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The effect of gunshot detection technology on evidence collection and case clearance in Kansas City, Missouri

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Abstract

Objectives This study tests whether (1) shots fired calls for service in the gunshot detection technology (GDT) target area are more likely to be classified as unfounded; (2) police responses to shootings in the GDT target area are more likely to recover ballistic evidence or firearms; and (3) shootings in the GDT target area are more likely to be cleared.

Methods Entropy balancing created a weighted control group that equaled the treatment group across a range of covariates. GDT effect was tested through logistic regression models with entropy balancing weights set as probability weights.

Results Shots fired occurring in the GDT target area were 15% more likely to be classified as unfounded compared to control cases. GDT did not significantly influence the likelihood of evidence collection or case clearance in shooting incidents.

Conclusions GDT may not add investigative value to police responses to shooting incidents and may increase patrol workload.

Keywords Case clearance · Entropy balancing · Matched quasi-experiment · Gunshot detection technology · Gun violence

Introduction

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. Following the terrorist attacks of September 11, 2001, a move toward

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intelligence-led policing began to emphasize technological solutions to crime and disorder, including data tracking and surveillance. Since then, data generated by technology systems have become increasingly central to contemporary policing strategies (Gaub & Koen, 2021). More recently, new technologies have led to advances in police investigations of gun crime (Flippin et al., 2022).

Gunshot detection technology (GDT) has greatly increased in popularity over recent decades. Over 250 public safety agencies worldwide have adopted the ShotSpotter platform developed by SoundThinking, the global industry leader in GDT.[1] Despite the increased adoption of GDT, the scientific evidence on GDT is underdeveloped in many respects. First, evaluations of GDT are sparse, especially in comparison to other contemporary police technologies such as body-worn cameras (Lum et al., 2019, 2020) and closed-circuit television (CCTV) (Piza et al., 2019). Second, the majority of evaluation studies have explored GDT's crime prevention capacity, despite the technology arguably offering more potential for investigative police functions (La Vigne et al., 2019; Lawrence et al., 2018). Third, evaluations of GDT's investigative benefits have largely incorporated quasi-experimental designs that do not directly account for pertinent variables that may influence crime control outcomes, which can compromise internal validity (Farrington et al., 2006).

The current study evaluates GDT's effect on evidence collection and case clearance in Kansas City, MO. We examine whether incidents of shots fired in the GDT target area are more likely to be classified as unfounded than those in the control area, indicating no confirmatory evidence of gunfire is found. We further examine whether shooting incidents in the GDT target area are more likely to result in recovery of ballistic evidence or firearms, and whether these cases are more likely to be cleared (i.e., solved) compared to incidents in the control area. Results indicate that shots fired calls for service occurring in the GDT target area were 15% more likely to be classified as unfounded compared to control cases. GDT did not significantly influence the likelihood of evidence collection or case clearance in fatal or nonfatal shooting incidents during the study period. Policy implications for the investigative benefits of GDT are discussed.

Literature review

Investigations and case clearance

Crime clearance rates represent the percentage of cases solved by police, either through the arrest of an offender or by exceptional means.[2] Clearance rates

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

[2] Cases are most often cleared by arrest. Police can clear a case by exception when they have probable cause to make an arrest but a reason outside of law enforcement control prevents the arrest and charging of an offender (e.g., the offender is dead or imprisoned) (see https://ucr.fbi.gov/crime-in-the-u.s/2018/crime-in-the-u.s.-2018/topic-pages/clearances).

nationally have either remained stable or declined over the last several decades. In 1961, 93% of homicides resulted in an arrest, as compared to only 59% by 2016 (Regoeczi, 2018). Clearance rates for other violent crimes such as rape, aggravated assault, and robbery have also declined during the same period (Jarvis et al., 2017). And clearance rates for property crime have been consistently low, with 82.8% of the 6.9 million property crimes in 2019 not cleared according to the FBI's Uniform Crime Reporting program.

Clearance rates have long been used as a measure of police performance and effectiveness (Baughman, 2020), reflecting the importance of incapacitation in disrupting patterns of violence and creating a general deterrence effect (Braga et al., 2022), and the public desire to deliver justice to crime victims and their families (Cook & Mancik, 2024). Maximizing clearance rates can further strengthen community trust in police, as residents may interpret the failure of police to arrest serious offenders as evidence that police do not care about victims of gun violence (Braga & Cook, 2023). In racial minority communities, low clearance rates may lead to residents feeling simultaneously underpoliced in the context of serious offenders being brought to account and overpoliced when it comes to minor legal infractions (Brunson, 2020). As such, any intervention that meaningfully increases case clearance can positively impact police practice.

