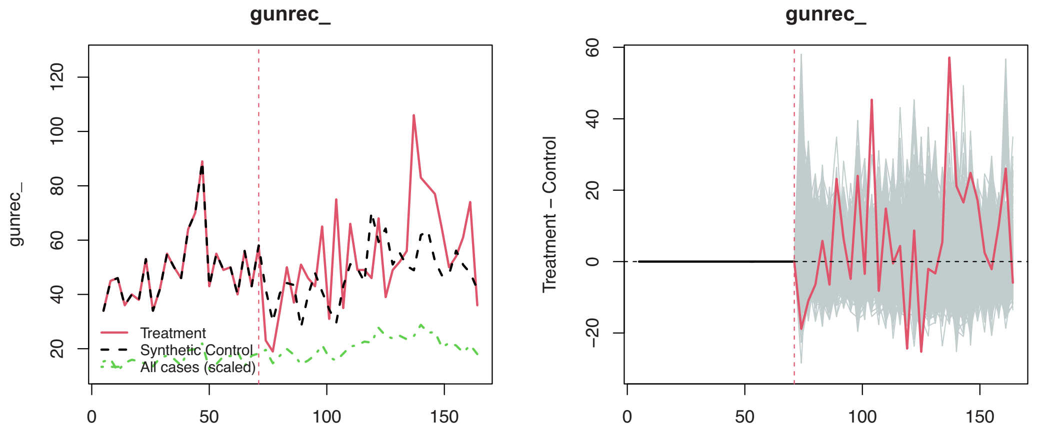

FIGURE 3 Gun recovery synthetic control estimates, displacement analysis. [Color figure can be viewed at wileyonlinelibrary.com]

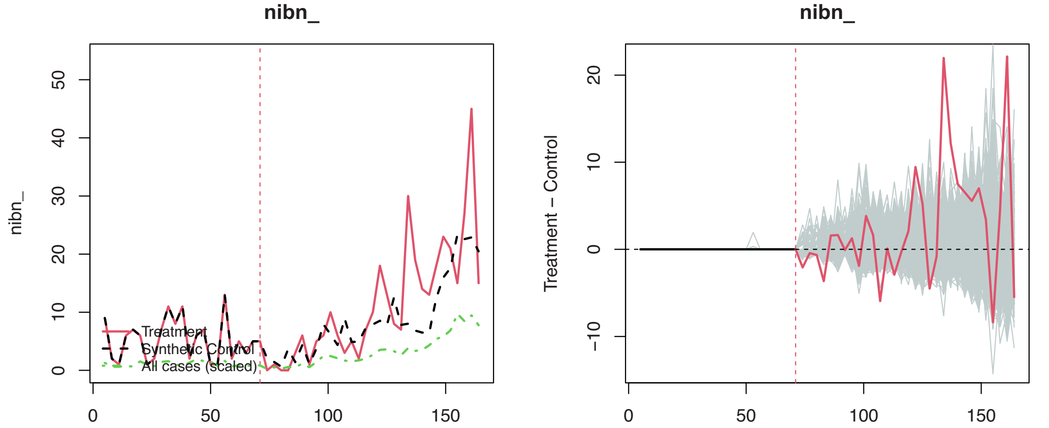

FIGURE 4 NIBIN evidence collection synthetic control estimates, displacement analysis. [Color figure can be viewed at wileyonlinelibrary.com]

catchment zone than the weighted control area (see Figure 4). As observed in the main analysis, no significant effects were observed for fatal shootings, non-fatal shootings, or gun assaults and robberies.[15]

5 | DISCUSSION AND CONCLUSION

This article reported the results of what we believe to be the first matched quasi-experimental evaluation of GDT. The results do not offer much empirical support for GDT as a gun violence prevention tool in Kansas City. This is despite GDT facilitating certain aspects of KCPD's gunfire response. The current study found that NIBIN ballistic evidence was collected significantly more often in the GDT target area and surrounding catchment zone than in the weighted control area. Gun recoveries also occurred significantly more often in the catchment zone. A process evaluation found that KCPD's GDT system detected sounds of gunshots a meaningful time period prior to subsequent calls for service and that calls for service were oftentimes a substantial distance away from the true location of the gunfire as measured by GDT (Piza et al., 2023). As such, GDT seems to offer the procedural benefits in Kansas City claimed by vendors—and that police agencies report as a primary motivation for procuring GDT (Lawrence et al., 2018). Unfortunately, such improved processes did not reduce gun violence. While shots fired calls for service were significantly lower in the GDT target area than the weighted control area, none of the crime types involving gun violence victims experienced significant reductions. The current study findings reflect the general pattern observed in prior process (Aguilar, 2015; Irvin-Erickson et al., 2017; Mazerolle et al., 1998; Ratcliffe et al., 2019; Wheeler et al., 2020) and outcome (Doucette et al., 2021; Lawrence et al., 2019; Mares & Blackburn, 2012, 2021; Vovak et al., 2021) evaluations of GDT.

