Document Title:	**The Impact of Gunshot Detection Technology on Gun Violence in Kansas City and Chicago: A Multi-Pronged Evaluation**
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Document Number:	**308357**
Date Received:	**January 2024**
Award Number:	**2019-R2-CX-0004**

The Impact of Gunshot Detection Technology on Gun Violence in Kansas City and Chicago: A Multi-Pronged Evaluation

Final report submitted to the National Institute of Justice in partial fulfillment of grant number 2019-R2-CX-0004
Grant period: 1/1/2020 – 3/31/2023
Total award amount: $503,129

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EXECUTIVE SUMMARY

This report presents what, to our knowledge, is the largest research project on gunshot detection technology (GDT) to date. We leverage over a decade of data from Kansas City, MO and Chicago, IL to measure how GDT contributes to policing and public safety. Both cities installed ShotSpotter GDT systems in 2012, allowing for a long-term quasi-experiment of program effects. Kansas City Police Department installed GDT in October 2012, with the target area covering approximately 3.5 square miles of the city and remaining unchanged to this day. Chicago Police Department installed GDT over approximately 3.0 square miles of the city in August 2012 with the coverage area expanding to 22 additional police districts between February 2017 and May 2018. This expansion led to approximately 100 square miles being covered by GDT in Chicago.

The GDT system in Kansas City detected 11,517 gunfire incidents through the end of our study period (12/31/2019). The GDT system in Chicago detected 85,572 gunfire incidents over the full installation period from 2/6/17 – 12/31/19.[1] Based upon ShotSpotter's reported annual subscription costs of between \$65,000 and \$90,000 per square mile[2], GDT coverage costs between \$227,500 and \$315,000 per year in Kansas City and between \$8.8M and \$12.3M per year in Chicago.

Our project explored three specific research questions in both study settings. The research questions and overview of pertinent findings appear below.

[1] Chicago PD's GDT system did not retain gunshot alert data for the initial installation phase, as this was considered a pilot project.
[2] See section 8 in the Shotspotter Frequently Asked Questions document: https://www.shotspotter.com/system/content-uploads/SST_FAQ_January_2018.pdf

What is the Effect of GDT on Officer Response and Search Behavior?

To explore this research question, we incorporated automated vehicle locator (AVL) data that allows for the tracking of patrol car movement throughout time and space. We measure the level to which officer responses to GDT alerts and calls for service (CFS) differ across response times, proportion of incidents during which vehicles stopped on scene, and distance between vehicle stop location and reported incident address.

Results indicate in Kansas City:

- Officers stopped their vehicles more often when responding to GDT alerts than citizen calls for service (CFS) for shots fired incidents (93.9% vs. 90.6%), and fatal shootings (100% vs. 97.5%).
- Officers stopped their vehicles closer to the reported/detected location of gunfire when responding to GDT alerts than CFS for shots fired incidents (35.66 m vs. 54.62 m), non-fatal shootings (42.5 m vs. 48.91 m), and fatal shootings (18.67 m vs. 45.43 m)
- Officers arrived on the scene quicker when responding to GDT alerts than CFS for shots fired incidents (266.82 s vs. 390.87 s) and fatal shootings (140.44 s vs. 417.80 s), and took longer to arrive on scene for non-fatal shootings (428.20 s vs. 383.19 s).

Results indicate in Chicago:

- Officers stopped their patrol car more often when responding to GDT alerts than CFS for shots fired incidents (74.2% vs. 61.0%), non-fatal shootings (91.4% vs. 85.2%), and fatal shootings (95.6% vs. 91.1%).

- Officers stopped their patrol car closer to the reported/detected location of the gunfire event when responding to GDT alerts than CFS for shots fired incidents (26.09 m vs. 30.69 m), non-fatal shootings (18.16 m vs. 21.95 m), and fatal shootings (15.58 m vs. 22.74 m).
- Officers arrived on the scene quicker when responding to GDT alerts than CFS for shots fired incidents (138.67 s vs. 148.55 s) and non-fatal shootings (85.05 s vs. 94.69 s), and took longer to arrive on scene for fatal shootings (63.22 s vs. 60.00 s).

What is the Effect of GDT on Crime Occurrence?

This analysis applies the microsynthetic control method (Robbins et al., 2017; Saunders et al., 2015) to longitudinally measure process and outcome variables across street segments in the GDT target area and a control area comprised of weighted street segments from other areas of the city. The microsynthetic control method approximates the conditions of a randomized experiment by creating a control area that mimics the pre-intervention trends of dependent variables and covariates that may influence their occurrence.

Given the static nature of the GDT target area in Kansas City, GDT effect was tested through an individual model. The staggered roll out of GDT in Chicago required a modified approach. A separate model was conducted for each of the 10 GDT installation phases, with the crime changes observed in each individual phase combined to measure the cumulative aggregate average treatment effect of GDT.

Results indicate in Kansas City:

- NIBIN evidence collection was 30.4% higher in the GDT target area than the weighted control area.
- Shots fired calls for service was 22.2% lower in the GDT target area than the weighted control area.
- Gun recovery was 11.2% higher in the GDT target area than the weighted control area, although this finding only approached statistical significance.
- NIBIN evidence collected was 29.7% higher in the surrounding catchment area than the weighted control area, indicting GDT generated a diffusion of benefits.

Results indicate in Chicago:

- 15.6 more fatal shootings occurred in GDT target areas over the duration of the intervention period, on average.
- 77.5 more non-fatal shootings occurred in GDT target areas over the duration of the intervention period, on average.
- 115 more gun assaults and robberies occurred in GDT target areas over the duration of the intervention period, on average.

What is the Effect of GDT on Evidence Collection and Case Clearance?

This final research question is explored through a case-control quasi-experiment that uses the entropy balancing approach (Hainmueller, 2012). Differences in process and outcome variables are measured across gun violence incidents occurring in the GDT target area and a control group comprised of weighted incidents occurring in other areas of the city. Entropy balancing weights all control groups incidents so that they cumulatively equal the treatment group across a range of covariates, similar to what the microsynthetic control method accomplishes with geographic units of analysis. Following entropy balancing, the effect of GDT was tested through using logistic regression models incorporating the weights from the entropy matching procedure as probability weights in a logistic regression model (Zhao & Percival, 2017).

Results indicate in Kansas City:

- Shots fired calls for service occurring in the GDT target area were 18% more likely to be classified as unfounded as compared to untreated cases.
- GDT did not significantly influence the likelihood of evidence collection or case clearance in non-fatal and fatal shooting incidents.

Results indicate in Chicago:

- Firearms were 45% more likely to be recovered from fatal shooting incidents occurring within the GDT target area as compared to the control area.
- GDT did not significantly influence the likelihood of case clearance in fatal shooting incidents.
- GDT did not significantly influence the likelihood of evidence collection or case clearance in non-fatal shooting incidents.

Policy Implications

Findings have important implications for the use of GDT as a crime control intervention. GDT seems to positively impact a number of procedural aspects of police response to gun fire. GDT further demonstrates a positive influence on evidence collection. Unfortunately, these procedural benefits did not translate to any meaningful improvements to crime control outcomes. Improving the effectiveness of GDT may rely on police deploying the technology within contexts that facilitate success. Research has allowed for such practical considerations with other technologies. Future GDT research should strive to identify contextual factors associated with heightened/lowered GDT performance. Continuing upon the current pace of GDT adoption in policing perhaps should be contingent upon the field gaining a better understanding of exactly how to deploy and integrate GDT in a manner that maximizes likelihood of success. Given the high cost of the technology, such an approach would be prudent.

CHAPTER ONE: BACKGROUND AND PROJECT OVERVIEW

Gunshot Detection Technology

The field of policing has experienced a great deal of change over recent decades. A main staple of this evolution has been the emphasis placed on technological solutions to crime and disorder. Gunshot Detection Technology (GDT) has particularly increased in popularity over recent decades. 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). These characteristics allow GDT to distinguish gunshots from other loud noises and enables the detection of gun shots based upon the unique signature of the sounds (Chacon-Rodriguez et al., 2011; Maher, 2007). GDT systems then assign precise geographic coordinates to gunfire incidents, allowing for more accurate measurement of crime incident locations than what is reported second hand via callers to the 9-1-1 emergency line (Piza et al., 2023). GDT was originally developed for earthquake detection and later amended for military use (Mares & Blackburn, 2012). The U.S. Department of Defense began partnering with the private sector in the mid-1990s for the purpose of re-formulating the technology for use by local law enforcement (Mazerolle et al., 1998), paving the way for the modern GDT systems used today.

ShotSpotter is the global industry leader in GDT. The popularity of ShotSpotter is reflected in its expanding business model, as the company is publicly traded on the stock market as of June 2017. GDT systems installed by ShotSpotter use acoustic sensors that are strategically placed in an array of approximately 20 sensors per square mile, according to the company's website.[3] Each gunshot detected by ShotSpotter is manually reviewed and verified by a team of gunshot acoustic experts at the company headquarters in Newark, CA. The gunshot acoustic experts are stationed

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

within the Real-Time Incident Review Center, established by the company in early 2011. When the gunshot acoustic expert confirms the nature of the recording, they verify the sounds as gunfire or mark the event as a false positive (see Mares, 2022 for more information on GDT detection error types). The acoustic expert notes the number of shots fired and general caliber of the weapon for each confirmed gunfire event and has the ability to append the alert with other critical intelligence (e.g., whether the shooter is on the move). This information is then relayed directly to the 9-1-1 dispatch center of the police department in question. ShotSpotter guarantees customers that the process from gunshot detection to dispatcher notification will be completed in an average of less than 60 seconds but claims to have a current average of less than 30 seconds. It is important to note that this process is an innovation to the original ShotSpotter model, as police departments were responsible for their own review of gunshots prior to the establishment of the Real-Time Incident Review Center.[4]

Researchers have previously heralded GDT as a tool that can greatly assist in the development of problem-oriented policing strategies (Irvin-Erickson et al., 2017; Watkins et al., 2002). Despite such proclamations, the research evidence on GDT is underdeveloped. 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 adoption of the technology. Over 200 public safety agencies worldwide have adopted ShotSpotter systems to date.[5] The level to which research evidence informed such widespread adoption is questionable.

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[4] The Principal Investigator learned about the gunshot review process during a site visit to ShotSpotter headquarters on 3/26/18. During the visit, the PI met and was given a presentation of the technology by the ShotSpotter leadership team and viewed the activities of acoustic gunshot experts in the Real-Time Incident Review Center.

[5] https://www.shotspotter.com/cities/

Review of Relevant Literature

GDT Process Evaluations

Much research on GDT has focused on the technology's performance in detecting gunfire and identifying the location of gunfire incidents. 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, failing to detect about 20%. The authors cautioned that their field trial involved blank firearm rounds, which emit a different muzzle blast wave form than live ammunition. In light of this caveat, they hypothesized that the GDT system would detect significantly more than 80% of gunfire incidents under real-life conditions. Evaluations of GDT detections conducted in real-life settings largely support Watkins et al.'s (2002) hypothesis, generally indicating that GDT can significantly increase the proportion of gunfire events that come to the attention of the police. Using data from Washington, DC and Oakland, CA, Carr & Doleac (2016) found that only 12% of gunfire incidents detected by GDT resulted in a 9-1-1 call to report gunshots and only 2-7% of GDT alerts resulted in reports of assaults with a deadly weapon. Irvin-Erickson et al. (2017) also used data from Washington, DC to calculate the relative sensitivity of GDT: the ratio of GDT detections to calls for service. Within the 20-minute window from GDT alerts (the default time frame used in the analysis), they found a relative GDT sensitity of 1.52. Their findings also showed that GDT sensitivity signfincatly varied by month, day of the year, weekends vs. weekdays, and hour of the day. However, in most cases GDT-to-calls ratios were above 1, supporting the general notion that GDT accurately detects gunfire events.

Findings from this body of research suggest GDT systems can help minimize the "dark figure of crime" reflecting unreported incidents that never come to the attention of the police. Such benefits may be particularly pronounced in high-violence, disenfranchised neighborhoods where police lack the legitimacy necessary for residents to trust that a police response would be helpful (Kirk & Matsuda, 2011). However, this research rests on the assumption that all GDT alerts accurately identify sounds of gunshots. It is possible that a proportion of GDT alerts are false positive events, where no actual gunshot occurred. 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. We should note, however, that the GDT systems analyzed in these studies were installed and operated by vendors other than ShotSpotter. Given ShotSpotter is the predominate manufacturer of GDT today, it is unclear whether findings from prior research on the effect of false positives apply to ShotSpotter systems.

Litch & Orrison (2011) observed that only 18% and 24% of GDT alerts had an associated 9-1-1 call in Hampton, VA and Newport News, VA, respectively. To examine the influence of potential false positive alerts on this findings, Litch & Orrison (2011) restricted their analysis to GDT alerts where physical evidence of a gunshot was found on-scene, finding only 39% and 43% of "confirmed" gunfire incidents had an associated 9-1-1 call in Hampton, VA and Newport News, VA, respectively. A partially block-randomized field experiment in Philadelphia, PA suggested that false positive GDT alerts may place a significant burden on police patrol operations (Ratcliffe et al., 2019). The experimental design assigned 17 surveillance camera sites to receive a GDT sensor, with another 17 surveillance camera sties designated as the control group. During an 8-month study period, police responses to gunshot incidents increased by over 259% in the 800 feet surrounding the GDT target locations with no significant increase in the number of confirmed gunfire-related crimes, as compared to the control group. Ratcliffe et al. (2019) concluded the GDT system substantially increased the workload of police attending to incidents for which no evidence of gunfire was found while having no effect on confirmed shooting events. Similar workload increases have been observed elsewhere, with police responses to gunfire events increasing 80% and 287% following the introduction of GDT in St. Louis (Mares & Blackburn, 2021) and Dallas (Mazerolle et al., 1998), respectively.

Further research has focused on the spatial accuracy of GDT alerts. Fields tests have measured the distance between locations of gunshots in the field and the geographic coordinates assigned by GDT systems. Aguilar's (2015) review of field tests in both urban and military environments reported gunfire scenes to be between 10 and 25 meters from their corresponding GDT-reported location, considered close enough to identify shooter locations in terms of street names and block numbers. A field trial conducted by Mazerolle et al. (2000) involved firing blank rounds from pre-determined locations to test the spatial accuracy of GDT in Redwood City, CA. The field trial results found an average margin of error of 25 feet. More recent research has quantified GDT accuracy by measuring the distance between GDT alerts and locations reported via calls for service (CFS). Such measures may better quantify the benefits provided by GDT, given officers are dispatched to CFS locations when GDT is unavailable. Wheeler et al. (2020) found reported addresses for shooting incidents were between 60 and 90 feet from the related GDT alert on average, depending on the geocoder used to map the data. In a pilot study conducted in preparation for the current project, Piza et al. (2023) found GDT and CFS locations were an average of 433.91 feet apart, with a median of 234.91. Furthermore, GDT and CFS locations were geocoded to the same street segment in 46.95% of cases. In other words, in more than half of gunfire incidents, officers responding to CFS locations would be a meaningful distance away from where the gunshot occurred, as reflected in the GDT data.

GDT Outcome Evaluations

A number of studies have evaluated the effect of GDT on pertinent crime and justice outcomes. The earliest outcome evaluations focused on the effect of GDT on police officer response times. Mazerolle et al. (1998) tested the effect of GDT on police officer response times and officer workloads. Findings suggested that GDT had a limited effect on response times, with a reduction of only 1 minute (7%) observed in the GDT coverage area, which did not outperform the control area. Mazerolle et al. (1998) further reported that no offenders were apprehended in response to either a GDT detection or citizen call for service (CFS) during the study period. They found further evidence that the implementation of a GDT system can significantly increase police officer workloads.

Using data from Brockton, Massachusetts, Choi et al. (2014) found that the introduction of GDT was associated with a 33% faster time to dispatch shots fired calls and a 12% increase in officer response times to these same events. They found no evidence of whether gunfire events were associated with any law enforcement activities, such as evidence collection or arrest.[6] Lawrence et al. (2019) analyzed GDT systems in Denver, CO, Milwaukee, WI, and Richmond, VA, finding response times to GDT activations to be between 14% and 28% faster as compared to responses to CFS. Mares and Blackburn twice evaluated the GDT system in St. Louis, MO. Their evaluation of the original GDT system demonstrated improved police response times to shots fired CFS (Mares & Blackburn, 2012). However, a more recent evaluation of the expanded system observed that both dispatch and travel time were statistically slower for GDT alerts during the expansion period (Mares & Blackburn, 2021).

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[6] Incidents with a disposition indicative of evidence identification (e.g. investigated, under investigation, report taken, or hot sheet) were considered as having generated an officer "action." Incidents marked "matter settled," "complaint filed", or "arrest made" were considered the highest desired outcome, indicative of case closure.

Recent research has tested the effect of GDT on non-police first responder responses to shooting scenes. This literature acknowledges the influence of EMS transport time on the mortality outcomes of gunshot victims (Circo & Wheeler, 2021; Hatten & Wolff, 2020). Goldenberg et al. (2019) examined 627 shooting events in Camden, NJ to quantify differences of police and EMS transport to trauma care across GDT activations and 9-1-1 calls for service. Their results showed no significant difference in mortality rates between GDT activations and 9-1-1 calls. Events originating from a GDT activation, however, were accompanied by faster response times by both police and EMS. Interestingly, police transported victims in 36% of events originating from GDT, as compared to just 4% of shooting events reported through 9-1-1, suggesting that GDT facilitated police-initiated "scoop and run" hospital transports that could lower a victim's time to trauma care (Band et al., 2014; Wandling et al., 2016).

Over recent years, researchers have increasingly evaluated the potential of GDT to prevent gun crime. Mares & Blackburn (2012) conducted an interrupted time series analysis in the neighborhoods covered by GDT, control neighborhoods without GDT, and the city-wide 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 & Blackburn (2012) found only approximately 2% of GDT gunfire alerts led to the ballistic evidence of a shooting, as compared to a city-wide rate of 17% for shots fired calls for service.

Mares & Blackburn (2021) once again evaluated the GDT system in St. Louis after the coverage area expanded in early 2013. They incorporated a longitudinal quasi-experimental panel design, selecting as control areas neighborhoods with similar levels of crime and socio-demographic conditions as the GDT target areas. The case control analysis was conducted to test

GDT effect across 3 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. Overall, 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 (Forthcoming) found GDT led to sizable crime reductions in Cincinnati, OH. Shots fired calls for service and gun assaults experienced statistically significant reductions of 45% and 46%, respectively, in the GDT target area as compared to the control area.

The aforementioned study by Lawrence et al. (2019) analyzed GDT systems in Denver, CO, Milwaukee, WI, and Richmond, VA. The initial deployment of GDT was followed by a subsequent expansion of the target area in each of the three cities. Analyses found disparate effects across the cities. GDT was associated with significant increases in gun crime calls for service with no significant changes in reported gun crimes in Milwaukee and Richmond. Less restrictive statistical models found some evidence of crime reduction in Richmond. No significant effects were observed for Denver. Lawrence et al. (2019) further found that following the installation of GDT the proportion of cases where canvases were conducted significantly increased across all sites and the number of victims interviewed significantly increased in Richmond. A marginally significant (*p.*=0.10) increase in the collection of shell casings at shooting scenes in the GDT target areas collectively, with the increase achieving statistical significance in Richmond. No significant increases were observed for the change in the number of cases resulting in an arrest or the retrieval of a weapon on scene wither within or across sites.

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 though a series of Bayesian structural time series modes, with data from other, similar jurisdictions incorporated as the control condition. Logistic regression models tested whether the likelihood of a case being cleared by arrest changed in the post-implementation period. Results indicate that the integrated GDT/CCTV system did not lead to any measurable improvements to public safety. Overall crime levels did not significantly change, homicides and shootings increased in the post-implementation phase, and case clearance of homicides and shootings decreased in the post-implementation period.

Doucette et al. (2021) analyzed the effect of GDT on firearm homicides and arrests through an analysis of 68 large metropolitan counties in the U.S. 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. Counites in states with permit-to-purchase firearms laws saw a 15% reduction in homicide incidence rates while counties with right-to-carry laws saw a 21% increase in homicide incidence rates. It should be noted, however, that GDT systems rarely cover entire municipalities—let alone counties— given the high cost of GDT and the geographically concentrated nature of firearm violence (Braga et al., 2010) and crime more generally (Lee et al., 2017). The inability to operationalize precise areas covered by GDT as the unit of analysis may bias the results of the study, which Doucette et al. (2021) acknowledge.

Litch & 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. Said differently, crime totals for individual districts do not truly reflect "GDT crimes" because the GDT system did not cover the entirety of the district in most instances, 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 clearances. However, we recommend caution in interpreting these results in light of the methodological limitations.