Case clearance appears to be influenced by both circumstantial factors (e.g., whether a witness was present at the crime scene) and investigative effort (e.g., faster response times and follow-up by detectives) (Wellford & Cronin, 1999). Interestingly, findings have been mixed regarding the impact of physical evidence collection on case clearance. Some scholars have found that recovery of weapons and other evidence at the crime scene increases the likelihood of case clearance for homicides (Wellford et al., 2019), and that collection of ballistic evidence (i.e., spent bullets or shell casings) increases the likelihood of case clearance for gun crime investigations (Flippin et al., 2022). However, others have found that forensic evidence did not influence criminal justice outcomes (Baskin & Sommers, 2010; McEwen & Regoeczi, 2015). The cumulative research evidence indicates that the increased role of video and other digital evidence in police investigations has not negated the importance of witness and other civilian cooperation, specifically in the form of first-hand testimony (Cook & Mancik, 2024).

Findings on the impact of technology on case clearance have also been mixed. For example, some studies on CCTV have found increases in case clearance, particularly for theft (Ashby, 2017; Jung & Wheeler, 2023) and other property crime (Morgan & Dowling, 2019; Sharp, 2016), while others have found no significant increase in case clearance (Gerell, 2021; Paine, 2012). Piza et al. (2014) found that in-progress crime incidents detected by CCTV resulted in on-scene arrests of suspects at a significantly higher rate than incidents reported by citizen calls for service (11% vs. 4%). In addition, there is some evidence that body-worn cameras (Lum et al., 2019) and license plate readers (Koper & Lum, 2019) may increase case clearance, although these may have to be combined with other technologies and policies in order to realize these benefits.

Background on gunshot detection technology

GDT systems deploy networks of acoustic sensors that detect sounds from firearm muzzle blasts or the sonic booms generated by bullets traveling through the air (Mares, 2022). Detection is based upon the unique signature of the sounds, which distinguishes gunshots from other loud noises (Chacon-Rodriguez et al., 2011; Maher, 2007). GDT systems then assign precise geographic coordinates to gunfire incidents (La Vigne et al., 2019), allowing police to more accurately identify crime incident locations than what is reported second hand via 911 calls for service (Piza et al., 2023a). 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 to reformulate the technology for use by local law enforcement (Mazerolle et al., 1998), paving the way for the modern GDT systems used today.

ShotSpotter—the most popular GDT system on the market—uses 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. 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).[4] This information is then relayed directly to the 911 dispatch center of the police department in question (La Vigne et al., 2019; Mares, 2022). 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 (Lawrence et al., 2018). The establishment of the Real-Time Incident Review Center was the cornerstone of the company's reorganization in 2011, following the appointment of a new chief executive officer.[5]

Gunshot detection technology's effect on gunshot reporting and criminal investigations

GDT evaluation studies have predominately tested the technology's crime prevention effect. The general takeaway from this body of research is that GDT

[3] See Sect. 3 in the ShotSpotter Frequently Asked Questions document: http://www.shotspotter.com/system/content-uploads/SST_FAQ_January_2018.pdf

[4] The lead author learned about the gunshot review process during a site visit to ShotSpotter (now SoundThinking) headquarters in Newark, CA on 3/26/18. During the visit, the lead author met and was given a presentation of the technology by the ShotSpotter leadership team, viewed the activities of acoustic gunshot experts in the Real-Time Incident Review Center, and spoke with acoustic gunshot experts about the gunshot review process, which included reviews of gunshot recordings.

[5] The lead author learned of this from personal communication with ShotSpotter (now SoundThinking) CEO Ralph Clark during the site visit.

most often leads to a reduction of shots fired calls for service but has little impact on the occurrence of Part 1 violent crime incidents (Doucette et al., 2021; Lawrence et al., 2019; Mares & Blackburn, 2012, 2021; Piza et al., 2023b; Vovak et al., 2021). Noteworthy exceptions were observed in Cincinnati, OH (Mares, 2023), and Winston-Salem, NC (CCSVP, 2023), which experienced significant reductions in gun assaults (46%) and overall violent crime (24%), respectively.