It is helpful to revisit the programmatic outputs and related causal mechanisms undergirding GDT when contextualizing the study findings: increased responses to sounds of gunfire, the increased collection of ballistic evidence, and the increased seizure of firearms. KCPD's GDT system generated a total of 11,517 gunfire alerts over the study period. The GDT target area experienced a combined 3,180 shots fired calls for service, fatal shootings, and non-fatal shootings during the pre-intervention period (see Table 1). As such, the GDT alerts account for 8,337 additional police responses to gunfire events in the target area following the installation of GDT. As discussed, our models also found significant increases in NIBIN evidence collection in both the target and catchment areas and gun recoveries in the catchment area as compared to the weighted control. In the context of GDT's ability to reduce response time to shootings (CCSVP, 2023; Piza et al., 2023), prior research has found that each minute of reduced response time to a trauma center improves shooting survivability by only approximately 0.5% (Circo & Wheeler, 2021). As such, reduced response times generated by GDT may be insufficient to significantly improve gunshot survival rates. The collective evidence suggests that alternative causal mechanisms may need to be generated for GDT to provide crime control benefits, not only in Kansas City but within most jurisdictions employing GDT (with Mares, 2023; CCVSP, 2023—to our knowledge the only studies to find clear evidence of a Part-1 gun violence reductions—as noteworthy exceptions).

However, we acknowledge that our study design was not able to examine a key theoretical mechanism in the context of increased NIBIN collection and gun recoveries. Police securing more physical evidence at shooting scenes is directly relevant for criminal investigations. The incapacitation of offenders through case clearance and prosecution would seem necessary for increased evidence collection to lead to a gun violence reduction. The research analyzing the relationship between NIBIN evidence collection and case clearance is mixed (King & Wells, 2015; King et al., 2017). However, recent studies evaluating Crime Gun Intelligence Centers in Phoenix (Flippin et al., 2022) and Milwaukee (Koper et al., 2019)—which utilize GDT—found increases in NIBIN evidence collection were associated with significant increases in gun-related crime clearance. Key attributes of the GCIC success with ballistic evidence collection is the partnership with external agencies, task forces, and units that can also access and input ballistic evidence through a shared access portal. It may be that such a model has transferable benefits to municipal police departments that deploy GDT. Testing the GDT effect of investigation outcomes alongside gun violence prevention was too ambitious to pursue within a single study. As such, we are unable to say the level to which the *crime prevention through case clearance* mechanism was generated in Kansas City.

It is somewhat challenging to contextualize the shots fired reduction. Prior research has found that residents with knowledge of GDT systems may stop reporting sounds of gunfire because they assume the technology will automatically notify the police of such incidents (La Vigne et al., 2019).

This raises the possibility that a reduction of shots fired calls for service may be more related to changes in citizen reporting practices than the preventive effect of GDT. KCPD does not publicize the location of the GDT target area, which may make Kansas City residents less knowledgeable of where the technology operates than residents of municipalities that publicly divulge GDT coverage areas. Nonetheless, we acknowledge the possibility that changes in citizen behavior may deserve more credit for the shots fired reduction than GDT.

Improving the effectiveness of GDT may require deploying the technology within contexts that facilitate success. Research has allowed for such practical considerations with other technologies. CCTV surveillance cameras, for example, achieve the largest effects within car parks and residential areas (Piza et al., 2019; Welsh & Farrington, 2009) and the active monitoring of cameras alongside multiple complementary interventions works better than passive monitoring and deploying CCTV as a stand-alone intervention (Piza et al., 2019). Similarly, BWCs have the largest effects when camera activation compliance by officers is high (Malm, 2019). Future GDT research should strive to identify such contextual factors associated with heightened/lowered performance. Such research would fit into the broader call to move evidence-based crime prevention toward a second-generation body of research that offers more practical guidance for practitioners who need scientific evidence relating to effective program implementation and maximizing return on investment (Sidebottom & Tilley, 2022; Weisburd et al., 2017).