Literature Review Summary and Scope of the Current Project

Results of process evaluations have consistently demonstrated that GDT systems identify most gunshots fired in the field, generate more spatially accurate incident locations than CFS, and increases police responses to gunfire events, which can heighten officer workloads (Aguilar, 2015; Irvin-Erickson et al., 2017; Mares & Blackburn, 2021; Mazerolle et al., 1998; Piza et al., 2023; Ratcliffe et al., 2019; Wheeler et al., 2020). In this sense, GDT seems to offer the procedural benefits claimed by vendors. Results of outcome evaluations, conversely, indicate that GDT effect on crime prevention and control is mixed. Some studies have found GDT lowers officer response times (Choi et al., 2014; Lawrence et al., 2019; Mares & Blackburn, 2012) with others finding null effects (Mazerolle et al., 1998) or that response to GDT events were significantly slower (Mares & Blackburn, 2021). Similar effect heterogeneity is reflected in evaluation studies on the crime prevention effect of GDT, with the magnitude and direction of crime level changes varying widely across study settings (Doucette et al., 2021; Lawrence et al., 2019; Mares, Forthcoming; 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.

Additional knowledge gaps are evident in the GDT literature. For one, the knowledge base is not nearly as developed as literature on other contemporary police technologies. A recent review of body-worn camera 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 measuring BWC effect on pertinent outcomes (Lum et al., 2020). This is despite BWC being a comparatively infant technology in policing. GDT research stands in stark contrast, as we were able to identify only 10 outcome evaluations, 7 of which tested the technology's crime prevention capacity. It should also be noted that much of the early research on ShotSpotter GDT systems analyze a version of the technology that differs from what is in operation today. ShotSpotter's Real-Time Incident Review Center was established in early 2011 after the current CEO took helm in August 2010.[7] Prior to this time, the review and confirmation of gunfire events was handled on-site by police departments. GDT evaluations incorporating study periods prior to 2011 have generated knowledge on a version of the ShotSpotter system that no longer exists. Furthermore, the benefits GDT could provide police investigations of gun violence have gone largely unexplored. While Choi et al. (2014) and Lawrence et al. (2019) measured GDT effect on on-scene evidence collection, studies have only recently begun to evaluate GDT's potential for facilitating criminal investigations and increasing case clearance (e.g., Vovak et al., 2021).

Looking more closely at study designs, we also note a number of methodological limitations in the GDT literature. 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 (Cook & Campbell, 1979;

[7] The Principal Investigator learned this information from personal communication with ShotSpotter CEO Ralph Clark during a site visit to ShotSpotter Headquarters on 3/26/18.

Farrington et al., 2006). While certain studies have taken efforts to select control areas with similar crime and sociodemographic conditions as the target areas (Mares & Blackburn, 2021; Vovak et al., 2021) this is not common place 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 quantitative matching techniques that ensure statistical equivalency between treatment and control areas. Such statistical matching approaches have increasingly been used to evaluate contemporary crime prevention practices such as hot spots policing (Braga et al., 2012; Rydberg et al., 2018), focused deterrence (Braga et al., 2013; Saunders et al., 2015), CCTV video surveillance (Piza, 2018), and neighborhood police substations (Piza et al., 2020). There is also the question of the appropriateness of units of analysis employed. Some studies on GDT have 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 datasets, 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).

Despite the knowledge gaps present in the literature, many medium and large cities have deployed GDT systems, some of which include sophisticated mobile and camera-integrated systems (Mares, 2022; Vovak et al., 2021). Such jurisdictions have largely adopted GDT within a low-information environment, with key questions pertaining to the efficiency and effectiveness of the technology unanswered or underexplored (Lum & Koper, 2017). The primary objective of this project is to bolster the knowledge-base on GDT through multifaceted evaluations of the GDT systems in Kansas City, MO and Chicago, IL. Both cities installed ShotSpotter GDT systems in 2012, allowing for a long-term quasi-experiment of program effects. Differences in how GDT was deployed in Chicago and Kansas City provide additional insight for both the research and practice communities. KCPD installed GDT in October 2012, with the target area covering approximately 3.5 square miles of the city and remaining unchanged to this day. CPD installed GDT over approximately 3.0 square miles of the city in August 2012 with the coverage area expanding to 22 additional police districts between February 2017 and May 2018. This expansion led to approximately 100 square miles being covered by GDT in Chicago. For both CPD and KCPD, we explore the effect associated with the initial deployment of GDT. For CPD, we have the additional ability to measure whether GDT effect remained static over time or if program effect changed as the system expanded throughout Chicago.

Our project explored three specific research questions in both study settings. The first research question—"What is the effect of GDT on officer response and search behavior?"—uses automated vehicle locator (AVL) data that allows for the tracking of patrol car movement throughout time and space. Leveraging this unique data set, we measure the level to which officer responses to GDT alerts and calls for service differ across response times, proportion of incidents during which vehicles stopped on scene, and distance between vehicle stop location and reported incident address. The second research question—"What is the effect of GDT on crime occurrence?"—applies the microsynthetic control method (Robbins et al., 2017; Saunders et al., 2015) to longitudinally measure process and outcome variables across street segments in the GDT target area and a control area comprised of weighted street segments from other areas of the city. The microsynthetic control method approximates the conditions of a randomized experiment by creating a control area that mimics the pre-intervention trends of dependent variables and covariates that may influence their occurrence. The third research question—"What is the effect of GDT on evidence collection and case clearance?"—uses entropy balancing (Hainmueller, 2012) to measure differences in process and outcome variables across gun violence incidents occurring in the GDT target area and a control group comprised of weighted incidents occurring in other areas of the city. Entropy balancing weights all control groups incidents so that they cumulatively equal the treatment group across a range of covariates, similar to what the microsynthetic control method accomplishes with geographic units of analysis. For each research question, the methodology, analytical approach, and analysis results are reported in a single chapter. This report concludes with a discussion of the policy implications the joint results have for the use of GDT in policing.

CHAPTER TWO: STUDY SETTINGS

Kansas City

Kansas City, Missouri is a large midwestern city with an estimated population of approximately 508,000 living in a land area just shy of 315 square miles. 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 Kansas City Police Department (KCPD) employed 1,299 sworn officers and 520 civilians in 2019 (the final year of our study period) according to the FBI's Police Employee Data.[8]

Kansas City leadership has often sought innovative strategies or technologies to thwart crime, frequently violent crime, over the years. The KCPD has a rich history of such innovation, including being the first law enforcement agency in the United States to share criminal justice information with field officers in the late 1960's[9] to the implementation of ShotSpotter GDT discussed within these pages. Given Kansas City's unfortunate record of high violent crime rates, including for homicide and aggravated assault, local government officials, community stakeholders, and KCPD executive command were seeking any tool possible to help with the city's rising crime rates in the early 2010's.

ShotSpotter's GDT system was brought to Kansas City in 2012 with the goal of enhancing the response to, and prevention of, gunfire-related crime. Congressman Emanuel Cleaver helped secure funding for ShotSpotter through a partnership with the Kansas City Area Transportation Authority (KCATA). The first five years of the ShotSpotter system's funding came from $720,000 made available when a separate KCATA project was completed under budget. The KCATA was

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[8] 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
[9] https://www.ibm.com/ibm/history/exhibits/valueone/valueone_bad.html

the lead agency in both planning and procuring the ShotSpotter system for KCPD. KCATA General Manager Mark Huffer described the joint effort as the first such deployment of ShotSpotter in the country, adding "[the KCATA] are pleased to partner with the City of Kansas City and the KCPD to play a role in elevating the level of safety to the community, as well as to our customers and employees."[10] Moreover, ShotSpotter was implemented with the aim to have "KCPD respond faster and more safely to gunfire incidents" while allowing officers "to proactively develop effective problem-oriented, data-driven policing strategies and tactical deployments." It was further expected that the KCPD would be able to gather ballistic evidence, ultimately resulting in increased prosecution for firearm-related crime.[11]

Kansas City's GDT system went live on 9/14/12. KCPD's ShotSpotter system detected 11,517 gunfire events through the end of 2019. The GDT system covers a target area of approximately 3.5 square miles.[12] Kansas City pays between $227,500 and $315,000 per year for their GDT system based on ShotSpotter's reported annual subscription cost of between $65K and $90K per square mile[13]. The GDT zone comprises slightly more than 1% of Kansas City's total geography (~315 square miles) and houses a disproportionate share of violent crime. The GDT zone accounted for approximately 11% of shots fired calls for service (6,770 of 60,348), 16% of fatal (123 of 751) and non-fatal (452 of 2,689) shootings, and over 15% (2,478 of 16,158) of assaults (non-shooting related) and robberies committed with a firearm from 9/14/12 to 12/31/2019. The percentage of residents who are non-white (67.72% vs. 31.91%) and the

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[10] https://mptaonline.typepad.com/missouri_public_transit_a/2012/06/kcata-is-first-transit-agency-to-implement-gunshot-detection-system-in-conjunction-with-kc-police-.html
[11] https://cleaver.house.gov/press-release/congressman-cleaver-announces-shotspotter-coming-kansas-city
[12] KCPD policy prohibits the disclosure of the GDT target area boundaries. We therefore do not present any maps of the GDT target area in this report.
[13] See section 8 in the Shotspotter Frequently Asked Questions document: https://www.shotspotter.com/system/content-uploads/SST_FAQ_January_2018.pdf

percentage of households under the poverty rate (34.33% vs. 15.63%) are more than twice as high in the GDT target area than the city-wide rate (see Table 1).

Table 1: Kansas City Study Area Characteristics

Measures	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 & robberies	2,478	16,158
Non-white population	67.72%	31.91%
Poverty rate	34.33%	15.63%

Notes: Crime and shots fired data cover the period 9/14/12-12/31/2019. All incidents involving shooting victims are excluded from the gun assault & robbery category so that the crime categories are mutually exclusive. GDT target area demographics are measured from the 20 intersecting Census tracts. American Community Survey 2019 5-year estimates are reported.

Chicago

Chicago, IL is the largest Midwestern city in the United States, with a total population of 2,695,598. U.S. Census Bureau figures indicate 33% of Chicago residents are Black and 29% Latino. Approximately 21% percent of all persons subsist below the poverty level. The Chicago Police Department (CPD) employed 13,160 sworn officers and 855 civilians in 2019 according to FBI figures.[14]

The City of Chicago has been embroiled in controversy over its use of crime control technology over recent years. In 2020, the Chicago Police Department (CPD) ended its person-based predictive policing program known as the "Strategic Subjects List," which assigned risk scores to individuals considered most likely to commit or be victims of gun violence (Foody, 2020). The algorithm considered previous arrests, victimizations, and affiliations to calculate the

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

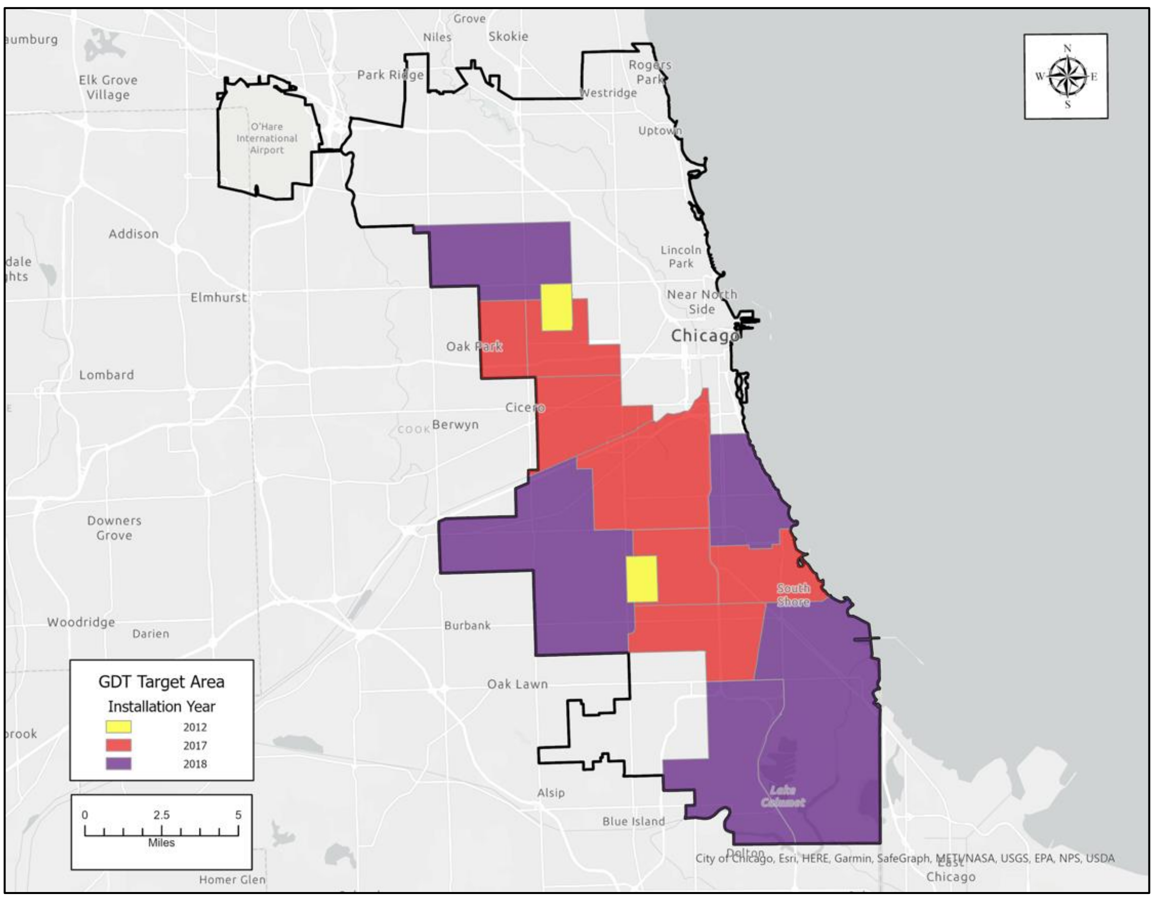
scores, which were then used to target individuals for outreach. A report by Chicago's Office of the Inspector General found the program relied too heavily on arrest records, some of which were nonviolent arrests and did not lead to convictions (City of Chicago Office of the Inspector General, 2021). A report by the RAND Corporation found the program was ineffective in predicting victimization (Saunders et al., 2016), and civil rights groups raised concerns about the program disproportionately targeting communities of color.

The city's deployment of GDT has generated similar controversy. CPD first installed GDT during a pilot phase in September 2012, covering a 3.05 square-mile target area. In February 2017, CPD began steadily increasing the GDT target area size. GDT sensors were installed over 10 subsequent phases between 2017 and 2018, expanding the target area to 136.70 square miles by the end of May 2018 (see Table 2 and Figure 1). This differs from the approach taken by many other police departments, namely focusing on covering only the most disproportionately violent places, which comprise much smaller geographies. This translates to an annual subscription cost of between \$8.8M and \$12.3M. The Chicago PD's GDT system did not retain gunshot alert data for the initial installation phase, as this was considered a pilot project. During the full installation period from 2/6/17 – 12/31/19, the GDT system detected 85,572 gunfire incidents.

Table 2: Chicago GDT Installation Phases

District Number	Size (sq. mi)	GDT Live Date
7 [initial]	1.51	9/1/12
11 [initial]	1.54	9/1/12
11 [full]	6.11	2/6/17
7 [full]	6.52	2/6/17
15	3.82	4/24/17
9	13.52	7/14/17
6	8.10	9/26/17
10	7.87	10/30/17
3	6.08	12/31/17
4	27.27	1/31/18
5	12.80	3/7/18
25	10.91	4/11/18
8	23.12	4/11/18
2	7.52	5/16/18

Figure 1: Chicago GDT Installation Years



The initial GDT target area accounted for about 1.4% of Chicago's total geography. The initial target area housed approximately 5% of the city's shots fired calls for service (13,811 of 271,985), fatal shootings (104 of 2,117), non-fatal shootings (876 of 18,470), and assaults, batteries, and robberies[15] committed with a firearm (1,576 of 36,460) between 9/1/2012 and 2/5/2017. The proportion of residents who are non-white (90.10% vs. 51.13%) and households under the poverty rate (33.88% vs. 21.59%) were higher in the initial GDT target area than Chicago as a whole. The fully installed GDT system covers approximately 60% of Chicago. From the beginning of the GDT system expansion (2/6/2017) to the end of our study period (12/31/2019) the full GDT coverage area housed approximately 70% (48,829 of 69,252) of shots fired calls for service, over 80% (1,268 of 1,578) of fatal shootings, and nearly 80% of non-fatal shootings (11,034 of 14,069) and assaults, batteries, and robberies committed with a firearm (18,276 of 23,675) in Chicago. The proportion of residents who are non-white (67.94% vs. 49.84%) and households under the poverty rate (23.81% vs. 18.31%) were higher in the full GDT target area than Chicago as a whole, although the differences were not as pronounced as those observed for the initial target area (see Table 3).

[15] Illinois law distinguishes between assaults during which bodily harm is threatened and batteries involving physical contact resulting in bodily injury. Battery was included alongside assault and robbery in this category to allow for consistency across our two study settings.

Table 3: Chicago Study Area Characteristics

Measures	INITIAL INSTALLATION (9/1/2012- 2/5/2017) GDT Target Area	Chicago	FULL INSTALLATION (2/6/2017-12/31/2019) GDT Target Area	Chicago
Area	3.05mi^2	227.63 mi^2	136.70 mi^2	227.63 mi^2
Shots fired calls for service	13,811	271,985	48,829	69,252
Fatal shootings	104	2,117	1,268	1,578
Non-fatal shootings	876	18,470	11,034	14,069
Gun assaults & robberies	1,576	36,460	18,276	23,675
Non-white population	90.10%	51.13%	67.94%	49.84%
Poverty rate	33.88%	21.59%	23.81%	18.31%

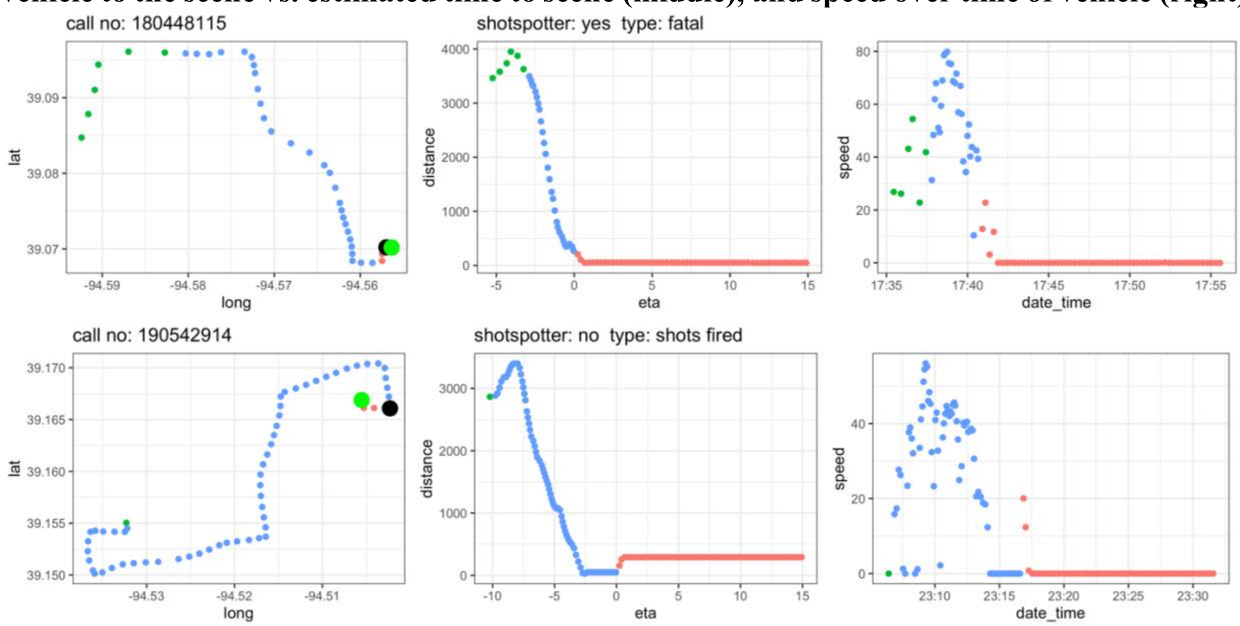
Notes: Initial GDT installation occurred on 9/1/2012. Full installation began on 2/6/2017, ending on 5/16/2017. For the initial installation, crime and shots fired data cover the period 9/1/12-2/5/2017. For the full installation, crime and shots fired data cover the period 2/6/2017-12/31/2019. The gun assaults & robberies category also includes battery incidents to reflect Illinois law. All incidents involving shooting victims are excluded from the gun assault & robbery category so that the crime categories are mutually exclusive. GDT target area demographics are measured from the 31 (initial installation) and 474 (full installation) intersecting Census tracts. American Community Survey 2016 and 2019 5-year estimates are reported.