Findings on the impact of GDT on investigative outcomes, such as evidence collection and case clearance, have been mixed. Research suggests that GDT systems can help police to detect gunfire that would not otherwise be reported (Huebner et al., 2022). This knowledge is useful for crime control and investigative efforts and can potentially aid in evidence collection to enhance case solvability. However, this research rests on the assumption that all GDT alerts accurately identify sounds of gunshots and that this increases the chances of evidence collection. It is possible that a proportion of GDT alerts are false positive events where no actual gunshot occurred (e.g., fireworks, and thunder), although modern GDT systems often include incident review processes that should reduce false positives (Mares, 2022). It is also possible that GDT alerts may increase police workload by dispatching officers to less serious incidents of "random" gunfire, with potentially limited investigative value (Mazerolle et al., 1998; Ratcliffe et al., 2019).

Litch and Orrison (2011) found that only 18% and 24% of GDT alerts had an associated 911 call in Hampton, VA, and Newport News, VA, respectively. When restricting their analysis to confirmed gunfire incidents (i.e., those in which evidence of a gunshot was found on-scene), the proportions increased to 39% in Hampton and 43% in Newport News. This suggests that GDT alerted police to gunshot incidents that would not have otherwise been reported. A partially block-randomized field experiment in Philadelphia, PA, suggested that GDT dispatches may place a significant burden on police patrol operations (Ratcliffe et al., 2019). Police responses to gunshot incidents increased by over 259% in the 800 feet surrounding the GDT target locations over the 8-month study period, but there was no significant increase in the number of confirmed, or "founded," gunfire incidents. 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. Police workload increases have also been observed elsewhere, with police responses to gunfire increasing 80% in St. Louis (Mares & Blackburn, 2021) and 287% in Dallas (Mazerolle et al., 1998) following the introduction of GDT.

Mares and Blackburn's (2012) evaluation of GDT in St. Louis, MO, found that approximately 2% of GDT gunfire alerts led to the recovery of ballistic evidence from a shooting, as compared to a city-wide rate of 17% for shots fired calls for service. The Center for Crime Science and Violence Prevention (CCSVP, 2023) found that firearms and shell casings were recovered in 3% and 37.1% of GDT alerts, respectively, over a one-year intervention period in Winston-Salem, NC. The shell casing recovery is particularly noteworthy given that the number of shell casings recovered in the 3 square mile GDT target area (1577) accounts for approximately 43% of all shell casings recovered across the entire 134 square mile city (3678).

A study by Lawrence et al. (2019) analyzed GDT systems in Denver, CO, Milwaukee, WI, and Richmond, VA. They found 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. They found GDT did not significantly influence the number of cases resulting in an arrest or the retrieval of a weapon on scene, either within or across sites. Mazerolle et al. (1998) reported that no offenders were apprehended in response to either a GDT alert or citizen call for service during their study period. Using data from Brockton, MA, Choi et al. (2014) similarly found no evidence that gunfire events were associated with any law enforcement activities, such as evidence collection or arrest. On the other hand, Vovak et al. (2021) analyzed GDT in Wilmington, DE, with results indicating that the clearance of homicides and shootings decreased during the post-implementation period. They note these findings should be interpreted with caution, however, as there was less time for cases to be cleared during the post-implementation period relative to prior years. In addition, it is possible the COVID-19 pandemic may have influenced the findings.

Doucette et al. (2021) found GDT was not associated with any significant changes in murder arrests or weapons arrests across 68 large metropolitan counties in the USA from 1999 to 2016. 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 may have biased the results of the study, making a null result more likely, which Doucette et al. (2021) acknowledge. Similar measurement difficulties were encountered in Litch and Orrison's (2011) aforementioned study. Crime data were only available at the district level, meaning the precise GDT coverage area was not operationalized. The findings of these studies suggest that neither GDT system had any significant effect on the occurrence of crime nor case clearance, but we recommend caution in interpreting these results in light of the target area measurement challenges.

Literature review summary and scope of the current study

Surveillance and investigative technologies are increasingly being adopted by law enforcement agencies across the country. The evidence base for these technologies is often lacking (Lum & Koper, 2017), with police agencies implementing technology absent rigorous analysis or evaluation (Weisburd & Neyroud, 2011). Prior evaluations of GDT have demonstrated mixed findings, and the knowledge base is not nearly as developed as the literature on other contemporary police technologies. Furthermore, research on GDT's potential for facilitating criminal investigations and increasing case clearance is also underdeveloped compared to research on other aspects of the technology. Finally, while some quasi-experimental evaluations have taken efforts to select control areas with similar crime and sociodemographic conditions as the GDT target areas, most studies have used a fuzzy matching approach. Quantitative matching techniques that ensure statistical equivalency between treatment and control groups have increasingly been used to evaluate a range of contemporary policing practices (Braga et al., 2012, 2013; Piza, 2018; Rydberg et al., 2018; Saunders et al., 2015), but these approaches are absent in the GDT literature, with a lone exception (Piza et al., 2023b).