We feel that our study findings also call into question the standard procedure of GDT coverage, with sensors installed across large, contiguous areas. Contiguous deployment of GDT sensors may lead to a large number of street segments at low risk of gun violence falling within the target area, given the highly concentrated nature of crime. The recent study by Ratcliffe et al. (2019) indicates that contiguous deployment could possibly be replaced with a method that better reflects the clustered nature of crime patterns. In this study, the Philadelphia Police Department installed 17 acoustic GDT sensors at pre-existing CCTV camera locations at high-crime places in the city. In addition to being more cost-effective, this approach may lead to more positive crime prevention outcomes by increasing the focus of police response within the most high-risk places (Piza, 2019). However, we should note that Ratcliffe et al. (2019) analyzed a GDT system from a vendor other than SoundThinking. It may be that unique aspects of the ShotSpotter system—namely, the review of GDT alerts by the acoustic experts stationed at the SoundThinking incident review center (La Vigne et al., 2019; Mares, 2022)—may work more efficiently within larger contiguous geographies where more sounds of gunfire can be detected. Furthermore, all GDT systems require clear acoustic pathways unobstructed by tall buildings, a nearby power source, and cooperation from private businesses or homeowners when GDT sensors need to be mounted on private property (La Vigne et al., 2019). All things considered, targeting only the most violent micro-places with GDT may be easier said than done.

Last, we acknowledge the current study, like most research, suffers from certain limitations that should be mentioned. The crime data we received from KCPD did not have a location type variable allowing us to exclude incidents occurring indoors from the analysis. This would have been helpful for the analysis, given that GDT is meant to detect gunfire occurring outdoors (Mares, 2022). In recent discussions with KCPD personnel, we were informed that 70% of fatal shootings over our study period occurred outdoors. They were unable to provide the outdoor percentage for non-fatal shootings.[16] Assuming non-fatal shootings occur outdoors at a similar rate as fatal shootings, most gunfire in Kansas City occurs in public outdoor areas.[17] However, while recognizing this fact—and noting that prior GDT research has predominately not excluded indoor events from their statistical analysis—we acknowledge the possibility that the inclusion of indoor gun crimes may have influenced the crime change estimates and/or confidence intervals of our models. The pre-intervention period is over 2 years shorter than the postintervention period, owing to some data incorporated in the matching algorithm being unavailable before 2007. While the covariate balance and parallel trends achieved by the microsynthetic control method allowed for valid crime change estimates, having a longer pre-intervention period would have increased sample size and statistical power. We were unable to disentangle underlying typologies of shots fired incidents for the analysis. Certain shots fired events may involve random or celebratory gunfire, where the suspects did not intend to hit any targets. Other shots fired events may involve suspects intentionally shooting property (e.g., unoccupied motor vehicles) to intimidate or vicariously harm specific intended victims. Classifying shots fired in such a manner would have added nuance to the observed reduction—and shed light on the aforementioned potential change in citizen reporting behavior—but required case report narratives we did not have access to.

Despite these data limitations, the current study has important implications for GDT use as a crime prevention tool. Despite increased collection of NIBIN ballistic evidence and gun recoveries, shots fired calls for service was the only outcome measure that reduced following GDT deployment. No violent crimes involving identified victims—fatal shootings, non-fatal shootings, and gun assault/robbery—were impacted by GDT. Agencies that highly prioritize increasing evidence collection and reducing unauthorized firearm discharges may consider dedicating necessary resources to acquire GDT. This may soon be facilitated by low-cost alternatives to current GDT solutions, which are in the early stages of development (Morehead et al., 2019). Agencies that prioritize the reduction of gun violence victimization, however, should consider whether resources are better used for solutions other than GDT.

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CONFLICT OF INTEREST

The authors confirm that they have no conflict of interest to declare.

ORCID

Eric L. Piza https://orcid.org/0000-0002-3753-5004

ENDNOTES

[1] https://www.soundthinking.com/company/.

[2] See http://www.shotspotter.com/system/content-uploads/SST_FAQ_January_2018.pdf.