CHAPTER THREE: GDT EFFECT ON OFFICER RESPONSE AND SEARCH BEHAVIOR

Methodology

In this chapter we analyze automatic vehicle locator (AVL) data to assess the impact of GDT on officer response to shots fired, non-fatal shootings, and fatal shootings. AVL data allows for a more precise understanding of when, where and how officers respond to shooting incidents. For example, in Figure 2, we see that the officer during the call 180448115 went directly to the location GDT indicated, whereas on call 190542914 that was citizen reported, the officer first drove to the reported location, but then drove to a second location where they were parked for most of the call. Furthermore, the time that officers report arriving on scene may not be precisely when they arrive and park, which can be inferred from GPS AVL data.

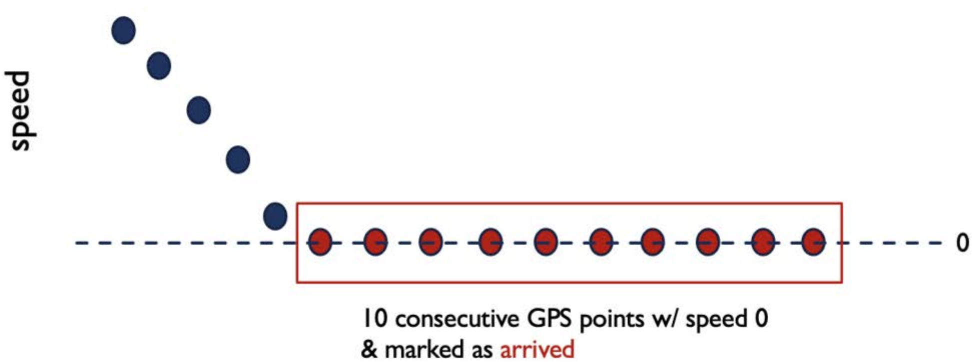
Figure 2: Officer GPS Traces for 2 Calls for Service in Kansas City (left), Distance of the vehicle to the scene vs. estimated time to scene (middle), and speed over time of vehicle (right)



Notes: Black circle indicates call location and green circle indicates where vehicle was parked for a majority of the call. Blue indicates enroute status whereas red indicates the officers have indicated that they are on scene.

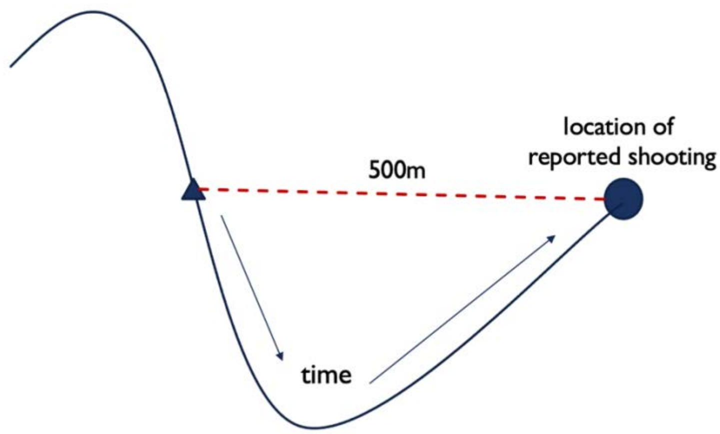
We perform three analyses of AVL and shots fired response data in Kansas City and Chicago. First, we investigate the fraction of shots fired calls where the officer stopped at the scene (as measured by having a speed of zero). Second, we investigate the accuracy of reported and detected shots fired locations in comparison to where the officer stopped. For this purpose, we define the AVL location of the call to be the first location where the officer stopped the vehicle upon arrival for at least 100 seconds (see Figure 3). This corresponds to 10 consecutive GPS points in Kansas City (which are sampled every 10 seconds) and 3 consecutive GPS points in Chicago (which are sampled every 30 seconds).

Figure 3: Officer AVL-defined arrival location, inferred as the place where the vehicle was parked for 10 consecutive GPS AVL samples (3 consecutive samples in Chicago)



Third, we investigate the time it takes for officers to arrive on scene. To control for differences in how far the car initially starts from the location, and to measure differences in how long it takes to search for the location of the event, we calculate the time between when the officer is first within 500m of the location of the shooting and when the officer arrives at the location (see Figure 4).

Figure 4: Time to location is measured as time it takes between when the vehicle is first within 500m of the shooting event location and when the officer arrives at that location



Kansas City Results

In Kansas City, we analyze data between 5/10/2017 and 12/31/2019. In Table 4, we report the fraction of calls where the officer's vehicle stopped on location. Here we see that for fatal shootings the vehicle stopped almost 100% of the time (we note that several vehicles may have responded). For shots fired incidents, the officer stops 90.6% of the time for citizen reported shots fired and 93.9% of the time for GDT incidents (a statistically significant difference). In the case of non-fatal shootings, the fraction difference was not statistically significant.

Table 4: Fraction of events where officer vehicle stopped in Kansas City.

Event	Type	Stopped frac.	St. err.	N
Shots fired	cfs	0.906	0.002	14282
Shots fired	gdt	0.939	0.005	2473
Non-fatal shooting	cfs	0.979	0.007	475
Non-fatal shooting	gdt	0.976	0.024	42
Fatal shooting	cfs	0.975	0.011	200
Fatal shooting	gdt	1.000	0.000	14

In Table 5, we report the average minimum distance between where the AVL indicated the officer's vehicle stopped and the reported/detected location of the gunfire event. For fatal shootings, we find that the average distance is 18.87m for GDT events, whereas the distance is 45.43m on average for citizen reported calls. The distance is also less in the case of non-fatal shootings (42.501 vs. 48.911) and shots fired (35.664 vs. 54.623).

Table 5: Average distance between reported/detected location and where officer stopped in Kansas City

Event	Type	Avg. min. dist. (m)	St. err.	N
Shots fired	cfs	54.623	0.863	14034
Shots fired	gdt	35.664	1.235	2464
Non-fatal shooting	cfs	48.911	4.723	453
Non-fatal shooting	gdt	42.501	7.814	40
Fatal shooting	cfs	45.429	4.803	197
Fatal shooting	gdt	18.668	3.832	14

In Table 6, we report the average time to scene for GDT and citizen reported shots fired. In Kansas City we find that the average time between when the officer was 500m away and when they arrived on scene wad 266.82 seconds for GDT events, compared to 390.87 seconds for citizen reported shots fired. The response time for GDT events was faster in the case of fatal shootings, 140.44 vs. 417.80) but slower for non-fatal shootings (428.20 vs. 383.19).

Table 6: Average time to scene in Kansas City

Event	Type	Time to scene (s)	St. err.	N
Shots fired	cfs	390.87	12.77	3707
Shots fired	gdt	266.82	16.87	826
Non-fatal shooting	cfs	383.19	45.60	308
Non-fatal shooting	gdt	428.20	202.96	15
Fatal shooting	cfs	417.80	98.43	127
Fatal shooting	gdt	140.44	50.98	9

Chicago Results

In Chicago, we analyze data between 1/1/2017 and 12/31/2019. In Table 7, we report the fraction of calls where the officer's vehicle stopped on location. Here we see that for fatal shootings the vehicle stopped 95.6% of the time for GDT events and 91.1% of the time for citizen reported calls. For non-fatal shootings the vehicle stopped 91.4% of the time for GDT events and 85.2% of the time for citizen reported calls. For shots fired incidents with no victim, the officer stops 61% of the time for citizen reported shots fired and 74% of the time for GDT incidents.

Table 7: Fraction of events where officer vehicle stopped in Chicago

Event	Type	Stopped frac.	St. err.	N
Shots fired	cfs	0.610	0.003	35409
Shots fired	gdt	0.742	0.003	26948
Non-fatal shooting	cfs	0.852	0.012	924
Non-fatal shooting	gdt	0.914	0.009	989
Fatal shooting	cfs	0.911	0.019	225
Fatal shooting	gdt	0.956	0.013	249

In Table 8, we report the average minimum distance between where the AVL indicated the patrol vehicle stopped and the reported/detected location of the shooting. For fatal shootings, we find that the average distance is 15.6m for GDT events, whereas the distance is 22.7m on average for citizen reported calls. The distance is also less in the case of non-fatal shootings and shootings without a victim.

Table 8: Average distance between reported/detected location and where officer stopped in Chicago

Event	Type	Avg. min. dist. (m)	St. err.	N
Shots fired	cfs	30.692	0.134	35409
Shots fired	gdt	26.087	0.138	26948
Non-fatal shooting	cfs	21.947	0.655	924
Non-fatal shooting	gdt	18.159	0.570	989
Fatal shooting	cfs	22.735	1.493	225
Fatal shooting	gdt	15.578	0.999	249

In Table 9, we report the average time to scene for GDT and citizen reported shots fired. In Chicago, we find that the average time to scene was closer between GDT and citizen calls in comparison to Kansas City. We observe a 10 second difference on average for shootings with no victim and non-fatal shootings.

Table 9: Average time to scene in Chicago

Event	Type	Time to scene (s)	St. err.	N
Shots fired	cfs	148.554	2.683	2157
Shots fired	gdt	138.669	1.713	4801
Non-fatal shooting	cfs	94.685	7.432	216
Non-fatal shooting	gdt	85.054	4.734	501
Fatal shooting	cfs	60.000	11.867	60
Fatal shooting	gdt	63.216	5.890	153

CHAPTER FOUR: GDT EFFECT ON CRIME OCCURRENCE

Methodology

Microsynthetic control matching

Contemporary policing research emphasizes the importance of "place" in understanding the distribution of crime, evolving from a reliance on larger administrative geographies, such as patrol beats, to micro-level geographic units that more accurately reflect the clustered distribution of crime in urban environments (Weisburd, 2015, 2018). In following this perspective, we use individual street segments as the unit of analysis (Kansas City N = 33,848; Chicago N = 51,650). Street segments are operationalized as the two block faces on both sides of a street between two intersections. They are both small enough to avoid aggregation errors and large enough to avoid coding errors associated with individual street addresses (Braga et al., 2010; Weisburd et al., 2012).[16] In Kanas City, a total of 1,597 street segments fall within the GDT target area.[17] Chicago's original 3.0 square mile GDT target area, in place from August 2012 to February 2017, comprised 816 street segments. The fully deployed GDT target area comprises 27,916 street segments in Chicago.[18]

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[16] A limitation of street segments is the over counting of crimes recoded 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 both Kansas City PD and Chicago PD 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 closest street segment for the analysis.

[17] The GDT target area included all street segments falling within the boundary created by the individual GDT sensors installed by ShotSpotter as well as all street segments within 0.25 mi^2 to reflect the fact that GDT sensors can detect sounds of gunfire typically 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 is underestimated when target areas are restricted to street segments with GDT sensors.

[18] GDT target area files provided by Chicago PD seem to account for the 0.25 mi^2 spatial lag, as over 99% of GDT alerts (84,939 of 85,572) fell within the target area boundaries. As such, we did not manually add a buffer in the selection of target area street segments in the Chicago portion of the analysis.

The microsynthetic control method was incorporated in order to maximize the internal validity of our study design. The microsynthetic control method modifies the well-known synthetic control method (Abadie et al., 2011; Abadie & Gardeazabal, 2003) for application to micro-geographic units of analysis. Crime-and-justice researchers have recently used this method to explore the crime mitigating or aggravating effect of drug market intervention strategies (Robbins et al., 2017; Saunders et al., 2016), hot spots police patrols (Rydberg et al., 2018), community policing substations (Piza et al., 2020), recreational marijuana dispensaries (Connealy et al., 2020), and large-scale de-policing policies (Piza & Connealy, 2022). The microsynthetic control approach 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 though unit-level averages as is done in alternate matching approaches such as propensity score matching (Piza et al., 2020).

The weighted control group is created through a weighted vector of individual control street segments, with pre-intervention trends and time-invariant and time-variant 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 & Davenport, 2021). By construction, the microsynthetic control approach meets the parallel trends assumption required of difference-in-differences analysis (Levin et al., 2002). We conducted the matching using the R package *microsynth* (Robbins & Davenport, 2021). Different matching covariates were incorporated for Kansas City and Chicago based upon data availability and the operationalize necessary to optimize the respective covariate matching processes.

In Kansas City, 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, nearly a quarter-year) to maximize matching efficiency. This process improves matching performance by reducing the pre-intervention matching outcome equivalence as a matching parameter and increasing the frequency of the event of interest being matched on which improves matching performance (see e.g., Piza & Connealy, 2022).

The miscrosynthetic model accounted for the pre-intervention presence of 18 covariates on each street segment in Kansas City:

1-4. Outcome measure incident counts (time-variant): shots fired calls for service, non-fatal shootings, fatal shootings, and gun assaults & robberies committed with a firearm.

5-6. Process measure incident counts (time-invariant): gun recoveries and NIBIN 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 part of another roadway classification (coded as "0"), as measured in the Kansas City street centerline file (Kansas City Open Data Portal).

11. Street segment length (time-invariant): measured in feet

12. Residential parcel percentage (time-invariant): standardized percentage of the parcels zoned for residential purposes, as measured in the Kansas City property parcel file (Kansas City Open Data Portal).
13. CCTV presence (time-invariant): whether a KCPD CCTV camera was 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 persons without a high-school diploma or equivalent, as measured in the annual American Community Survey 5-year estimates (census tract).
15. Demographic index (time-invariant): summed standardized percentages of non-White residents, residents aged 15-29, vacant properties, and renter-occupied properties, as measured in the annual American Community Survey 5-year estimates (census tract).
16. Population density (time-invariant): standardized average of the number of residents per square mile, as measured in the annual American Community Survey 5-year estimates (census tract).
17. Geographic mobility (time-invariant): standardized percentage of residents who lived at a different address 1 year prior, as measured in the annual American Community Survey 5-year estimates (census tract).

18. Ambient population index (time-invariant): summed standardized ambient population, as measured in the annual Oak Ridge Laboratory Land Scan data (1.5 km^2 grid).

In Chicago, data were analyzed from 2008 through 2019.[19] Incident data were aggregated into calendar month temporal periods. Similar to the approach taken with Kansas City, matching was conducted across three temporal periods (i.e., 90 days, a quarter-year) to maximize matching efficiency. The microsynthetic model accounted for the pre-intervention presence of 15 covariates on each street segment in Chicago:

1-4. Outcome measure incident counts (time-variant): shots fired calls for service, non-fatal shootings, fatal shootings, and gun assaults & robberies committed with a firearm.

5. Process measure incident counts (time-invariant): gun recoveries.

6. Concentrated 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 residents under 18, as measured in the annual American Community Survey 5-year estimates (census tract). The index was dichotomously operationalized as the total number of units above/below the mean value for the level of disadvantage.

7. Demographic index (time-invariant): summed standardized percentages of non-White residents, residents aged 15-29, vacant properties, and renter-

[19] The Chicago data was operationalized with a start date of 2008 because some of the datasets examined in the analysis only had data available to that year (as opposed to 2005).

occupied properties, as measured in the annual American Community Survey 5-year estimates (census tract). The index dichotomously operationalized as the total number of units above/below the mean value for the level of disadvantage.

8. Ambient population (time-invariant): summed standardized ambient population, as measured in the annual Oak Ridge Laboratory Land Scan data (1.5 km^2 grid).

9. Principal roadway (time-invariant): whether the street segment was classified as a principal or arterial roadway (coded as "1") or as part of another roadway classification (coded as "0"), as measured in the Chicago centerline file (Chicago Open Data Portal).

10. Parcel zoning (time-invariant): the parcel zoning (residential, commercial, or mixed) assigned to the segment.

11. Street segment length (time-invariant): measured in feet

12. CCTV presence (time-invariant): whether a CCTV camera was present on the street segment (coded as "1") or not (coded as "0").

13-14. Enforcement incident counts (time-variant): arrests and field contacts.

15. Pre-intervention non-firearm related crime counts (time-variant): part-1 crime incidents that did not involve the use of a firearm.

Treatment effect estimation

Both process and outcome measures were tested in the analysis. In Kansas City, process measures included gun recoveries and NIBIN evidence collection while outcome measures included shots fired calls for service, non-fatal shootings, fatal shootings, and gun assaults and robberies. NIBIN data were not available for Chicago, but all other process and outcomes measures were incorporated in that portion of the analysis.

The *microsynth* R package was used to measure treatment effect following the creation of the weighted control group (Robbins & Davenport, 2021). The effect is calculated via 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. Statistical significance of the treatment effect is determined through the use of iterative permutation-based placebo tests. 250 permutations are used in the current analysis, following the approach of (Robbins et al., 2017).[20] 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 post-intervention time periods, allowing for a control of the multiple comparisons (Robbins et al., 2017).

A modified approach was incorporated for Chicago given the staggered intervention roll out. Executing an individual model for each associated GDT phase was determined to be the most appropriate methodological strategy for Chicago because many of the new developments in

[20] Some prior microsynth studies have used 999 permutations to calculate *p.* values. We were unable to use that many permutations in light of our sample sizes. The longitudinal database (with observations set at months across street segments) used for the microsynth analysis included over 5 million observations and 4 million observations for Kansas City and Chicago, respectively. Using Northeastern University's high-speed cloud computing service, running the cumulative analyses for each city with 250 permutations took approximately 18 hours in each instance. Models never converged after 24 hours when 999 permutations were used. Nonetheless, we believe 250 permutations are sufficient given that total was provided as a benchmark by the originators of the microsynthetic control technique (Robbins et al., 2017; Robbins & Davenport, 2021).

difference-in-difference analyses, particularly those attempting to wrestle with the challenges of staggered treatment design approaches, are not robust to the present study's parameters. Newer staggered approaches including partially pooled synthetic weights (Ben-Michael et al., 2021, 2022), group time effects modeling (Callaway & Sant'Anna, 2021), and synthetic difference-in-difference (Arkhangelsky et al., 2021; Porreca, 2022), have been successfully leveraged for synthetic controls – but not microsynthetic controls. These newer staggered DID designs are not yet robust to the number of micro-level units (individual street segments), the number of time periods (individual months in a multi-year longitudinal capacity), the number of covariates matched on (15), the inclusion of multiple outcome variables in a singular model (five), and the ability to seamlessly scale the observed results relative to permutations (250 permutations per model). The variety of matching and model parameters incorporated in the present study prohibits the use of many newer staggered DID approaches and/or makes the convergence of such complex models impossible.[21] Additionally, the mixed evidence produced by prior GDT studies regarding potentially heterogenous crime effects and the ability to still ascertain a cumulative treatment effect further justified the study's individual modeling approach.

The analytical framework of the present project involves an empirically situated two-stage approach. The first stage in the approach involves testing each phase of GDT through an individual microsynth model. Individual microsynth models were deemed the appropriate modeling approach as microsynth is also not capable of running a single, staggered treatment model across phases.[22] In each model, the target units of the specific phase were identified and compared to a weighted

[21] We attempted to trial each new staggered DID approach for the present study, but each method failed to fit the parameters of the dataset or resulted in non-converging models.

[22] Microsynth is not able to parse out when a target unit became "treated" when treatment is staggered, and can only dichotomously operationalize a treatment variable. Thus, accounting for the time at which a target unit became treated is only achievable with individual models.

pool of not yet treated and control units. This allows for conclusions to be discerned regarding the treatment effect of GDT for each unique area and time of deployment for all outcomes of interest. Since the modeling approach is the same, and each phase is only distinguished by unique timing and target area, the results are amenable for comparison in post-hoc comparisons and tests of effect size. This allowed us to explore a key research question of interest in Chicago: whether the effect of GDT differed as the target area grew in size. Though, we were not able to consider potential GDT effects across displacement models in Chicago because of the size of the target areas. The size, and coverage, of GDT in Chicago did not render appropriate displacement units or areas.

Following the individual, heterogenous effects analyses, the second stage of the study cumulatively tested the aggregate average treatment effect (AATE) across all study phases (Meager, 2019). This method is designed to aggregate evidence on causal effects studies, ranging from iterative interventions to meta-analyses, that have several, separate time points that form groups (or in this case, “phases”) (Meager & Wiecek, 2023). The aggregate average treatment effect (AATE) for each study outcome of interest was produced using the “R” package “baggr” (Meager, 2019; Meager & Wiecek, 2023). This metric is an indicator of effect size measured by the Tau statistic, with a measure of AATE significance depicted as the estimated average difference between aggregate target and control units for each group (or “phase”). The AATE is effective at indicating the aggregate effect of treatment by producing an expected difference value between target and control units that is articulated as the average difference we would expect to see in each phase.

Kansas City Results

The balance achieved across the treated and weighted control areas is displayed in Table 10. The matching algorithm succeeded in creating a weighted control area that perfectly matched the aggregate characteristics of the GDT target area.