The current study seeks to bolster the knowledge base on GDT as an investigative tool through an evaluation of the GDT system in Kansas City, MO. We explore three research questions: (1) are shots fired calls for service in the GDT target area more likely to be classified as unfounded, indicating no confirmatory evidence of gunfire is found?; (2) are shootings in the GDT target area more likely to result in the recovery of ballistic evidence or firearms?; (3) are shootings in the GDT target area more likely to be cleared? Each research question is explored through an entropy balancing approach that creates a weighted control group of untreated incidents for comparison (Hainmueller, 2012).

Study setting

Kansas City is the largest city in Missouri 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 1299 sworn officers and 520 civilians in 2019—the final year of our study period—according to the FBI's Police Employee Data.

Kansas City has suffered from elevated levels of gun violence for decades. Each year since 1970, Kanas City's homicide rate has been substantially higher than both the national average and the average for similarly sized cities (250,000 to 499,999 population) (Novak & King, 2020). The 2010s particularly saw a steep increase in gun homicides, with the city's third-highest annual homicide rate on record occurring in 2017 (30.53 per 100,000). Monthly trends in non-fatal shootings were largely correlated with gun homicides in this same period. These heightened levels of gun violence led Kansas City leadership to seek innovative strategies to combat gun violence over the years.

The ShotSpotter GDT system went live in Kansas City on September 14, 2012. 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.[6] Kansas City spends between $227,500 and $315,000 per year on its GDT system based on ShotSpotter's reported annual subscription cost of between $65 K and $90 K per

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

square mile.[7] Upon classification of a GDT alert as gunfire by the SoundThinking acoustic experts, a call of “ShotSpotter Sound of Shots” appears in the KCPD CAD system and the patrol car computer terminal. The nearest available patrol car is automatically dispatched to the location of the GDT alert. Officers typically use the point reflecting the location of the GDT alert and accompanying map displayed on the computer terminal to direct their response. The discovery of a gunshot victim is followed by the response of detectives and crime scene technicians to secure the crime scene, perform an area canvas, and interview relevant witnesses. The discovery of ballistic evidence absent any victims results in officers collecting the evidence and submitting it for analysis in the NIBIN system.[8]

Kansas City’s GDT system has been the focus of two prior empirical evaluations. An exploratory process evaluation found the GDT system increased the spatial and temporal precision of KCPD responses to gunfire (Piza et al., 2023a). The analysis found that GDT and CFS locations were geocoded to the same street segment in only 46.95% of cases, suggesting officers responding to the CFS location would potentially be a meaningful distance from where the gunshot occurred, as recorded by the GDT alert. Piza et al. (2023a) further found that GDT alerts occurred a median of 93 s before the first call for service reporting the gunfire event in question. The median time is nearly 12% of the summated police response, EMS response, and EMS travel times to the nearest trauma center in Kansas City, which represents a potentially important head start for the victim transport process.

A place-based evaluation of the system suggests these procedural benefits generated limited violence prevention benefits, however. Piza et al. (2023b) incorporated the microsynthetic control matching approach, finding higher levels of ballistic evidence collection in the GDT target area and surrounding catchment area, higher levels of gun recoveries in the surrounding catchment area, and lower levels of shots fired calls for service in the GDT target area. However, the GDT system did not influence any of the gun violence categories involving confirmed victims (non-fatal shootings, fatal shootings, and aggravated assaults and robberies committed with a firearm). A supplemental analysis further found the GDT had no impact on shooting fatality rates, measured as the ratio of fatal shootings to non-fatal shootings as compared between the target and control areas.