[3] https://ucr.fbi.gov/crime-in-the-u.s/2019/crime-in-the-u.s.-2019/tables/table-78/table-78-state-cuts/missouri.xls

[4] https://giffords.org/lawcenter/state-laws/concealed-carry-in-missouri/.

[5] KCPD's response to GDT alerts was ascertained through personal communication with KCPD Detective Mindy Earle, Homeland Security Unit, Kansas City Regional Fusion Center.

[6] KCPD policy prohibits the public disclosure of the GDT target area boundaries. We therefore do not present any maps of the GDT target area. It should be noted that KCPD's decision to keep the GDT target area confidential echoes policies enacted by police in other jurisdictions (Lawrence et al., 2018).

[7] See section 8 in the ShotSpotter Frequently Asked Questions document: https://www.shotspotter.com/system/content-uploads/SST_FAQ_January_2018.pdf.

[8] Geocoding match rates for all project data were at least 95%, well above the minimum acceptable geocoding rates identified by past empirical research (Andresen et al., 2020; Briz-Redón et al., 2020; Ratcliffe, 2004).

[9] The GDT target area included all street segments falling within the boundary created by the individual GDT sensors as well as all street segments within 0.25 mi^2 to reflect the fact that GDT sensors can typically detect sounds of gunfire to that distance (Irvin-Erickson et al., 2017). In Kansas City, approximately a quarter (2,852 of 11,510) of GDT alerts occurred within this 0.25 mi^2 buffer, which demonstrates how GDT coverage would have been underestimated if the target areas was restricted to street segments with GDT sensors. The catchment zone includes all street segments within a 0.25 mi^2 of the treated area (i.e., the boundary created by the individual GDT sensors as well as all street segments within an additional radius of 0.25 mi^2).

[10] A limitation of street segments is the over counting of crimes recorded as occurring on street intersections, given that such crimes overlap with all street segments that comprise the intersection (Braga et al., 2011). In the current study, data provided by KCPD were geocoded with an offset distance, meaning they did not overlap with any underlying street segments. This allowed all data points to be aggregated to a single street unit for the analysis. One of the anonymous article reviewers stated that street segments may not accurately reflect the true location of an incident, offering a victim who "drags themselves a block over before collapsing," "victims who show up in a hospital and give fake incident addresses," and shots fired coming from "quite far away" as examples. In the first case, only the small subset of the 1597 street segments comprising the GDT area boundary would seemingly be at risk (and only for incidents where victims drag themselves away—rather than toward—other GDT-covered street segments). In the second case, victim dishonestly would seemingly threaten all geographic units of analysis, as victims would likely choose to report a location substantially far away from the crime scene if they wish to conceal the true shooting location. While shots fired may be reported from a substantial distance away, any shot reported within the ~3.5 mi^2 GDT target area will be counted toward the treatment group, even if the address reported by the citizen does not accurately reflect the street segment the gunshot occurred on. Kansas City's GDT target area is twice as large as census tracts on average (~3.5mi^2 vs. ~1.58 mi^2 as measured in ArcGIS Pro). Given this, using census tracts as the unit of analysis may have presented a higher risk of misclassification for gunfire events occurring toward the boundary.

[11] Ferman et al. (2020) demonstrated that longer pre-intervention periods reduce the influence of matching algorithm specification on the calculated treatment effect in synthetic control models. This minimizes the chance of a Type I error. Similarly, the simulation analysis of Abadie and Vives-i-Bastida (2022) demonstrated that the threat of overfitting in synthetic control analysis is minimized when pre-treatment periods total at least 20 and when control weight variance is no higher than 0.25. While we are unaware of any such research specific to the microsynthetic control method, our pre-intervention period is longer than 14 of the 16 synthetic control studies reviewed by Ferman et al. (2020; see Table 1) and the control weight variance is below 0.25 in both the main and displacement analysis (see Tables 3 and 5).

[12] The U.S. Census Bureau's American Community Survey 5-year estimates are available only back to 2009. Observations from earlier were assigned the 2009 5-year (2005–2009) values of all census measures.

[13] We attempted to also include arrests made by patrol officers while responding to gun violence related calls for service as a process measure, but this measure was observed sparsely throughout the study period (e.g., only 55 occurred in the GDT target area during the ~7-year intervention period). The sparsity of this measure prevented the microsynthetic control model from converging. For those interested, the distribution of this measure can be explored through the "gcarrests_" variable in the analysis database.