Table 10: Balance Table for Treated and Weighted Control Areas in Kansas City

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	2973.00	2973.00
fatal shootings (sum)	84.00	84.00
non-fatal shootings (sum)	123.00	123.00
gun assaults & robberies (sum)	1091.00	460.00
gun recovery (sum)	1542.00	1542.00
NIBIN (sum)	144.00	144.00
non-firearm crime (sum)	14151.00	14151.02
arrests (sum)	19884.00	19884.04
field interviews (sum)	2708.00	2708.00
principal roadway	350.00	350.00
street segment length	727138.90	727139.63
residential parcel percentage	-249.81	-249.82
cctv presence	88.00	88.00
disadvantage index	5317.32	5317.32
demographic index	239162.59	239162.96
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 msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 11 presents the results of the crime change estimates. Potentially notable findings were observed for both process measures. The collection of NIBIN evidence was approximately 30% higher in the GDT target area than the weighted control area (476 vs. 364.98), with the difference significant at *p.*<0.01. Gun recoveries were approximately 11% higher in the GDT target area than the weighted control area (1939 vs. 1744.08), although the difference only approached statistical significance (*p.*=0.05). While *p.*=0.05 is commonly considered indicative of statistical significance in the social sciences, the lower bound of the confidence interval crosses zero (-0.03%) meaning a null effect cannot be definitively ruled out. Shots fired calls for service was the lone outcome measure to experience a statistically significant change (*p.*<0.01), with incident levels approximately 22% lower in the GDT target area than the weighted control area (5665 vs. 7285.84).

Table 11: Kansas City Crime Change Estimates: Main Analysis

					95% confidence interval	
Crime category	**Target**	**Control**	**Difference**	***p.***	**Lower**	**Upper**
Gun recoveries	1939	1744.08	11.2%	0.05	-0.3%	24.3%
NIBIN evidence**	476	364.98	30.4%	0.00	7.4%	59.1%
Shots fired**	5665	7285.84	-22.2%	0.00	-29.2%	-14.1%
Fatal shootings	107	108.31	-1.2%	0.97	-25.5%	31.1%
Non-fatal shootings	389	394.71	-1.4%	0.94	-24.2%	15.0%
Gun assaults & robberies	1768	1783.83	-0.9%	0.85	-10.2%	8.0%
Omnibus	.	.	.	0.00	.	.

N=5,383,214
**p<0.01
Notes: 95% confidence interval and *p.* value based on 250 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.

Figures 5 (gun recoveries), 6 (NIBIN), and 7 (shots fired cfs) graphically display the synthetic control estimates longitudinally for the measures that achieved or approached statistical significance. This allows for visual inspection of how trends in the treated and control units varied over time, which adds nuance to the crime change estimates. Gun recovery trends were volatile over the intervention period, with counts visibly higher in the GDT target area through temporal period 100 (November 2014) before coming more in-line with the levels observed in the control area. NIBIN evidence collection counts were very similar in the treated and control areas in the early portions of the intervention period. Around mid-2013, NIBIN evidence collection in the GDT target area began an upward trajectory 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.

Figure 5: Gun Recovery Synthetic Control Estimates, Kansas City Main Analysis

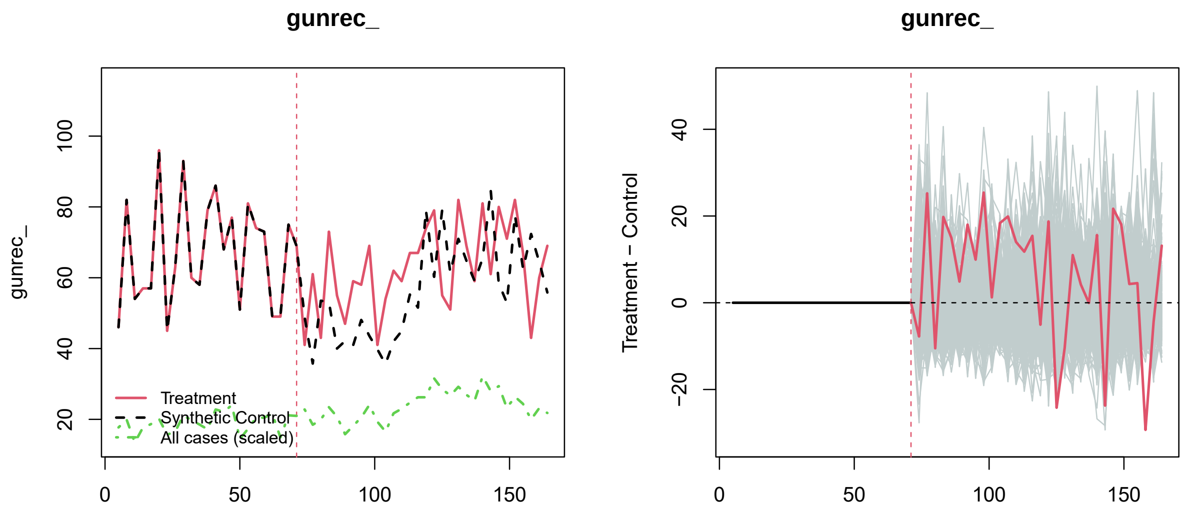


Figure 6: NIBIN Evidence Collection Synthetic Control Estimates, Kansas City Main Analysis

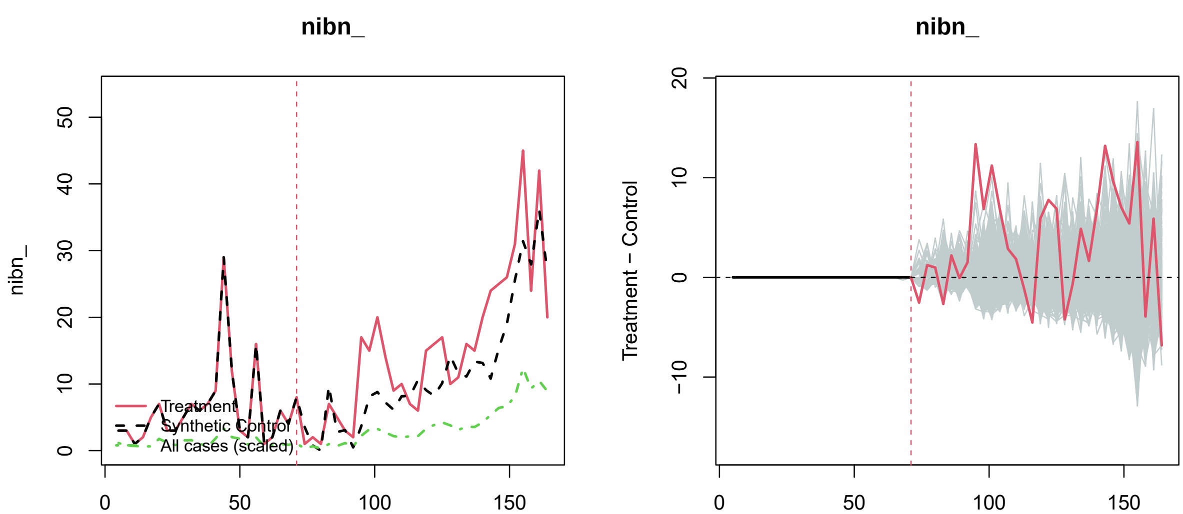
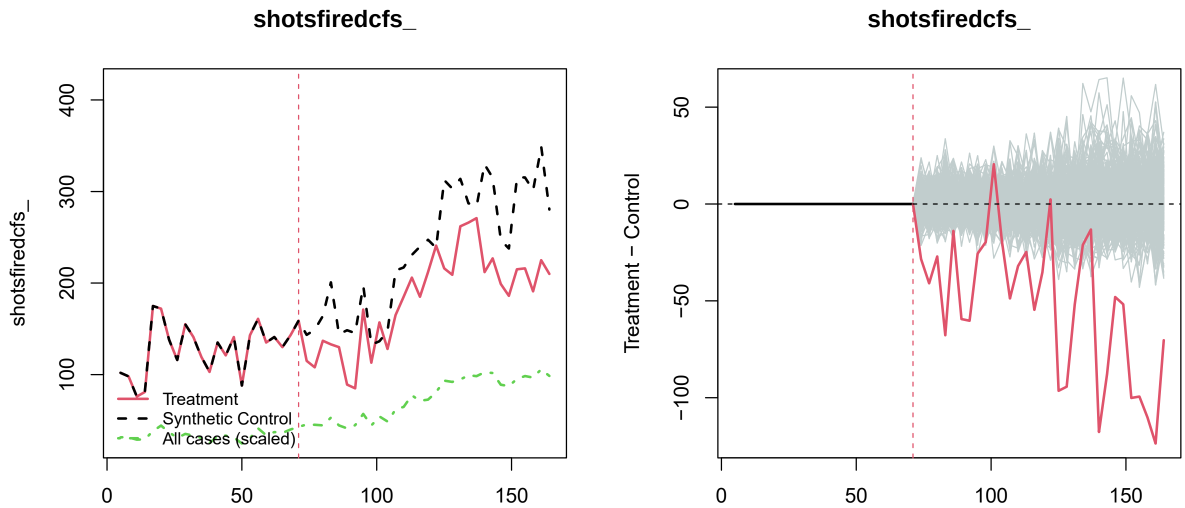


Figure 7: Shots Fired CFS Synthetic Control Estimates, Kansas City Main Analysis



Following the main analysis, we repeated the microsynthetic control approach to test for the presence of spatial displacement or diffusion of benefits (Clarke & Weisburd, 1994) in the area immediately surrounding the GDT target area. We designated the 1,419 street segments within a quarter-mile of the GDT target area boundary as catchment units for this analysis. The aforementioned microsynthetic control approach was then repeated to created weighted control group for the catchment units.

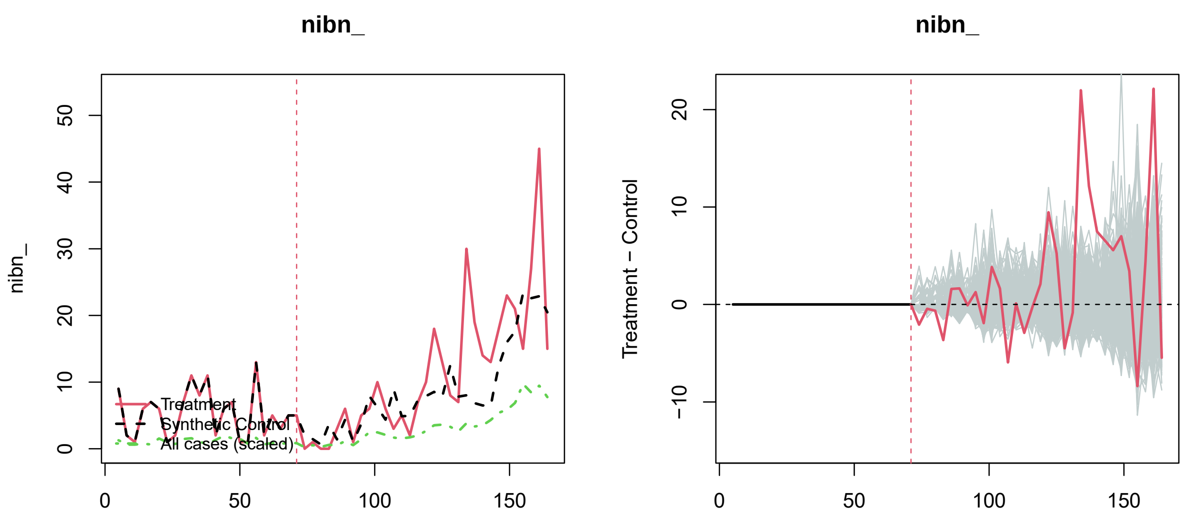
Table 12 displays the results of catchment zone crime change estimates. NIBIN evidence collection was nearly 30% higher in the catchment zone than the weighted control area. This difference was statistically significant (*p.*<0.01). Interestingly, NIBIN counts were similar in the catchment zone and control area through about early 2015. From that point forward, NIBIN counts were consistently higher in the catchment zone than the weighted control area (see Figure 8).

Table 12: Kansas City Crime Change Estimates: Catchment Analysis

Crime category	Target	Control	Difference	*p.*	95% confidence interval Lower	Upper
Gun recoveries	1668	1477.28	12.9%	0.07	-1.2%	31.3%
NIBIN evidence**	351	270.52	29.7%	0.00	4.8%	53.3%
Shots fired	4623	4488.58	3.0%	0.55	-7.6%	11.3%
Fatal shootings	77	64.98	18.5%	0.26	-11.8%	55.4%
Non-fatal shootings	328	299.47	9.5%	0.44	-19.5%	31.5%
Gun assaults & robberies	1386	1323.49	4.7%	0.40	-6.3%	16.1%
Omnibus	.	.	.	0.00	.	.

N=5,353,666
* = $p<0.05$; ** $p<0.01$
Notes: 95% confidence interval and *p.* value based on 250 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.

Figure 8: NIBIN Evidence Collection Synthetic Control Estimates, Kansas City Catchment Analysis



Chicago Results

The matching model performed well in each of the 10 phase iterations for Chicago. Microsynth achieved an exact match between the target and control units across all of the phase specific models. Thus, the parallel trends assumption of equal pre-period trends was satisfied for each of the five outcomes tested, and the covariates included were exactly balanced. Table 13 below shows the balance results for the Phase 1 installation, which was the initial pilot test of GDT deployment in Chicago. Balance tables for the other phases are available in the appendix.

Table 13: Balance Table for Treated and Weighted Control Areas in Chicago (Phase 1)

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	17160	17160
fatal shootings (sum)	122	122
non-fatal shootings (sum)	1250	1250
gun assaults & robberies (sum)	1469	1469
gun recovery (sum)	1657	1657
part I non-firearm crime (sum)	39396	39396
arrests (sum)	38868	38868
field contacts (sum)	90042	90042
principal roadway	133	133
street segment length (sum)	412783.3	412783.3
street segment parcel zoning	416	416
cctv presence	36	36
dichotomous disadvantage index	4	4
dichotomous demographic index	175	175
dichotomous ambient population index	422	422

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

The microsynth results indicate that there is considerable variation in the crime control effects of GDT across deployment phases in Chicago. Some phases recorded significant increases in the outcomes observed, while other phases indicated no effects or significant decreases. The heterogenous effects observed indicated that specific outcomes often went in and out of significance or changed effect direction across the phases. As the pilot trial of GDT, phase one began in September of 2012. As a standalone and longer running pilot trial with unique treatment timing, results for phase one are presented separately, with an analysis period from 1/1/2008 –

12/31/2014. Models for all subsequent phases transpired between 1/1/2015 and 12/31/2019. The number of target area segments in each GDT deployment phase, the timing of GDT across each associated phase, and the timeline for each subsequent microsynth model (the number of pre and post months) is depicted in Table 14.

Table 14: GDT Phase Timing and Microsynth Model Parameters

Phase	Target Segments	Model N	ShotSpotter Timing	Microsynth Model Timeframe
1	914	4,338,600	September 2012	57 month pre – 27 month post
2	3761	3,081,540	February 2017	24 month pre – 33 month post
3	997	2,868,780	April 2017	27 month pre – 30 month post
4	3702	2,814,960	July 2017	30 month pre – 30 month post
5	2157	2,595,900	September 2017	33 month pre – 27 month post
6	1660	2,474,580	October 2017	33 month pre – 27 month post
7	1578	2,382,060	December 2017	36 month pre – 24 month post
8	3423	2,294,340	January 2018	36 month pre – 21 month post
9	7824	2,122,500	April 2018	39 month pre – 18 month post
10	1870	1,664,700	May 2018	39 month pre – 18 month post

Phase one results are presented separately due to the unique timing of the intervention (see Table 15), with significant results and associated microsynth plots included in-text.[23] In phase one, shots fired calls for service in target areas were 44.7% higher than control areas ascribing a statistically significant difference (p<0.01). Additionally, gun assaults and robberies were 28.4%

[23] Microsynth results and plots are not presented in text for phases 2-10, though, the full model results and plots for all phases can be found in the appendix.

higher in target areas, with this result also ascribing statistical significance ($p<0.01$). The other outcome variables tested did not demonstrate significant differences between target and control units. The associated plots for both significant results in phase one are included below in Figures 9 and 10. For both shots fired and gun assaults and robberies, post-intervention counts were somewhat volatile for both treatment and control groups, but significantly higher in the treatment area.

Table 15: Chicago Crime Change Estimates: Phase 1

					95% confidence interval	
Crime category	**Target**	**Control**	**Difference**	***p.***	**Lower**	**Upper**
Gun recoveries	559	597.10	-6.4%	0.42	-25.8%	12.9%
Shots fired**	6807	4705.51	44.7%	0.00	28.1%	57.1%
Fatal shootings	52	39.76	31.0%	0.22	-20.0%	90.0%
Non-fatal shootings	419	398.84	5.1%	0.69	-13.6%	21.6%
Gun assaults & robberies**	503	391.61	28.4%	0.00	8.4%	45.2%
Omnibus	.	.	.	0.00	.	.

N=4,338,600
**$p<0.01$
Notes: 95% confidence interval and *p.* value based on 250 permutation tests. Time periods were set to three 30-day intervals (i.e., approximately a quarter year) for plots and results. Aggregation to three temporal periods resulted in 19 30-day pre-periods from 1/1/2008-9/30/2012 and 11 30-day post-periods from 10/1/2012-12/31/2014. GDT treatment was assigned to the first month full month following implementation. Omnibus tests control for multiple outcome measures in a singular model.

Figure 9: Shots Fired Synthetic Control Estimates, Chicago Phase 1

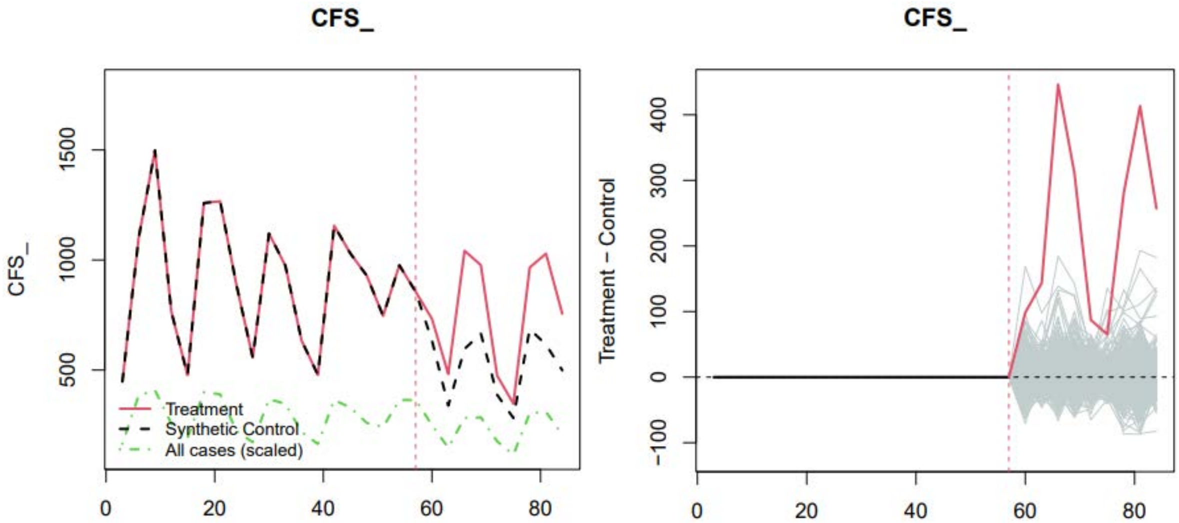
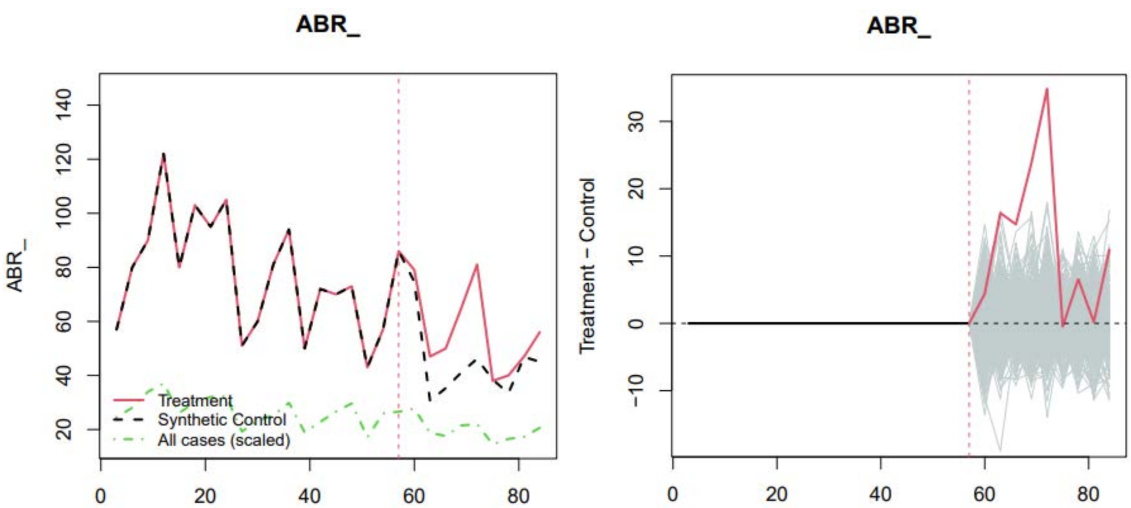


Figure 10: Gun Assaults and Robberies Synthetic Control Estimates, Chicago Phase 1



Across all phases (see Table 15 and Table 16), the process-related outcome of gun recoveries experienced heterogenous effects. In six of the phase specific models, GDT had no effect on gun recoveries (1, 2, 3, 7, 9, 10). Alternatively, though, GDT also led to a significant reduction in gun recoveries in phase 4 and a significant increase in gun recoveries in phases 5, 6, and 8. The highly differentiated effects of GDT on gun recoveries may be a byproduct of differences in localized gun enforcement approaches in Chicago. Unique leadership strategies associated with different precinct areas, in addition to GDT, may have produced the heterogenous effects observed for gun recoveries across the phases.