[14] Figures for measures that did not achieve statistical significance are presented in the appendix (see Figures A1 - A8).

[15] Given our use of count dependent variables in the microsynthetic control models, we were unable to analyze proportional measures, such as shooting fatality rate. However, we used the Campbell Collaborations' Effect Size Calculator to test whether the proportion of fatal shootings differed across the target and control areas in both the main and displacement analyses. In both cases, 95% confidence intervals crossed 0, meaning observed differences were not statistically significant. These findings are presented in Table A1 in the Appendix.

[16] The outdoor proportion of fatal shootings was ascertained through personal communication with KCPD Intelligence Analyst Logan Konopasek, Homicide Unit, Perpetrator Information Center, Special Investigations Division.

[17] Recent research has found that indoor shootings are more lethal than outdoor shootings (Circo & Wheeler, 2021; P. J. Cook et al., 2019), which raises the prospect that a higher percentage of non-fatal shootings occurred outdoors than fatal shootings over the study period.

[18] Some prior *microsynth* studies have used 999 permutations for statistical inference tests. We were unable to use that many permutations in light of our large sample sizes, with the databases including over 5 million observations. Using Northeastern University's high-speed cloud computing service, running the cumulative analyses with 500 permutations took approximately 18 h. Models did not converge after 24 h when 999 permutations were used. Nonetheless, we believe 500 permutations are sufficient given that total is twice as large as the benchmark recommended by the creators of the microsynthetic control method (Robbins & Davenport, 2021; Robbins et al., 2017).

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APPENDIX

TABLE A1 A 2 by 2 contingency table testing shooting fatality rates.

Main analysis		
	Fatal	**Non-fatal**
Treatment	107	389
Control	108	395
Test statistics		
r	0.0012	
95% confidence interval	−0.0607	0.0632
Fisher's Zr	0.0012	
95% confidence interval	−0.0608	0.0632
v	0.001	
Displacement analysis		
	Fatal	**Non-fatal**
Treatment	77	328
Control	65	299
Test statistics		
r	0.0149	
95% CI	−0.0558	0.0854
Fisher's Zr	0.0149	
95% CI	−0.0558	0.0856
v	0.0013	

Note: Test statistics in this table were calculated via the Campbell Collaboration's Effect Size Calculator: https://www.campbellcollaboration.org/research-resources/effect-size-calculator.html. Findings can be replicated by entering the treatment and control fatal and non-fatal shooting counts in the 2 by 2 Frequency Table tool in the Correlation Coefficient (*r*) menu.

A1–A8

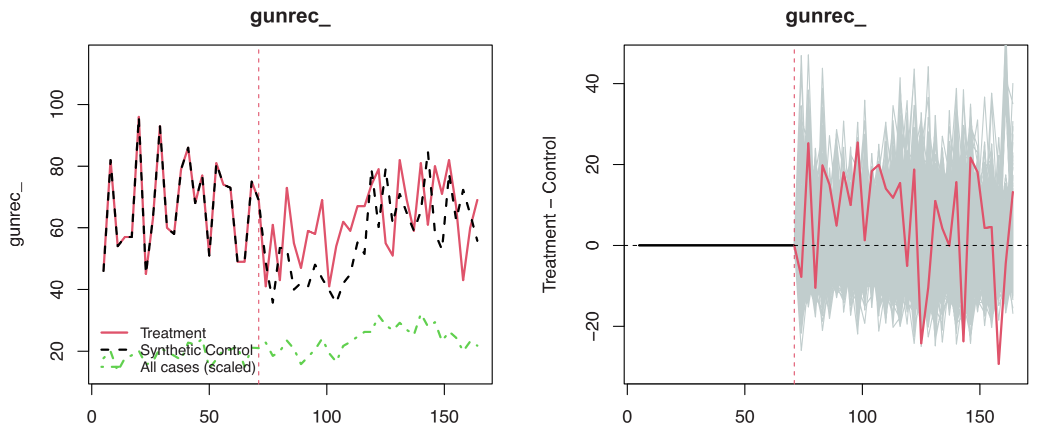

FIGURE A1 Gun recovery synthetic control estimates, main analysis. [Color figure can be viewed at wileyonlinelibrary.com]