The results indicate that fatal shootings significantly increased in several of the GDT phases (2, 3, 5, 6). Although, the majority of the models reflected that GDT had no effect on fatal shootings. The heterogenous effects in this observed outcome may be related to smaller n values for gun violence homicides recorded in each target area. The models indicated that the potential crime reduction capacities of GDT related to fatal shootings may have been most salient in the early phases. GDT had no observable effect on gun fatal shootings in phases 7-10, which may suggest that the presumed deterrence potential, if any, of GDT had time diminishing returns.

The individual phase models suggested that GDT had little effect on non-fatal shootings. The majority of models again indicated that GDT had no observable effect on non-fatal shootings. However, non-fatal shootings were found to have significantly increased in three GDT phases (5, 6, 7).

The third crime tested, which included all assaults/batteries/robberies committed with a firearm, also produced heterogenous results. The models indicated that GDT target areas experienced a significant increase in 8 of 10 phases (1, 2, 3, 5, 6, 7, 8, 10). It may that GDT is not positioned to reduce these types of gun crimes that are not predicated on shots being fired. Though, in phase 4, the model indicated that GDT significantly reduced assaults/batteries/robberies with a gun, while phase 8 yielded no significant effects.

Table 16: Chicago Crime Change Estimates: Phase 2 – Phase 10

	Phase 2			**Phase 3**			**Phase 4**		
	T	**C**	**P**	**T**	**C**	**P**	**T**	**C**	**P**
Gun recoveries	4814	4370.21	10.2%	1055	1200.24	-12.1%	874	967.90	-9.7%*
Shots fired	10254	8982.02	14.2%**	2743	2745.19	-0.1%	3254	3269.81	-0.5%
Fatal shootings	330	232.61	41.9%*	125	62.07	101.4%***	75	65.69	14.2%
Non-fatal shootings	2636	2413.61	9.2%	815	760.24	7.2%	655	682.91	-4.1%
Gun assaults & robberies	1963	1482.14	32.4%***	684	493.95	38.5%***	472	529.20	-10.8%*
	Phase 5			**Phase 6**			**Phase 7**		
	T	**C**	**P**	**T**	**C**	**P**	**T**	**C**	**P**
Gun recoveries	1732	1174.77	47.4%***	1499	890.50	68.3%**	860	759.21	13.3%
Shots fired	3057	2824.46	8.2%*	2869	2458.45	16.7%*	2426	2704.03	-10.3%
Fatal shootings	92	53.53	71.9%***	59	36.44	61.9%*	59	55.02	7.2%
Non-fatal shootings	926	809.11	14.4%*	708	437.33	61.9%***	658	461.28	42.6%***
Gun assaults & robberies	770	588.76	30.8%***	421	348.09	20.9%*	461	317.51	45.2%***
	Phase 8			**Phase 9**			**Phase 10**		
	T	**C**	**P**	**T**	**C**	**P**	**T**	**C**	**P**
Gun recoveries	1002	771.93	29.8%***	1328	1472.78	-9.8%	379	357.23	6.1%
Shots fired	2435	2797.49	-13.0%	5205	4463.33	16.6%	1149	1377.14	-16.6%**
Fatal shootings	53	61.74	-14.2%	75	71.99	4.2%	39	25.00	56.0%
Non-fatal shootings	556	500.85	11.0%	860	805.38	6.8%	306	275.49	11.1%
Gun assaults & robberies	400	399.80	0.1%	695	505.15	37.6%***	292	203.81	43.3%**

Note: all phase models were statistically significant with an omnibus value of $p. < 0.0001$.
***$p.<0.001$; **$p.<0.05$; *$p.<0.05$
T: treatment unit total; C: control unit total; P: percent difference between treated and control units

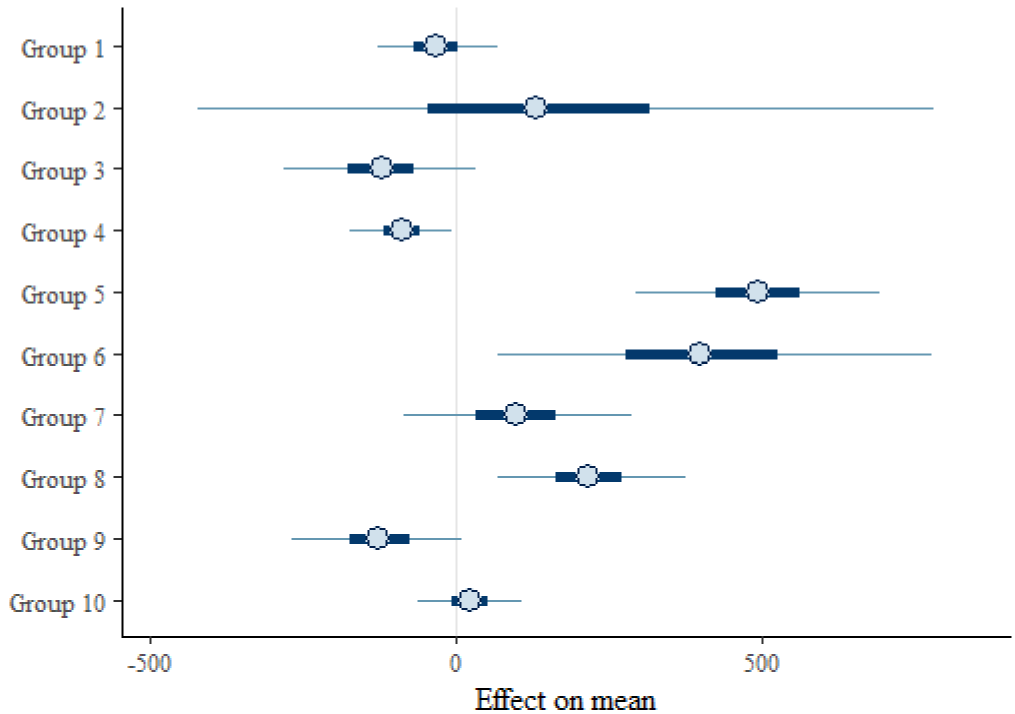
The individual effects for each phase were then pooled into a cumulative value that calculates the average difference between target and control units for each outcome based on the differences observed across each individual phase. This value, the aggregated average treatment effect (AATE), can then be articulated as the expected difference between target and control units for each phase. Several outcomes resulted in statistically significant differences between the expected target and control units. Table 17 below includes the AATE for each outcome tested and the associated significance level. Outcome specific interpretations of AATE values are included in the following paragraphs, with relevant plots depicting differences in phase specific contributions to the calculated AATE value.

Table 17: Aggregated Average Treatment Effect, Chicago Phase 1-10

Crime Category	AATE	p-value
Gun Recoveries	100	0.197
Shots Fired	340	0.079
Fatal Shootings	15.6	0.000
Non-Fatal Shootings	77.5	0.000
Gun Assaults & Robberies	114	0.000

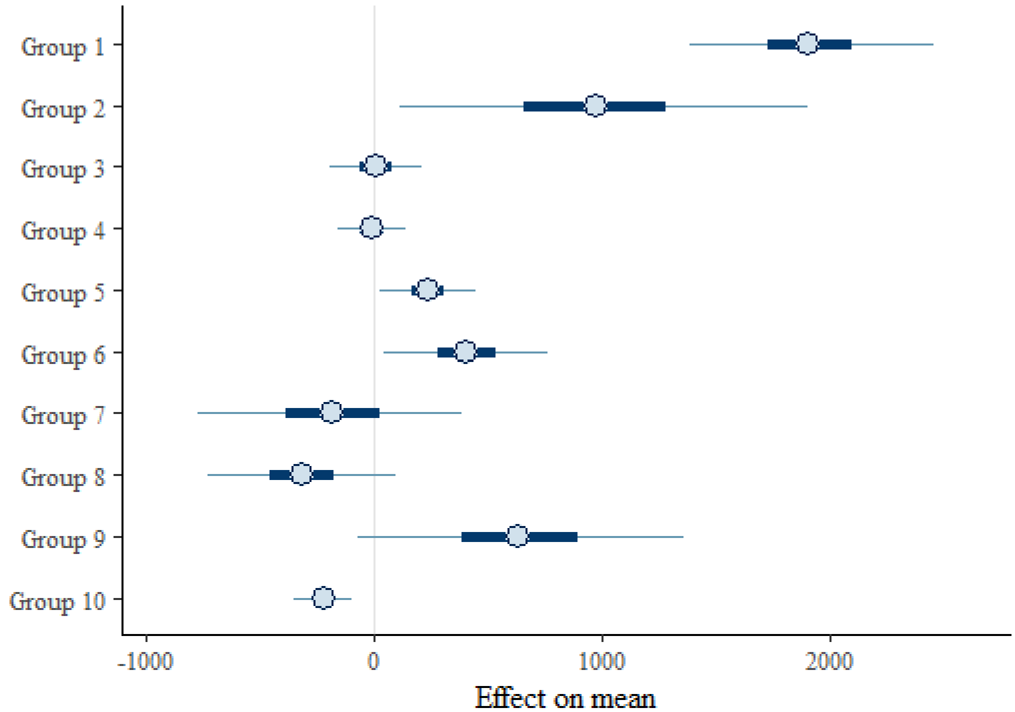
The gun recoveries AATE was calculated by pooling the observed average treatment effects (count difference between target and control units) for each phase. The AATE value is interpreted as the expected difference in target and control area gun recoveries during the post-period while accounting for variation in phase specific post-period lengths. The AATE for gun recoveries was found to be 100. The results indicate that we would expect 100 more gun recoveries in each GDT target area during the post-period (accounting for varied post-period lengths) However, this value was not found to be statistically significant (p<0.197). This is likely due to the directionally heterogeneous effects observed across each individual phase model (four models indicated less gun recoveries in GDT areas). The AATE statistic had a large standard error due to the inconsistent and directionally differential effects for gun recoveries, rendering the AATE value insignificant. The effect, and presumed direction, of GDT on gun recoveries is particularly inconclusive. The individual effects of each phase model on the AATE are included in Figure 11.

Figure 11: Gun Recoveries AATE by Phase



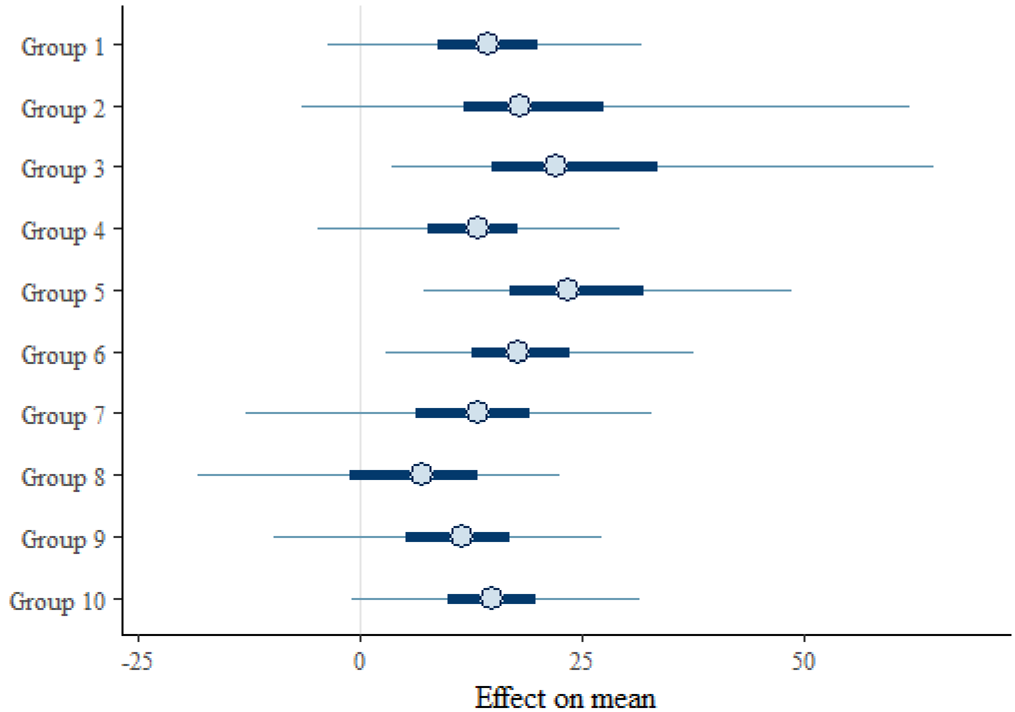
Next, the AATE for shots fired calls for service indicates we would expect 340 more calls for service in each GDT target area, on average, compared to the control areas (accounting for varied post-period lengths). Though, this value was found to be insignificant (p<0.079), indicating that there was no significant difference between shots fired calls for service in target and control areas cumulatively. There were four phases with less calls for service in the GDT area, likely leading to the large standard error and insignificant result produced (despite the presumably large quantity). The effect of each phase on the AATE value produced are illustrated in Figure 12. Phases one and two were particularly salient to the calculation of the AATE.

Figure 12: Shots Fired Calls for Service AATE by Phase



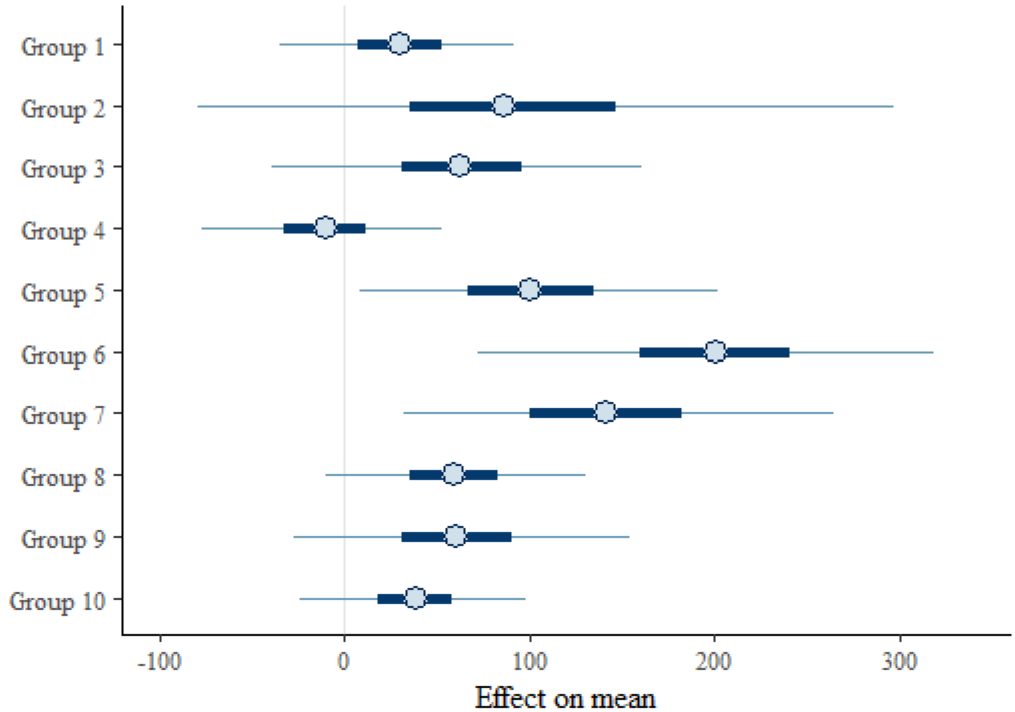
The fatal shootings AATE results indicate that on average, we would expect about 15.6 more fatal shootings to occur in each GDT target area over the duration of the post-period (accounting for varied post-period lengths). Relatedly, the results indicate that the estimated increase in the AATE of fatal shootings may have been driven in part by phases three and five, which recorded substantial discrepancies in gun violence homicides across target and control units (62.93 and 38.47 more homicides in the target areas, respectively). The AATE value of an expected increase of 15.6 homicides per GDT target area was found to be statistically significant ($p<0.01$). The effect on the AATE of each phase is visualized in Figure 13 below.

Figure 13: Fatal Shooting AATE by Phase



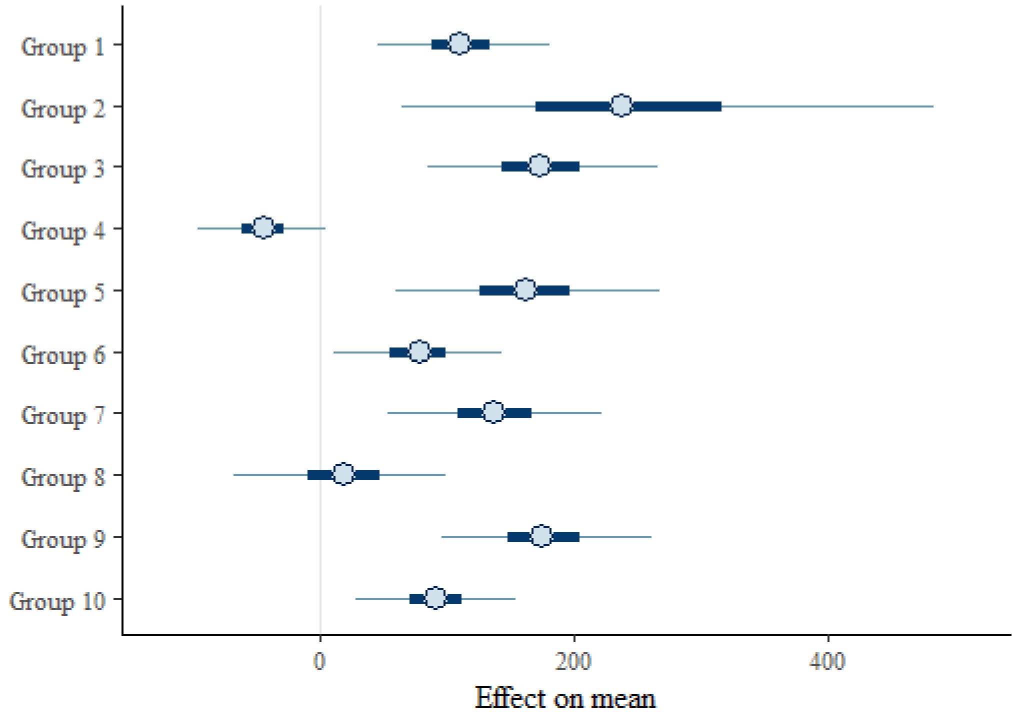
The AATE value for non-fatal shootings suggests that we would expect 77.5 more non-fatal shootings in each GDT target area relative to the associated control areas during the duration of the post-period (accounting for varied post-period lengths). The expected value of the AATE in each phase (77.5) was found to be statistically significant (p<0.01). The effect on the AATE value was most pronounced in phase six, which recorded 270.67 more non-fatal shootings in the target area compared to controls. The effect of each phase on the non-fatal shootings AATE is detailed in Figure 14.

Figure 14: Non-Fatal Shooting AATE by Phase



The AATE of assaults and robberies with a gun was 114. Thus, we would expect to see about 114 more ABR with a gun events in each GDT area during the post-period (accounting for varied post-period lengths). This value was also found to be statistically significant in terms of difference between target and control areas ($p<0.01$). Though, this crime type may be the least likely to be affected by GDT as it does not involve the physical firing of a gun to activate a GDT sensor. The effect was most pronounced in phase two, which recorded 479.86 more ABR with a gun events than the synthetic comparison area. Figure 15 below depicts the unique effect on the AATE across phases.

Figure 15: Firearm Assaults & Robberies AATE by Phase



CHAPTER FIVE: GDT EFFECT ON EVIDENCE COLLECTION AND CASE CLEARANCE

Methodology

This chapter explores the question of whether GDT systems facilitate evidence collection and case clearance activities of gun violence investigations. Individual gun violence incidents serve as the unit of analysis. Different incident types are included for Kansas City and Chicago due to data availability. We focus on city-wide incidents of shots fired (N = 80,110), fatal shootings (N = 1,150), and nonfatal shootings (N = 4,137) occurring between 2007 and 2019 for Kansas City. For Chicago, we include fatal shootings (N =6,349) and non-fatal shootings (N =64,884) in the analysis, as the shots fired data did not include the disposition status needed to link to relevant outcome measures (as discussed below). Data are available from 2007 – 2019 for Kansas City and from 2005 – 2019 for Chicago.

We used the entropy balancing method to conduct an equivalent case-control evaluation. Entropy balancing is a quasi-experimental design that matches treatment and control units by reweighting covariates based on propensity for treatment (Zhao & Percival, 2017). The approach does not require researchers to manually iterate models and check balance until a satisfactory balancing solution is achieved, an approach which commonly results in low balance levels. Rather, entropy balancing applies a reweighting scheme that directly incorporates covariate balance into the function, which removes the need for statistical balance testing (Hainmueller, 2012). The balance function imposes the balance constraints that involve the first, second, and possibly higher moments, based upon research commands and the data structure (Hainmueller & Xu, 2013). Entropy balancing has been shown to outperform alternative matching approaches, such as propensity score matching and coarsened exact matching, on a range of incident-level data and contexts (Black et al., 2020; Parish et al., 2018; Zhao & Percival, 2017).

A key function of entropy balancing is the retaining of all observations for the analysis, which can maximize statistical power. Given their reliance on one-to-one matches between units, alternate balancing approaches commonly drop units from the final analysis when an appropriate match cannot be identified within the pool of control units. This can present potential problems with statistical power as well and bias of effect estimates (Black et al., 2020; Hainmueller, 2012). Entropy balancing can be particularly effective when applied for sample pre-processing to improve balance prior to regression analysis (Black et al., 2020; Zhao & Percival, 2017), as the group equivalence makes calculation of treatment effects less dependent on the precise model employed (Hainmueller, 2012).

Entropy balancing was conducted through the *ebalance* command in Stata (Hainmueller & Xu, 2013). Seventeen covariates were used in the entropy matching process:

1. Outcome measure period total: the total count of the outcome measure on the encompassing street segment during the relevant intervention period. For Kansas City, totals were calculated for either the pre-intervention (1/1/2007-9/13/12) or post-intervention (9/14/12-12/31/19) period based on the incident date. For Chicago, totals were calculated for either the pre-intervention (1/1/2005 – 8/31/2012), initial-intervention (9/1/12 – 2/5/17), or full-intervention (2/6/17 – 12/31/2019) period based on the incident date.

2. Lagged outcome measure period total: The average count of the outcome measure on the street segments that are spatially contiguous to the encompassing street segment during the relevant intervention period.

3. Enforcement period total: the total count of police enforcement actions on the encompassing street segment during the relevant intervention period.

4. Lagged enforcement period total: The average count of police enforcement actions on the street segments that are spatially contiguous to the encompassing street segment during the relevant intervention period.[24]

5. Weekend: whether the incident occurred on a Friday, Saturday, or Sunday.

6-8. Quarter of the year: whether the incident occurred during the second (April – June), third (July – September), or fourth (October – December) quarter of the year. The first quarter (January – March) was the reference category.

9. CCTV presence: whether a CCTV camera was present on the encompassing street segment (coded as "1") or not (coded as "0").

10. Principal roadway: whether the encompassing street segment was classified as a principal or arterial roadway (coded as "1") or as part of another roadway classification (coded as "0").

11. 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

[24] Lagged enforcement was ultimately excluded from the Kansas City entropy matching process due to collinearity.

the age of 18, and persons without a high-school diploma or equivalent, as measured in the encompassing census tract (American Community Survey 5-year estimates).[25]

12. Demographic index (time-invariant): summed standardized percentages of non-White residents, residents aged 15-29, vacant properties, and renter-occupied properties, as measured in the encompassing census tract (American Community Survey 5-year estimates).

13. Population density (time-invariant): standardized average of the number of residents per square mile, as measured in the encompassing census tract (American Community Survey 5-year estimates).

14. Geographic mobility: standardized percentage of residents who lived at a different address 1 year prior, as measured in the encompassing census tract (American Community Survey 5-year estimates).

15. Ambient population index: standardized annual ambient population, as measured in the annual Oak Ridge Laboratory Land Scan data (1.5 km^2 grid).

16. Daily temperature: standardized average (for Kansas City) or maximum (for Chicago)[26] temperature on the date of incident occurrence, as measured in the National Oceanic and Atmospheric Administration's climate database.

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[25] American Community Survey 5-year estimates were collected through the *tidycensus* R package, with estimates available only back to 2009. All incidents occurring earlier we assigned the 2009 5-year (2005-2009) values of all census measures.

[26] The ebalance function did not run for Chicago when average temperature was included as a matching covariate, leading us to instead use maximum temperature.

17. Daily precipitation: the standardized inches of total precipitation on the date of incident occurrence, as measured in the National Oceanic and Atmospheric Administration's climate database.

Incidents in Kansas City were considered treated if they occurred within the GDT target area following the installation of GDT (9/14/2012). 12,422 shots fired calls for service, 397 non-fatal shootings, and 111 fatal shootings were treated in Kansas City. Because a phased rollout occurred in Chicago over multiple years, the treatment variable was created based on the dates GDT went live in each district. Incidents were coded as treated if the GDT system was live in the encompassing district on the date of occurrence. 1,043 fatal shootings and 9,357 non-fatal shootings were treated in Chicago.

Incident-specific measures related to police investigative functions were incorporated as dependent variables. Dependent variables differed across study settings based upon data availability. In Kansas City, the shots fired analysis included whether the case was coded as having an unfounded case disposition, meaning no evidence surfaced confirming that a firearm was discharged (e.g., property damage form a bullet, an eye witness statement, etc.). This dependent variable reflects prior research findings that GDT may increase police responses to false-positive gunfire events (Ratcliffe et al., 2019). For both non-fatal shootings and fatal shootings, two binary variables measuring whether a gun was recovered from the scene and whether NIBIN evidence was recovered from the scene were incorporated as process measures. Crime incidents were merged to gun recovery and NIBIN data through a common incident case number that appeared across all datasets. Lastly, whether the incident was marked as cleared by investigators was included as the outcome measure. NIBIN evidence was not available for Chicago. As such, the regression models for Chicago tested GDT effect on gun recoveries and case clearance.

The influence of GDT was tested through logistic regression models incorporating the weights from the entropy matching procedure (Hainmueller, 2012). The entropy weights were incorporated as probability weights in the logistic regression models, enabling the cumulative control and treatment groups to exert similar influence on the dependent variable (Zhao & Percival, 2017) The explanatory variable was the aforementioned “treated” variable. Odds ratios and associated *p.* values for the “treated” variable communicate the level to which GDT impacts the outcome measure.

Additional variables were included as controls to account for other factors that may influence investigative outcomes. In both cities, logistic regression models controlled for the opening of a gun crime intelligence center (GCIGs) in Kansas City and district-level Strategic Decision Support Centers (SDSCs) in Chicago. Such facilities support day-to-day police operations by providing crime analysis and intelligence products to officers, detectives, and commanders; monitoring camera, GDT sensor, and radio feeds, and; facilitating data sharing across districts and agencies (Hollywood et al., 2019; Przeszlowski et al., 2022). Differences in how the centers were established and operated led to different approaches across the study settings. In Kansas City, the GCIG was established in 2014 and assisted with gun cases throughout the entire city (Novak & King, 2020).[27] As such, all incidents occurring in 2014 or later were coded as “1” for the CGIG variable, with all other cases coded as “0.” In Chicago, separate SDSCs were

[27] Kansas City’s GCIC made strategic changes in 2017, moving from an analytical unit that disseminated leads for other detectives to follow to an enforcement unit that followed its own leads and made its own cases (Novak & King, 2020). Operationalizing the GCIG variable using 2017 instead of 2014 as the start date and including two variables that separately note 2014 and 2017 as the GCIG intervention dates do not alter the findings of the logistic regression models discussed subsequently.

instituted at the police-district level, with 13 established by the end of 2019 (Hollywood et al., 2019). A year variable was included to account for any annual trends in the outcome measures. The police division the incident occurred in was the final control variable to reflect the fact that different police districts may have different staffing levels and organizational practices that could influence investigative practices.

Kansas City Results

Results of entropy balancing for shots fired calls for service are presented in Table 17.[28] As expected, the treatment and unweighted control group differ greatly across all of the matching covariates. We succeed in specifying the ebalance algorithm to the first moment, resulting in near identical means for all covariates across treated and weighted control group. While variance differs for many of the covariates, the difference is not nearly as pronounced as what was observed for the unweighted control group.[29]

[28] In the shots fired analysis, all incidents occurring on July 4th, July 5th, December 31st, and January 1st, when there is unusually high activity of both fireworks and gunshots, were excluded given the higher likelihood of unfounded case dispositions on these dates.
[29] The ebalance model did not initially converge for shots fired. We increased the maximum number of iterations from 20 to 25 (see Hainmueller & Xu, 2013 p. 15) in order to run the above mentioned ebalance model.

Table 17: Entropy Matching Balance, Shots Fired (Kansas City)

Covariates	Treatment mean	Treatment variance	Control (unweighted) mean	Control (unweighted) variance	Control (weighted) mean	Control (weighted) variance
Outcome period total	22.46	241.60	17.64	2371.00	22.44	1746.00
Lagged outcome period total	13.10	48.96	5.13	61.64	13.08	618.60
Enforcement period total (z)	1.28	60.11	1.19	40.33	1.28	53.56
Weekend	0.53	0.25	0.44	0.25	0.53	0.25
2nd quarter	0.28	0.20	0.27	0.20	0.28	0.20
3rd quarter	0.27	0.20	0.25	0.19	0.27	0.20
4th quarter	0.26	0.19	0.26	0.19	0.26	0.19
CCTV	0.08	0.07	0.06	0.05	0.08	0.07
Primary road	0.13	0.12	0.10	0.09	0.13	0.12
Concentrated disadvantage (z)	3.64	4.31	2.03	7.63	3.64	5.71
Demographic index (z)	150.50	497.60	132.70	454.40	150.50	420.00
Population density (z)	-0.15	0.00	2.07	26840.00	-0.15	0.02
Geographic mobility (z)	0.31	0.41	-0.01	0.77	0.31	0.63
Ambient population (z)	1.27	0.48	1.45	3.07	1.27	1.50
Average temperature (z)	0.16	0.83	0.11	0.83	0.16	0.81
Precipitation (z)	-0.02	0.92	0.00	1.02	-0.02	0.88

N treated=11,562

N control= 68,548

N weighted control= 11,562

Note: Lagged enforcement period total (z) and 1st quarter excluded due to collinearity

Table 18 displays the findings of the logistic regression model testing the influence of GDT on unfounded case dispositions. Results indicate that GDT-treated shots fired calls for service have an 18% increased likelihood of being unfounded as compared to untreated cases (Odds Ratio = 1.17; *p.*<0.01).

Table 18: Logistic Regression Results for Unfounded Dispositions, Shots Fired (Kansas City

					95% C.I.	
Unfounded	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	1.18	0.04	5.02	0.00	1.10	1.25
GCIC	1.06	0.06	0.93	0.36	0.94	1.18
Year	1.05	0.01	6.65	0.00	1.04	1.07
PD division						
2	1.11	0.04	2.48	0.01	1.02	1.20
3	1.40	0.05	10.33	0.00	1.32	1.49
4	1.39	0.11	4.33	0.00	1.20	1.62
5	1.40	0.08	6.07	0.00	1.25	1.55
6	1.55	0.09	7.52	0.00	1.39	1.74

N (observations)= 79700

N (population)= 23047.21

F (8, 79692) = 52.76

Table 19 displays entropy balancing results for fatal shootings. We succeed in specifying the ebalance algorithm to the first moment (mean). Nonetheless, variance levels are also very similar across the treatment and weighted control cases for most covariates.

Table 19: Entropy Matching Balance, Fatal Shootings (Kansas City)

Covariates	Treatment mean	Treatment variance	Control (unweighted) mean	Control (unweighted) variance	Control (weighted) mean	Control (weighted) variance
Outcome period total	1.35	0.40	1.25	0.34	1.35	0.48
Lagged outcome period total	0.01	0.01	0.02	0.02	0.01	0.01
Enforcement period total (z)	0.94	2.09	0.69	2.43	0.94	4.39
Weekend	0.43	0.25	0.37	0.23	0.43	0.25
2nd quarter	0.20	0.16	0.23	0.18	0.20	0.16
3rd quarter	0.30	0.21	0.32	0.22	0.30	0.21
4th quarter	0.30	0.21	0.24	0.18	0.30	0.21
CCTV	0.06	0.05	0.07	0.07	0.06	0.05
Primary road	0.10	0.09	0.08	0.07	0.10	0.09
Concentrated disadvantage (z)	3.48	2.72	2.45	8.07	3.48	4.38
Demographic index (z)	155.50	392.70	136.80	491.60	155.50	420.00
Population density (z)	-0.15	0.00	-0.08	0.07	-0.15	0.02
Geographic mobility (z)	0.26	0.41	0.03	0.70	0.26	0.57
Ambient population (z)	1.21	0.43	1.44	2.89	1.21	1.14
Average temperature (z)	0.07	0.98	0.15	0.91	0.07	0.95
Precipitation (z)	-0.01	0.66	0.02	1.00	-0.01	1.00

N treated=109

N control=1,041

N weighted control=109

Note: Lagged enforcement period total (z) and 1st quarter excluded due to collinearity

Tables 20-22 display findings of the logistic regression models testing the influence of GDT on NIBIN collection, gun recoveries, and case clearance. In each case, GDT treatment was not significantly associated with the dependent variable.

Table 20: Logistic Regression Results for NIBIN, Fatal Shootings (Kansas City)

					95% C.I.	
NIBIN	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	1.28	0.38	0.83	0.41	0.71	2.31
GCIC	0.65	0.33	-0.85	0.40	0.24	1.76
Year	1.14	0.08	1.82	0.07	0.99	1.30
PD division						
2	1.64	0.59	1.36	0.17	0.80	3.33
3	1.00	0.33	0.01	0.99	0.53	1.91
4	0.23	0.23	-1.46	0.14	0.03	1.66
5	1.08	0.48	0.18	0.86	0.45	2.57
6	0.48	0.39	-0.90	0.37	0.10	2.39

N (observations)= 1148

N (population)= 216.98

F (8, 1140) = 1.81

Table 21: Logistic Regression Results for Gun Recovery, Fatal Shootings (Kansas City)

					95% C.I.	
GUN RECOVERY	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	1.24	0.90	0.29	0.77	0.29	5.20
GCIC	0.00	0.00	-3.73	0.00	0.00	0.00
Year	9.73	6.01	3.68	0.00	2.90	32.69
PD division						
2	1.36	1.36	0.31	0.76	0.19	9.70
3	2.12	2.16	0.73	0.46	0.28	15.73
4	1.00	(empty)				
5	2.73	3.54	0.77	0.44	0.21	34.68
6	11.38	15.11	1.83	0.07	0.84	154.13

N (observations)= 1136

N (population)= 216.65

F (7, 1129) = 3.40

Table 22: Logistic Regression Results for Case Clearance, Fatal Shootings (Kansas City)

					95% C.I.	
CLEARED	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	1.48	0.41	1.44	0.15	0.87	2.54
GCIC	0.60	0.29	-1.07	0.29	0.24	1.53
Year	0.98	0.06	-0.37	0.71	0.86	1.11
PD division						
2	1.56	0.49	1.40	0.16	0.84	2.89
3	1.23	0.36	0.72	0.48	0.70	2.18
4	0.58	0.50	-0.63	0.53	0.10	3.18
5	2.52	0.99	2.36	0.02	1.17	5.44
6	5.16	3.64	2.33	0.02	1.29	20.61

N (observations)= 1148

N (population)= 216.98

F (8, 1140) = 2.14

Table 23 displays entropy balancing results for non-fatal shootings. Similar to fatal shootings, we successfully specified the algorithm to the first moment, but mean and variance levels are nearly identical across the treatment and weighted control cases for most covariates. Logistic regression results indicate GDT exhibited no significant impact on NIBIN collection, gun recoveries, and case clearance for non-fatal shootings (see Tables 24-26).

Table 23: Entropy Matching Balance, Non-Fatal Shootings (Kansas City)

Covariates	Treatment mean	Treatment variance	Control (unweighted) mean	Control (unweighted) variance	Control (weighted) mean	Control (weighted) variance
Outcome period total	3.15	5.41	4.50	165.60	3.15	67.71
Lagged outcome period total	0.55	0.59	0.28	0.48	0.55	2.61
Enforcement period total (z)	0.93	3.82	1.54	29.98	0.93	9.46
Weekend	0.53	0.25	0.42	0.24	0.53	0.25
2nd quarter	0.27	0.20	0.28	0.20	0.27	0.20
3rd quarter	0.28	0.20	0.30	0.21	0.28	0.20
4th quarter	0.26	0.19	0.23	0.18	0.26	0.19
CCTV	0.13	0.11	0.11	0.10	0.13	0.11
Primary road	0.09	0.09	0.09	0.08	0.09	0.09
Concentrated disadvantage (z)	3.72	3.43	2.57	6.81	3.72	4.99
Demographic index (z)	154.20	412.50	136.90	394.70	154.20	428.90
Population density (z)	-0.15	0.00	-0.09	0.09	-0.15	0.02
Geographic mobility (z)	0.21	0.43	0.02	0.73	0.21	0.52
Ambient population (z)	1.21	0.36	1.59	3.29	1.21	1.14
Average temperature (z)	0.18	0.92	0.20	0.89	0.18	0.84
Precipitation (z)	0.03	1.45	0.03	1.23	0.03	1.12

N treated=391

N control=3,746

N weighted control=391

Note: Lagged enforcement period total (z) and 1st quarter excluded due to collinearity

Table 24: Logistic Regression Results for NIBIN, Non-Fatal Shootings (Kansas City)

					95% C.I.	
NIBIN	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	0.92	0.16	-0.50	0.61	0.65	1.29
GCIC	1.90	0.55	2.22	0.03	1.08	3.36
Year	1.05	0.05	1.00	0.32	0.96	1.15
PD division						
2	1.27	0.29	1.04	0.30	0.81	2.00
3	1.02	0.21	0.09	0.93	0.68	1.51
4	0.82	0.47	-0.35	0.73	0.26	2.55
5	1.12	0.34	0.37	0.71	0.62	2.01
6	0.37	0.22	-1.68	0.09	0.12	1.18

N (observations)= 4128

N (population)= 781.33

F (8, 4120) = 5.58

Table 25: Logistic Regression Results for Gun Recovery, Non-Fatal Shootings (Kansas City)

					95% C.I.	
GUN RECOVERY	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	0.71	0.26	-0.91	0.36	0.35	1.47
GCIC	0.65	0.35	-0.80	0.43	0.22	1.88
Year	0.98	0.06	-0.25	0.81	0.87	1.11
PD division						
2	1.31	0.50	0.72	0.47	0.63	2.76
3	1.08	0.43	0.18	0.85	0.49	2.38
4	2.32	1.37	1.42	0.16	0.73	7.40
5	0.79	0.34	-0.55	0.58	0.34	1.85
6	2.37	1.36	1.52	0.13	0.78	7.27

N (observations)= 4128

N (population)= 781.33

F (8, 4120) = 1.81

Table 26: Logistic Regression Results for Case Clearance, Non-Fatal Shootings (Kansas City)

					95% C.I.	
CLEARED	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	1.07	0.16	0.48	0.63	0.80	1.43
GCIC	0.75	0.19	-1.15	0.25	0.46	1.22
Year	0.76	0.03	-7.07	0.00	0.70	0.82
PD division						
2	0.74	0.14	-1.59	0.11	0.52	1.07
3	0.98	0.16	-0.13	0.90	0.71	1.36
4	1.50	0.69	0.89	0.38	0.61	3.70
5	1.18	0.29	0.66	0.51	0.73	1.91
6	1.60	0.46	1.65	0.10	0.92	2.80

N (observations)= 4128

N (population)= 781.33

F (8, 4120) = 31.03

Chicago Results

Table 27 presents results of the entropy balancing process for non-fatal shootings in Chicago. We succeeded in applying ebalance to both the first and second moments, making both means and variances practically identical across the treated and weighted control group for all covariates. Table 28 and Table 29 display findings of the logistic regression model testing the influence of GDT on gun recoveries and case clearance. GDT exhibited no significant influence in either model.