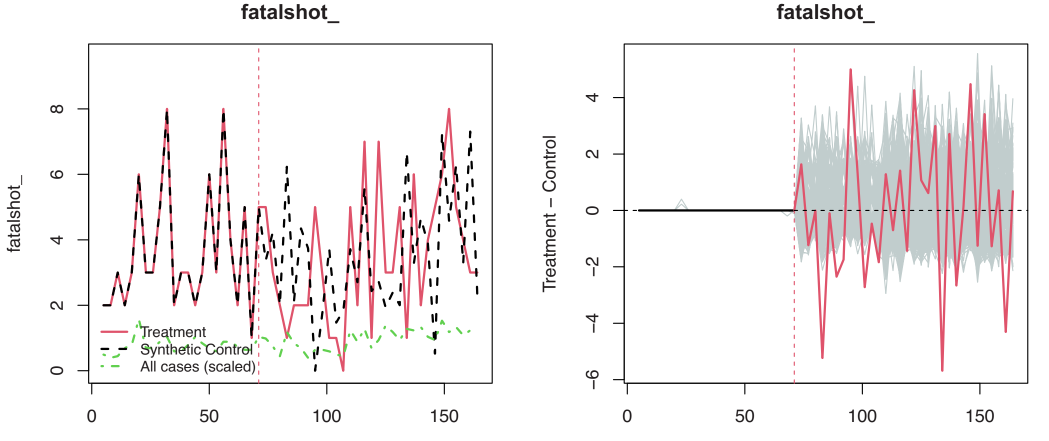

FIGURE A2 Fatal shootings synthetic control estimates, main analysis. [Color figure can be viewed at wileyonlinelibrary.com]

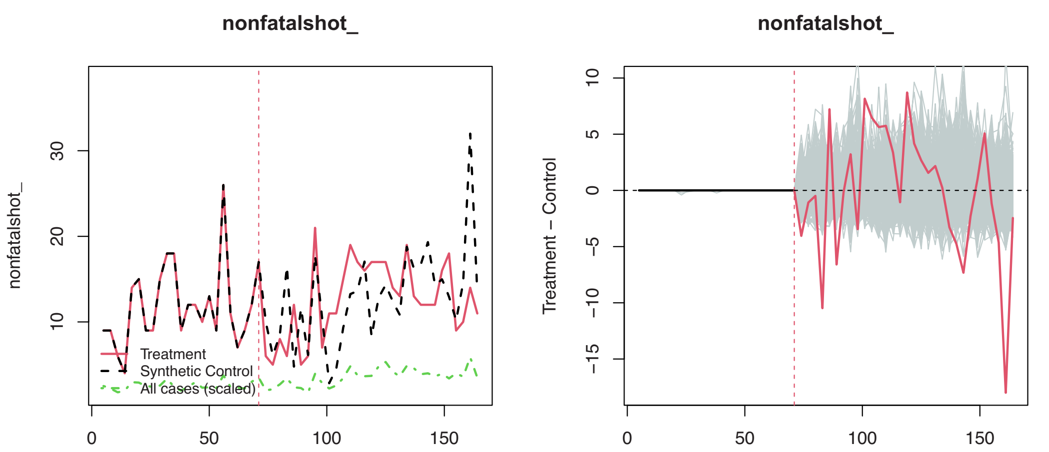

FIGURE A3 Non-fatal shootings synthetic control estimates, main analysis. [Color figure can be viewed at wileyonlinelibrary.com]