Table 27: Entropy Matching Balance, Non-Fatal Shootings (Chicago)

Covariates	Treatment mean	Treatment variance	Control (unweighted) mean	Control (unweighted) variance	Control (weighted) mean	Control (weighted) variance
Outcome period total	2.72	4.45	3.51	10.64	2.72	4.45
Lagged outcome period total	0.92	0.67	1.41	1.88	0.92	0.67
Enforcement period total (z)	32.10	2559.00	87.49	35243.00	32.10	2557.00
Lagged enforcement period total (z)	18.78	535.50	49.33	5164.00	18.78	535.40
Weekend	0.49	0.25	0.47	0.25	0.49	0.25
2nd quarter	0.28	0.20	0.28	0.20	0.28	0.20
3rd quarter	0.30	0.21	0.30	0.21	0.30	0.21
4th quarter	0.26	0.19	0.22	0.17	0.26	0.19
CCTV	0.12	0.11	0.06	0.06	0.12	0.11
Primary road	0.14	0.12	0.14	0.12	0.14	0.12
Concentrated disadvantage (z)	2.51	5.54	1.70	6.43	2.51	5.54
Demographic index (z)	132.30	426.90	129.30	576.30	132.30	427.20
Population density (z)	-0.21	0.09	-0.06	0.30	-0.21	0.09
Geographic mobility (z)	-0.28	0.58	-0.15	0.55	-0.28	0.59
Ambient population (z)	0.34	0.29	0.55	2.62	0.34	0.30
Maximum temperature (z)	0.20	0.93	0.21	0.88	0.20	0.93
Precipitation (z)	0.01	0.95	-0.02	0.91	0.01	0.95

N treated=9338

N control=51427

N weighted control=9338

Table 28: Logistic Regression Results for Gun Recovery, Non-Fatal Shootings (Chicago)

GUN RECOVERY	Odds ratio	S.E.	t	P>t	95% C.I. Lower	Upper
Treated	1.06	0.10	0.62	0.54	0.88	1.27
SDSC	1.07	0.10	0.75	0.45	0.89	1.29
Year	0.99	0.01	-1.80	0.07	0.98	1.00
PD division						
2	0.55	0.19	-1.69	0.09	0.27	1.10
3	0.65	0.22	-1.25	0.21	0.33	1.28
4	0.75	0.26	-0.84	0.40	0.38	1.47
5	0.69	0.24	-1.09	0.27	0.35	1.35
6	0.71	0.24	-1.00	0.32	0.36	1.39
7	0.75	0.25	-0.85	0.39	0.38	1.46
8	0.66	0.23	-1.18	0.24	0.33	1.31
9	0.57	0.20	-1.62	0.11	0.29	1.12
10	0.50	0.18	-1.95	0.05	0.25	1.00
11	0.56	0.19	-1.70	0.09	0.28	1.09
12	0.53	0.21	-1.60	0.11	0.25	1.15
13	0.59	0.23	-1.36	0.17	0.28	1.26
14	0.47	0.18	-1.98	0.05	0.23	0.99
15	0.56	0.20	-1.64	0.10	0.28	1.12
16	0.91	0.34	-0.25	0.80	0.44	1.91
17	0.60	0.23	-1.34	0.18	0.29	1.26
18	0.55	0.32	-1.04	0.30	0.18	1.70
19	0.80	0.33	-0.54	0.59	0.36	1.80
20	0.51	0.23	-1.50	0.13	0.21	1.23
22	0.61	0.21	-1.44	0.15	0.31	1.20
24	0.86	0.34	-0.38	0.71	0.40	1.87
25	0.53	0.19	-1.80	0.07	0.27	1.06

N (observations)=60765

N (population)=18676

F (25, 60740) =2.13

Table 29: Logistic Regression Results for Gun Recovery, Non-Fatal Shootings (Chicago)

					95% C.I.	
CLEARED	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	1.09	0.06	1.45	0.15	0.97	1.22
SDSC	1.15	0.07	2.28	0.02	1.02	1.29
Year	0.94	0.00	-15.57	0.00	0.93	0.95
PD division						
2	0.56	0.13	-2.49	0.01	0.35	0.88
3	0.75	0.17	-1.22	0.22	0.48	1.19
4	0.84	0.19	-0.77	0.44	0.53	1.31
5	0.73	0.17	-1.37	0.17	0.47	1.15
6	0.81	0.19	-0.89	0.37	0.52	1.28
7	0.74	0.17	-1.34	0.18	0.47	1.15
8	0.68	0.16	-1.68	0.09	0.43	1.07
9	0.61	0.14	-2.11	0.04	0.39	0.97
10	0.57	0.13	-2.41	0.02	0.36	0.90
11	0.60	0.14	-2.25	0.02	0.38	0.93
12	0.56	0.14	-2.31	0.02	0.34	0.92
13	0.50	0.13	-2.62	0.01	0.30	0.84
14	0.43	0.11	-3.35	0.00	0.27	0.71
15	0.66	0.15	-1.79	0.07	0.42	1.04
16	1.15	0.29	0.58	0.57	0.71	1.88
17	0.63	0.16	-1.88	0.06	0.39	1.02
18	0.86	0.29	-0.46	0.65	0.44	1.67
19	0.69	0.21	-1.25	0.21	0.38	1.24
20	0.52	0.16	-2.10	0.04	0.29	0.96
22	0.65	0.15	-1.82	0.07	0.42	1.03
24	0.86	0.23	-0.55	0.58	0.51	1.46
25	0.67	0.16	-1.72	0.09	0.42	1.06

N (observations)=60765

N (population)=18969

F (25, 60740) =18.91

Table 30 displays entropy balancing results for fatal shootings. We again succeeded in applying ebalance to the first and second moments, resulting in nearly identical means and variances across covariates.

Table 30: Entropy Matching Balance, Fatal Shootings (Chicago)

	Treatment		Control (unweighted)		Control (weighted)	
Covariates	**mean**	**variance**	**mean**	**variance**	**mean**	**variance**
Outcome period total	1.30	0.36	1.32	0.45	1.30	0.36
Lagged outcome period total	0.12	0.03	0.14	0.04	0.12	0.03
Enforcement period total (z)	28.24	1612.00	72.57	38979.00	28.25	1612.00
Lagged enforcement period total (z)	20.59	588.40	49.17	5428.00	20.59	588.20
Weekend	0.52	0.25	0.51	0.25	0.52	0.25
2nd quarter	0.29	0.21	0.28	0.20	0.29	0.21
3rd quarter	0.33	0.22	0.31	0.21	0.33	0.22
4th quarter	0.24	0.18	0.23	0.18	0.24	0.18
CCTV	0.12	0.11	0.06	0.06	0.12	0.11
Primary road	0.11	0.10	0.10	0.09	0.11	0.10
Concentrated disadvantage (z)	2.67	4.93	1.97	6.49	2.67	4.93
Demographic index (z)	133.30	402.30	130.90	590.10	133.30	402.10
Population density (z)	-0.21	0.08	-0.09	0.29	-0.21	0.08
Geographic mobility (z)	-0.29	0.65	-0.18	0.49	-0.29	0.65
Ambient population (z)	0.33	0.27	0.50	2.49	0.33	0.28
Maximum temperature (z)	0.26	0.86	0.25	0.88	0.26	0.86
Precipitation (z)	0.01	0.71	-0.01	1.07	0.01	0.71

N treated=1042

N control=1946

N weighted control=1042

Table 31 displays the findings of the logistic regression model testing the influence of GDT on gun recoveries. Firearms were 45% more likely to be recovered from a fatal shooting incident within the GDT-treated target area as compared to the control group (Odds Ratio = 1.45; *p.*<0.01). GDT exhibited no effect on case clearance of fatal shootings (see Table 32).

Table 31: Logistic Regression Results for Gun Recovery, Fatal Shootings (Chicago)

GUN RECOVERY	Odds ratio	S.E.	t	P>t	95% C.I. Lower	Upper
Treated	1.45	0.21	2.59	0.01	1.09	1.91
SDSC	1.07	0.13	0.58	0.56	0.84	1.37
Year	0.99	0.01	-0.78	0.43	0.96	1.02
PD division						
2	0.24	0.16	-2.19	0.03	0.06	0.86
3	0.29	0.19	-1.93	0.05	0.08	1.02
4	0.27	0.18	-2.01	0.04	0.08	0.97
5	0.32	0.20	-1.79	0.07	0.09	1.12
6	0.31	0.19	-1.87	0.06	0.09	1.06
7	0.27	0.17	-2.09	0.04	0.08	0.92
8	0.19	0.12	-2.54	0.01	0.05	0.68
9	0.28	0.18	-2.00	0.05	0.08	0.97
10	0.23	0.15	-2.24	0.03	0.06	0.83
11	0.21	0.14	-2.43	0.02	0.06	0.74
12	0.25	0.17	-2.00	0.05	0.06	0.97
13	0.33	0.25	-1.48	0.14	0.08	1.43
14	0.15	0.12	-2.43	0.02	0.03	0.69
15	0.16	0.10	-2.85	0.00	0.04	0.56
16	0.67	0.48	-0.56	0.58	0.16	2.74
17	0.22	0.19	-1.79	0.07	0.04	1.16
18	0.56	0.53	-0.61	0.54	0.08	3.65
19	0.36	0.29	-1.27	0.20	0.08	1.73
20	1.04	1.02	0.05	0.96	0.15	7.05
22	0.20	0.13	-2.47	0.01	0.05	0.71
24	0.54	0.44	-0.75	0.45	0.11	2.67
25	0.16	0.11	-2.68	0.01	0.04	0.61

N (observations)=5988

N (population)=2084

F (25, 5963) =1.44

Table 32: Logistic Regression Results for Gun Recovery, Fatal Shootings (Chicago)

					95% C.I.	
CLEARED	**Odds ratio**	**S.E.**	**t**	**P>t**	**Lower**	**Upper**
Treated	0.98	0.12	-0.15	0.88	0.78	1.24
SDSC	0.89	0.09	-1.16	0.25	0.73	1.08
Year	0.92	0.01	-7.10	0.00	0.89	0.94
PD division						
2	0.57	0.38	-0.85	0.39	0.15	2.09
3	0.48	0.31	-1.14	0.26	0.14	1.70
4	0.53	0.34	-0.97	0.33	0.15	1.89
5	0.37	0.24	-1.53	0.13	0.11	1.32
6	0.32	0.21	-1.75	0.08	0.09	1.14
7	0.42	0.26	-1.38	0.17	0.12	1.44
8	0.45	0.30	-1.22	0.22	0.13	1.63
9	0.51	0.33	-1.03	0.30	0.15	1.82
10	0.50	0.33	-1.06	0.29	0.14	1.79
11	0.46	0.30	-1.20	0.23	0.13	1.62
12	0.54	0.38	-0.87	0.38	0.14	2.14
13	0.26	0.19	-1.82	0.07	0.06	1.11
14	0.57	0.44	-0.74	0.46	0.13	2.55
15	0.39	0.25	-1.47	0.14	0.11	1.37
16	1.46	1.11	0.49	0.62	0.33	6.52
17	1.04	0.77	0.05	0.96	0.24	4.41
18	1.37	1.27	0.34	0.73	0.22	8.37
19	0.77	0.64	-0.31	0.76	0.15	3.92
20	0.62	0.60	-0.49	0.62	0.09	4.18
22	0.28	0.19	-1.91	0.06	0.08	1.04
24	0.95	0.75	-0.06	0.95	0.20	4.42
25	0.59	0.39	-0.81	0.42	0.16	2.14

N (observations)=5988

N (population)=2084

F (25, 5963) =4.54

CHAPTER SIX: POLICY IMPLICATIONS AND CONCLUSION

This report outlined the findings of what we believe is the largest GDT study conducted to date. Findings have important implications for the use of GDT as a crime control intervention. GDT positively impacts a number of procedural aspects of police response to gun fire. Our analysis of AVL data indicates that officers respond to most gun fire events quicker when the gunfire is detected by GDT rather than reported by CFS. The lone exception was for non-fatal shootings in Kansas City. For all other crime types in Kansas City, and all crime types in Chicago, GDT led to faster responses than CFS. Furthermore, police officers stop their vehicles more often and closer to the detected/reported crime scene on GDT alerts than CFS for all crime types across both Chicago and Kansas City.

GDT further demonstrates a positive influence on evidence collection. Results of our microsynthetic control analysis found that NIBIN evidence was collected significantly more often in the GDT target area and surrounding catchment zone than the weighted control area in Kansas City. While only approaching significance, gun recoveries also occurred more often in Kansas City's GDT target area than the weighted control area. Incident-level analysis in Chicago further speaks to the evidence collection benefits of GDT. Fatal shootings were 45% more likely to result in the recovery of a firearm within the GDT-treated target area as compared to the weighted control area.

Unfortunately, these procedural benefits did not translate to any meaningful improvements to crime control outcomes. While in Kansas City shots fired calls for service were significantly lower in the GDT target area than the weighted control area, none of the Part 1 crime types (which involve confirmed victims) experienced any significant reductions. In Chicago, GDT was associated with significantly higher levels of fatal shootings, non-fatal shootings, and gun assaults and robberies, as compared to the weighted control area. While a minority of GDT installation phases drove the cumulative increase in Chicago, significant reductions of crime outcomes were only observed in two instances (gun assaults and robberies in phase 4 and shots fired CFS in phase 10).

It is helpful to consider the assumed causal mechanisms undergirding GDT use when interpreting the study results. Given the small and inconspicuous nature of microphones installed in GDT systems, the 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). As previously discussed, findings suggest that GDT did result in the type of accurate responses that are considered necessary for public safety benefits to take hold. The fact that public safety benefits—in the form of the reduction and increase clearance of gun violence—did not result suggests that GDT may need to activate alternative casual mechanisms to generate crime control benefits.

Improving the effectiveness of GDT may rely on police deploying the technology within contexts that facilitate success. Research has allowed for such practical considerations with other technologies. For example, CCTV video surveillance cameras achieve largest effects within car parks and residential areas (Piza et al., 2019; Welsh & Farrington, 2009). Further, the active monitoring of cameras and use of CCTV alongside multiple complementary interventions works better than passive monitoring and deploying CCTV as a stand-alone intervention (Piza et al., 2015, 2019). Similarly, body-worn cameras have largest effects when camera activation compliance by officers is high (Malm, 2019). Future GDT research should strive to identify contextual factors associated with heightened/lowered GDT performance. Such research would fit into the broader call to move evidence-based crime prevention towards 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). Continuing upon the current pace of GDT adoption in policing should perhaps be contingent upon the field gaining a better understanding of exactly how to deploy and integrate GDT in a manner that maximizes the likelihood of success. Given the high cost of the technology, such an approach would be prudent.

In considering the overall research evidence on GDT, we should note the complete absence of randomized controlled trials (RCTs) in the literature. RCTs provide the best venue for reducing selection bias and maximizing the internal validity of research designs (Farrington et al., 2006). Random assignment, however, can be exceedingly difficult in technology interventions. Technology systems with a built physical architecture are not easily reconfigured in response to evidence or experimentation (Piza, 2018; Piza et al., 2019). GDT acoustic sensors present many such challenges that complicate randomization, including the high price of annual subscriptions and the need for acoustic sensors to be placed in close proximity to one another in order to form a "mesh network" over the target area. It is not beyond the realm of possibility, nonetheless, that certain jurisdictions may provide sufficient study settings to conduct an RCT of GDT. This is particularly the case with large jurisdictions where a sufficient number of prospective target areas allow for block randomized designs that maximize equivalence and statistical power (Weisburd et al., 2022). To be clear, the matched quasi-experimental designs employed in the current study can achieve adequate statistical power and equivalence between treated and control units when practical considerations prevent randomization. As such, these methods can serve as guidance to researchers needing to conduct rigorous post-facto evaluations of GDT system. Nonetheless, a randomized experiment on GDT effect would generate valuable empirical evidence.

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APPENDIX

Supplemental Microsynth Outputs for Kansas City

Figure 9: Fatal Shootings Synthetic Control Estimates, Kansas City Main Analysis

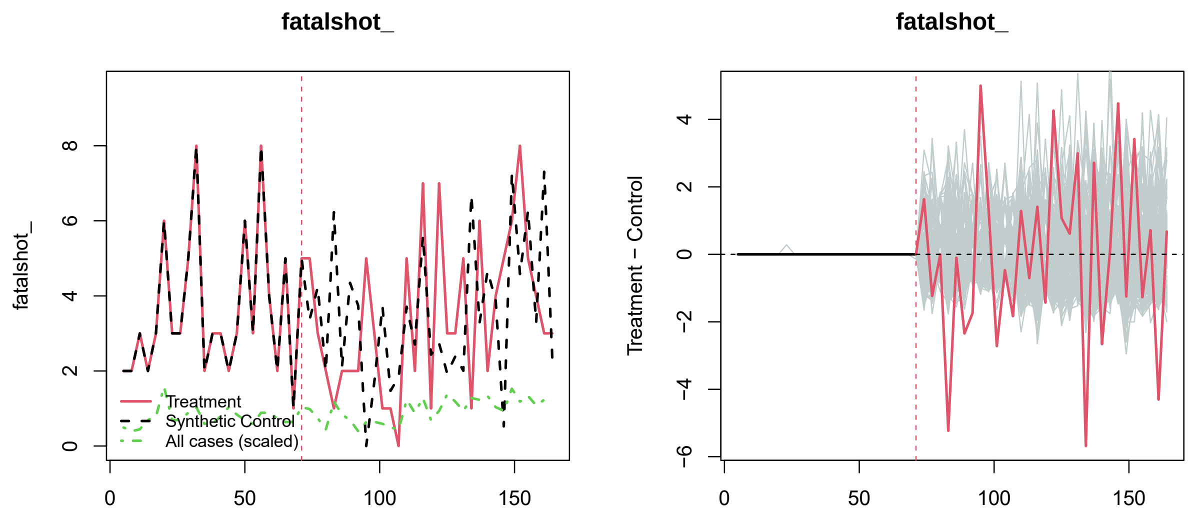


Figure 10: Non-Fatal Shootings Synthetic Control Estimates, Kansas City Main Analysis

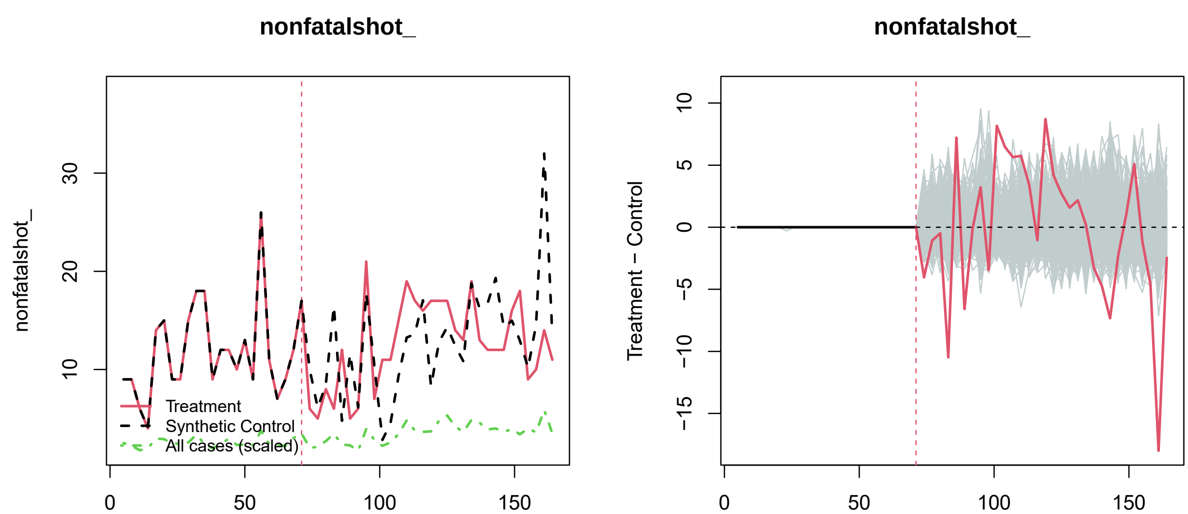


Figure 11: Firearm Assault and Robbery Synthetic Control Estimates, Kansas City Main Analysis

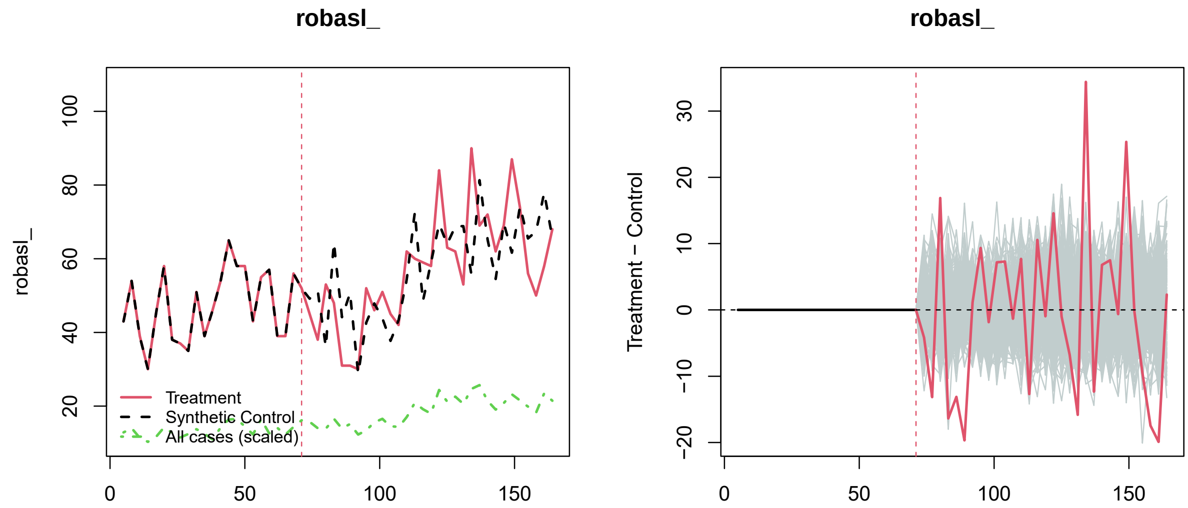


Figure 12: Gun Recovery Synthetic Control Estimates, Kansas City Catchment Analysis

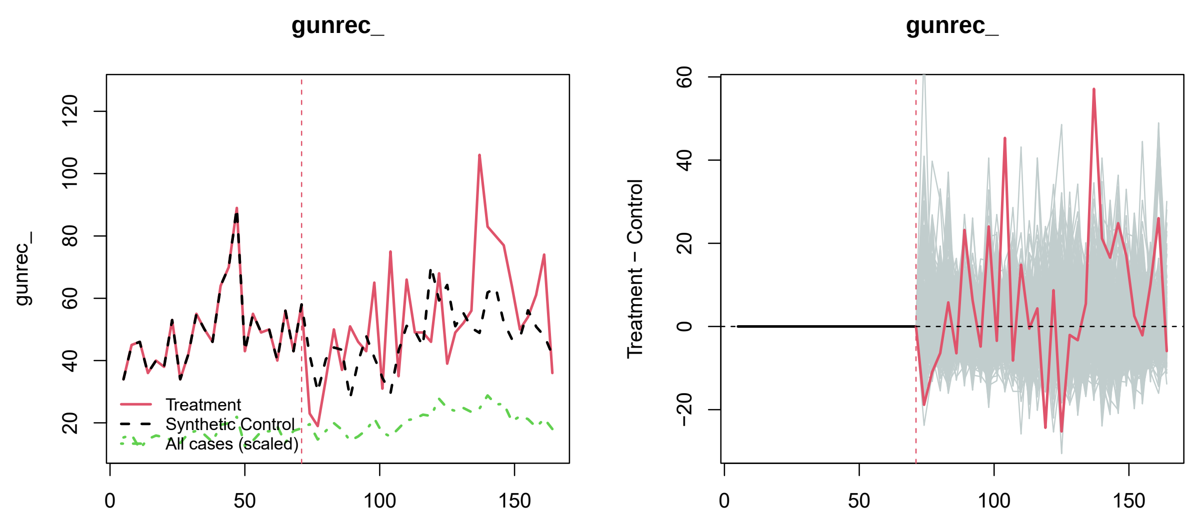


Figure 13: Shots Fired CFS Synthetic Control Estimates, Kansas City Catchment Analysis

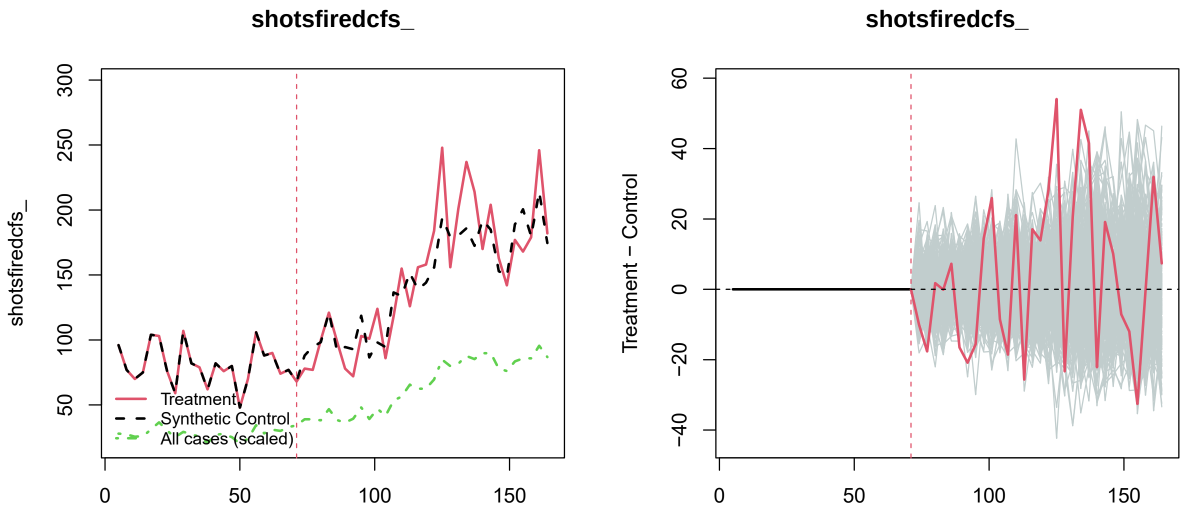


Figure 14: Fatal Shootings Synthetic Control Estimates, Kansas City Catchment Analysis

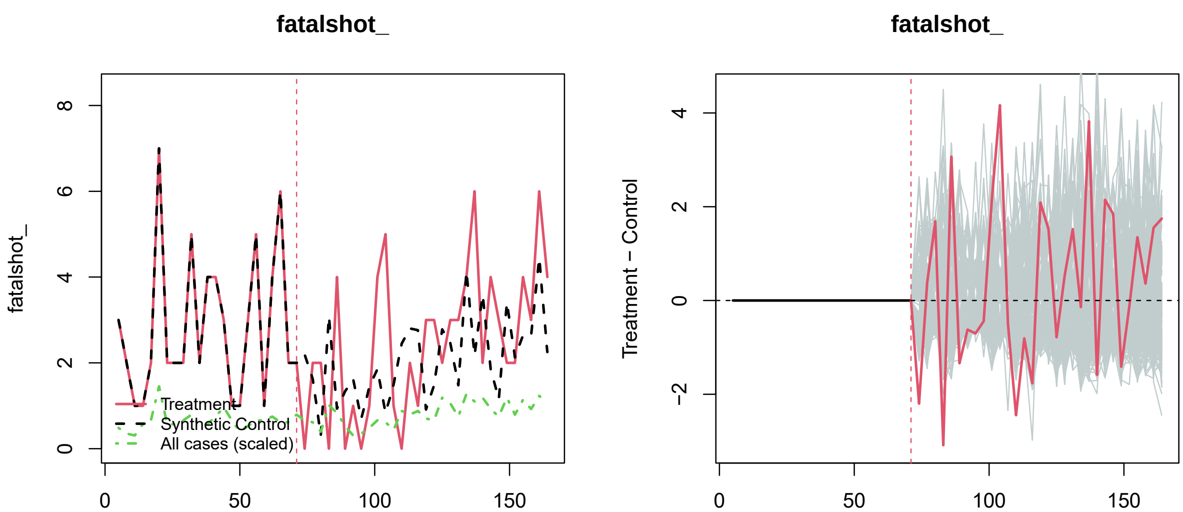


Figure 15: Non-Fatal Shootings Synthetic Control Estimates, Kansas City Catchment Analysis

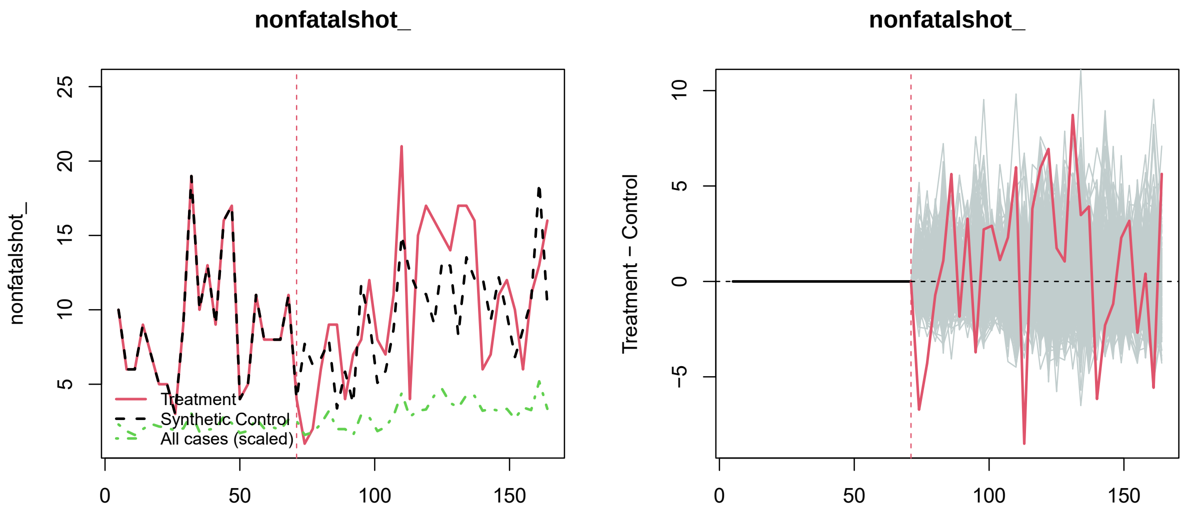
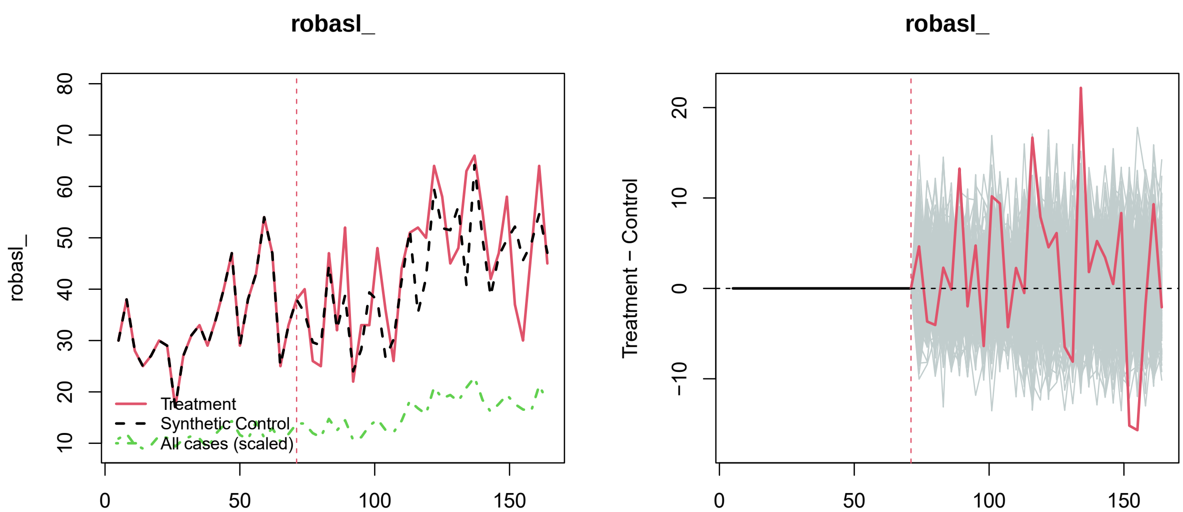


Figure 16: Firearm Assault and Robbery Synthetic Control Estimates, Kansas City Catchment Analysis



Supplemental Microsynth Outputs for Chicago

Table 33: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 2

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	24315	24315
fatal shootings (sum)	297	297
non-fatal shootings (sum)	2161	2161
gun assaults & robberies (sum)	1486	1486
gun recovery (sum)	2402	2402
part I non-firearm crime (sum)	40194	40194
arrests (sum)	44221	44221
field contacts (sum)	149226	149226
principal roadway	450	450
street segment Street Segment Length (sum)	1563145	1563145
street segment parcel zoning	1203	1203
cctv presence	263	263
dichotomous disadvantage index	11	11
dichotomous demographic index	137	137
dichotomous ambient population index	1939	1939

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 34: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 3

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	7735	7735
fatal shootings (sum)	108	108
non-fatal shootings (sum)	772	772
gun assaults & robberies (sum)	745	745
gun recovery (sum)	764	764
part I non-firearm crime (sum)	15246	15246
arrests (sum)	15219	15219
field contacts (sum)	42344	42344
principal roadway	154	154
street segment Street Segment Length (sum)	452948.6	452948.6
street segment parcel zoning	293	293
cctv presence	85	85
dichotomous disadvantage index	32	32
dichotomous demographic index	128	128
dichotomous ambient population index	292	292

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 35: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 4

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	11904	11904
fatal shootings (sum)	111	111
non-fatal shootings (sum)	910	910
gun assaults & robberies (sum)	655	655
gun recovery (sum)	822	822
part I non-firearm crime (sum)	21168	21168
arrests (sum)	13069	13069
field contacts (sum)	57193	57193
principal roadway	483	483
street segment Street Segment Length (sum)	1481550	1481550
street segment parcel zoning	989	989
cctv presence	111	111
dichotomous disadvantage index	1038	1038
dichotomous demographic index	1219	1219
dichotomous ambient population index	1995	1995

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 36: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 5

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	11268	11268
fatal shootings (sum)	138	138
non-fatal shootings (sum)	1101	1101
gun assaults & robberies (sum)	1234	1234
gun recovery (sum)	1366	1366
part I non-firearm crime (sum)	30424	30424
arrests (sum)	18510	18510
field contacts (sum)	44902	44902
principal roadway	257	257
street segment Street Segment Length (sum)	968736.1	968736.1
street segment parcel zoning	1158	1158
cctv presence	67	67
dichotomous disadvantage index	245	245
dichotomous demographic index	287	287
dichotomous ambient population index	1621	1621

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 37: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 6

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	10652	10652
fatal shootings (sum)	107	107
non-fatal shootings (sum)	1022	1022
gun assaults & robberies (sum)	773	773
gun recovery (sum)	1168	1168
part I non-firearm crime (sum)	21577	21577
arrests (sum)	18374	18374
field contacts (sum)	52876	52876
principal roadway	210	210
street segment Street Segment Length (sum)	712607.8	712607.8
street segment parcel zoning	136	136
cctv presence	118	118
dichotomous disadvantage index	252	252
dichotomous demographic index	365	365
dichotomous ambient population index	431	431

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 38: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 7

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	12092	12092
fatal shootings (sum)	113	113
non-fatal shootings (sum)	982	982
gun assaults & robberies (sum)	1103	1103
gun recovery (sum)	1018	1018
part I non-firearm crime (sum)	27032	27032
arrests (sum)	13734	13734
field contacts (sum)	56447	56447
principal roadway	214	214
street segment Street Segment Length (sum)	683863.9	683863.9
street segment parcel zoning	482	482
cctv presence	60	60
dichotomous disadvantage index	120	120
dichotomous demographic index	154	154
dichotomous ambient population index	808	808

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation

Table 39: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 8

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	12069	12069
fatal shootings (sum)	118	118
non-fatal shootings (sum)	964	964
gun assaults & robberies (sum)	921	921
gun recovery (sum)	1177	1177
part I non-firearm crime (sum)	29543	29543
arrests (sum)	16132	16132
field contacts (sum)	42043	42043
principal roadway	311	311
street segment Street Segment Length (sum)	1580802	1580802
street segment parcel zoning	1612	1612
cctv presence	88	88
dichotomous disadvantage index	751	751
dichotomous demographic index	1417	1417
dichotomous ambient population index	2885	2885

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 40: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 9

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	26540	26540
fatal shootings (sum)	233	233
non-fatal shootings (sum)	2094	2094
gun assaults & robberies (sum)	2051	2051
gun recovery (sum)	2416	2416
part I non-firearm crime (sum)	67108	67108
arrests (sum)	37786	37786
field contacts (sum)	103839	103839
principal roadway	1018	1018
street segment Street Segment Length (sum)	3505617	3505617
street segment parcel zoning	4385	4385
cctv presence	236	236
dichotomous disadvantage index	3595	3595
dichotomous demographic index	5106	5106
dichotomous ambient population index	4072	4072

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Table 41: Balance Table for Treated and Weighted Control Areas in Chicago, Phase 10

Covariates	Targets	Weighted Controls
shots fired cfs (sum)	8406	8406
fatal shootings (sum)	75	75
non-fatal shootings (sum)	733	733
gun assaults & robberies (sum)	945	945
gun recovery (sum)	768	768
part I non-firearm crime (sum)	25531	25531
arrests (sum)	10390	10390
field contacts (sum)	42232	42232
principal roadway	217	217
street segment Street Segment Length (sum)	806956.7	806956.7
street segment parcel zoning	565	565
cctv presence	83	83
dichotomous disadvantage index	589	589
dichotomous demographic index	371	371
dichotomous ambient population index	697	697

Note: For time variant measures, the msynth output provides values across all temporal periods. The above table sums the individual periods to allow for easier interpretation.

Figure 17: Gun Recovery Synthetic Control Estimates, Chicago Phase 1

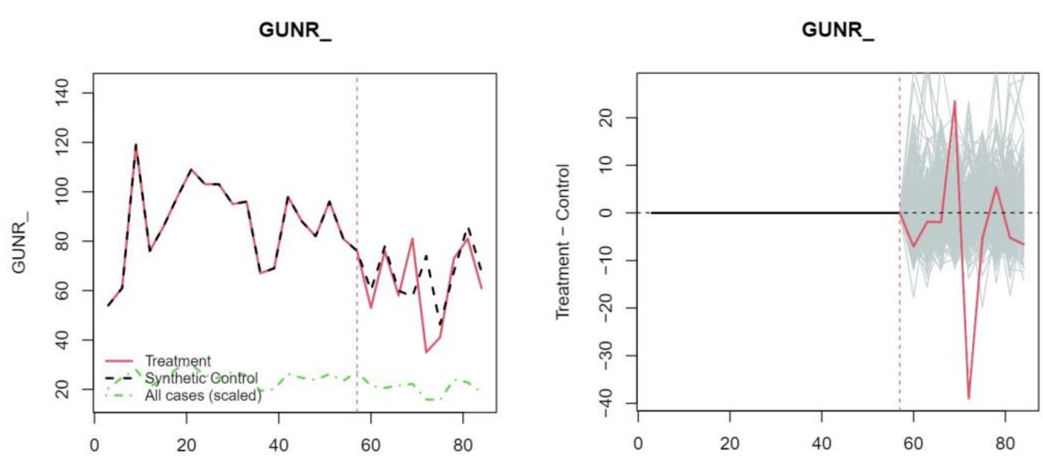


Figure 18: Fatal Shootings Synthetic Control Estimates, Chicago Phase 1

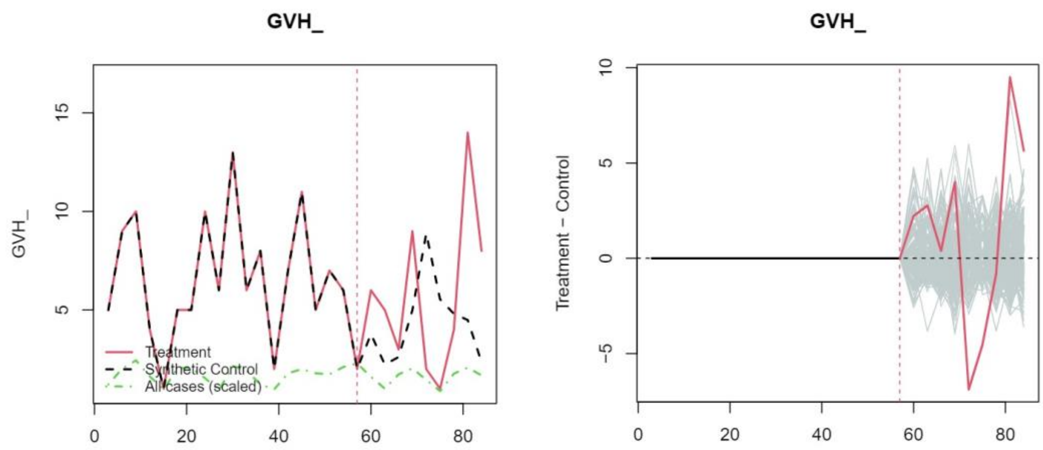


Figure 19: Non-Fatal Shootings Synthetic Control Estimates, Chicago Phase 1