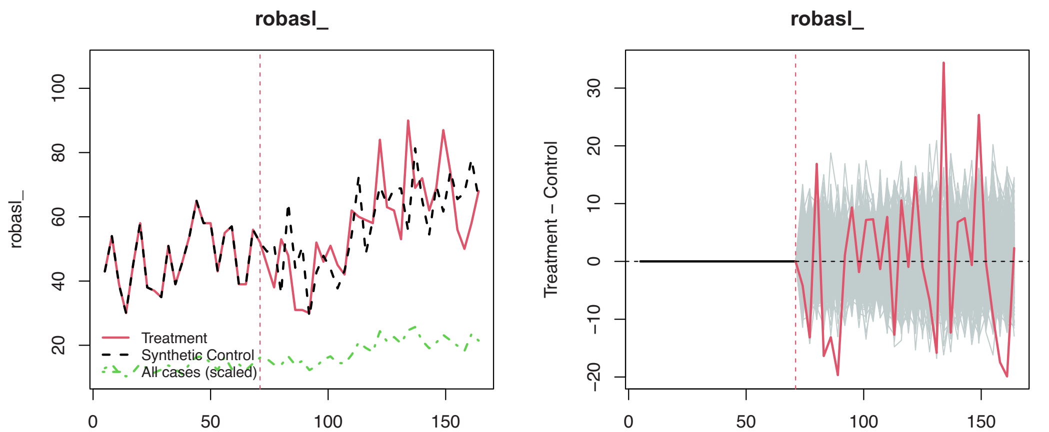

FIGURE A4 Firearm assault and robbery synthetic control estimates, main analysis. [Color figure can be viewed at wileyonlinelibrary.com]

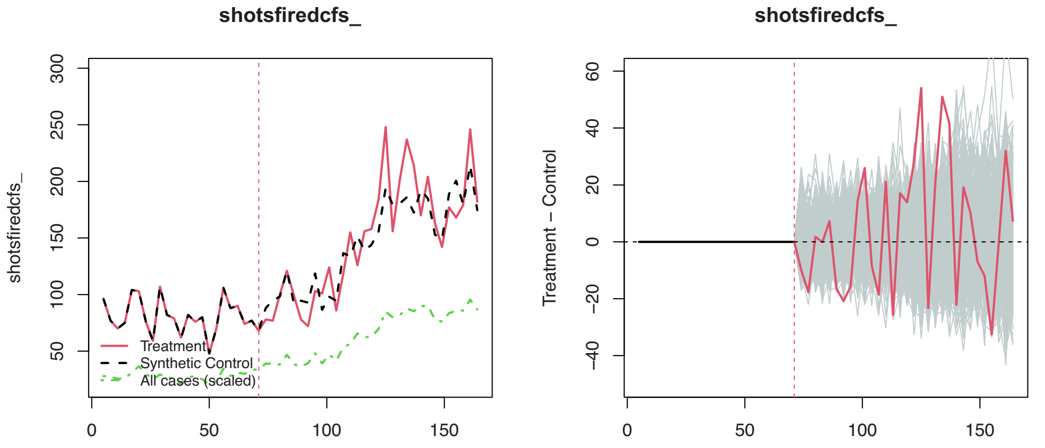

FIGURE A5 Shots fired CFS synthetic control estimates, displacement analysis. [Color figure can be viewed at wileyonlinelibrary.com]

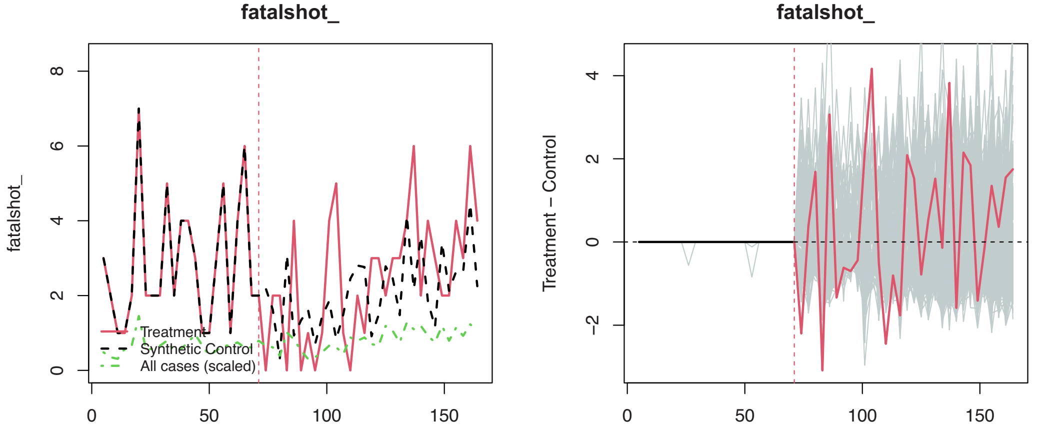

FIGURE A6 Fatal shootings synthetic control estimates, displacement analysis. [Color figure can be viewed at wileyonlinelibrary.com]

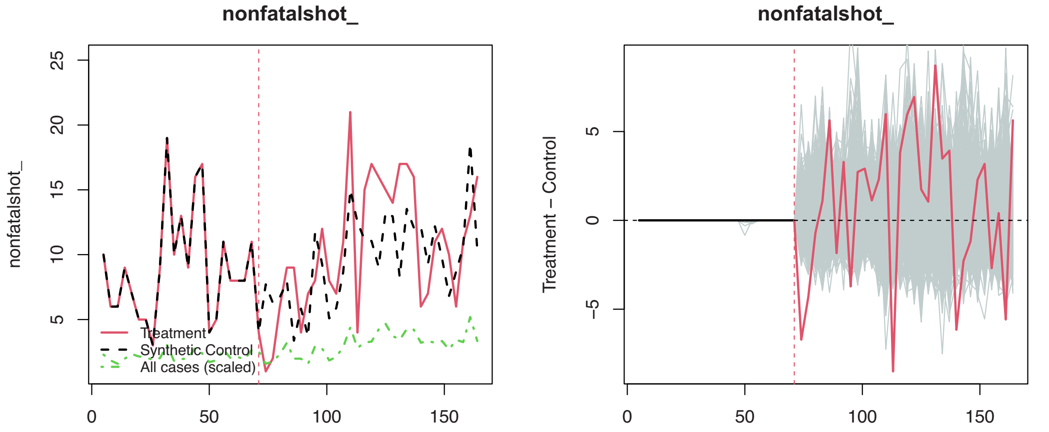

FIGURE A7 Non-fatal shootings synthetic control estimates, displacement analysis. [Color figure can be viewed at wileyonlinelibrary.com]

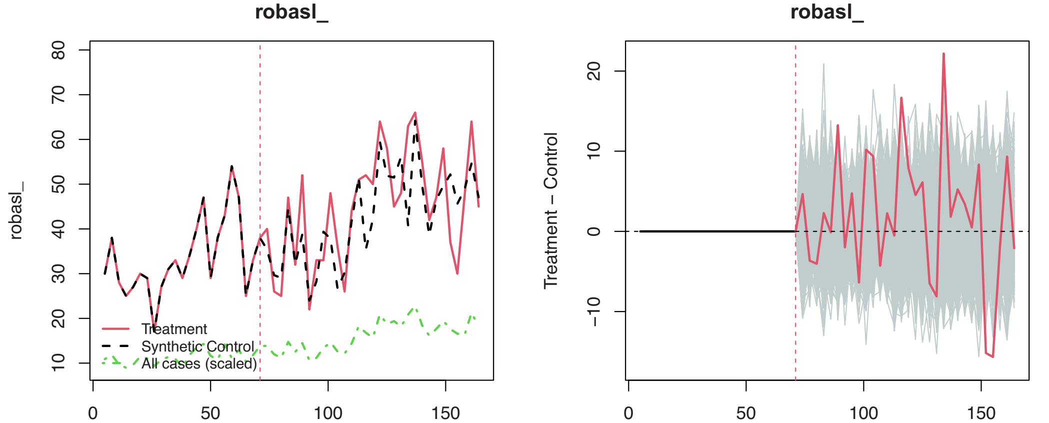

FIGURE A8 Firearm assault and robbery synthetic control estimates, displacement analysis. [Color figure can be viewed at wileyonlinelibrary.com]

AUTHOR BIOGRAPHIES

Eric L. Piza is professor of Criminology and Criminal Justice, director of Crime Analysis Initiatives, and co-director of the Crime Prevention Lab at Northeastern University. His research is centered on the spatial analysis of crime patterns, evidence-based policing, crime control technology, and the integration of academic research and police practice.

David N. Hatten is a Ph.D. researcher at the Boston Area Research Initiative (BARI), Northeastern University. His research interests include spatial and temporal crime analysis, place-based policing evaluation, and neighborhood effects.

George O. Mohler is the Daniel J. Fitzgerald professor of Computer Science at Boston College. His research centers on statistical and deep learning approaches to solving problems in spatial, urban, and network data science.

Jeremy G. Carter is professor and executive associate dean at the Paul H. O'Neill School of Public and Environmental Affairs at Indiana University—Purdue University Indianapolis. His primary research interests are in policing, law enforcement intelligence, crime analysis, criminal justice technology, and evidence-based policy.

Jisoo Cho is a Ph.D. student at John Jay College of Criminal Justice, City University of New York Graduate Center. Her research interests include hotspot policing, crime prevention through environmental design, and geographic information systems.