Prior evaluation research has yet to speak to the effect of KCPD’s GDT system on investigative outcomes. KCPD’s GDT system operates within an expanding apparatus aimed at enhancing the investigation of gun crimes. In particular, the KCPD established a regional Crime Gun Intelligence Center (CGIC) in 2014 to facilitate gun violence investigations and prosecutions. The CGIC built upon KCPD’s existing crime gun investigative infrastructure—which included the Bureau of Alcohol, Tobacco, and Firearms’ (ATF) National Integrated Ballistics

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

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

Imaging Network (NIBIN) and internet-based eTrace system for firearms tracing and analysis—by establishing collaborative inter-agency partnerships to enhance the process of collecting and analyzing ballistic evidence. Between 2017 and 2018, KCPD implemented a range of strategic changes in the CGIC, specifically by developing formal partnerships with various local and federal law enforcement agencies, adjusting NIBIN processes to facilitate faster turnaround of ballistic analysis, and empowering CGIC detectives to establish and pursue their own cases (Novak & King, 2020).

Methods

Unit of analysis and treatment designation

The current study builds upon the prior evaluation of Piza et al. (2023b) by measuring GDT effect at the incident-level. This allows for an assessment of GDT that is more granular in nature than what is possible through a place-based approach. For example, while Piza et al. (2023b) found an increase in evidence collection within the GDT target area, the methodology did not allow for the identification of specific cases for which evidence was obtained, which may have implications for the investigatory benefits provided by GDT. For example, police recovering evidence from incidents in which the shooter did not intend to strike anyone (e.g., celebratory gunfire) may be of less investigative value than evidence collected from an incident involving gunshot victims. Analyzing incidents also allows for the measurement of investigation-related process and outcome variables for specific cases, which speaks directly to whether GDT significantly impacts case solvability.

Data for this study were provided by KCPD. Individual gun violence incidents serve as the unit of analysis. We focus on city-wide incidents of shots fired ($N=80{,}624$),[9] fatal shootings ($N=1157$), and non-fatal shootings ($N=4168$) occurring between 2007 and 2019. Incidents were considered treated if they occurred within the GDT target area following the installation of GDT (September 14, 2012). The GDT target area was operationalized as all street segments falling within the boundary created by the individual GDT sensors as well as all street segments within 0.25 square miles of the boundary, to reflect the fact that GDT sensors can typically detect sounds of gunfire to that distance (Irvin-Erickson et al., 2017). In the current study period, approximately a quarter (2852) of GDT alerts occurred within this 0.25-square-mile buffer, which supports prior research finding that GDT coverage is underestimated when operationalized as the GDT sensor boundary (Mares, 2023). A total of 12,422

[9] In the shots fired analysis, all incidents occurring on July 4th, July 5th, December 31st, or 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.

Table 1 Dependent variable descriptive statistics

	Treatment				Control			
	Yes	%	No	%	Yes	%	No	%
Shots fired								
Unfounded	3925	33.70	7722	66.30	20,910	30.31	48,067	69.69
Fatal shootings								
NIBIN	36	32.43	75	67.57	243	23.23	803	76.77
Gun recovery	4	3.60	107	96.40	32	3.06	1,014	96.94
Cleared	59	53.15	52	46.85	642	61.38	404	38.62
Non-fatal shootings								
NIBIN	80	20.15	317	79.85	629	16.68	3142	83.32
Gun recovery	10	2.52	387	97.48	206	5.46	3565	94.54
Cleared	158	39.80	239	60.20	2104	55.79	1667	44.21

shots fired calls for service, 397 non-fatal shootings, and 111 fatal shootings were considered treated in the sample.[10]

Dependent variables

Incident-specific measures related to police investigative functions were incorporated as dependent variables. The shots fired analysis considered whether the case was classified as unfounded, meaning no evidence surfaced confirming that a firearm was discharged (e.g., property damage from a bullet and an eyewitness statement). This dependent variable reflects the prior research finding that GDT may increase police responses to non-confirmed gunfire events, potentially impacting resources and workload (Ratcliffe et al., 2019). For both non-fatal shootings and fatal shootings, two binary variables measured whether responding patrol officers recovered a firearm or ballistic evidence for entry into NIBIN. Crime incidents were merged with gun recovery and NIBIN data through a common incident case number that appeared across all datasets. Whether the incident was marked as cleared by investigators was the final dependent variable considered for the shooting models.

Table 1 displays descriptive statistics for the dependent variables across the treatment (GDT target area) and control incidents. Over 33% of treated shots fired incidents were unfounded compared to about 30% of control group shots fired incidents.

[10] KCPD's ShotSpotter data did not include case numbers, which prevented us from identifying the precise gunfire events that were detected by GDT. This influenced our decision to classify all incidents occurring within the geographic target area as treated. However, prior research has consistently demonstrated the reporting sensitivity of GDT systems resulting in heightened levels of gunfire events coming to the attention of police (Carr & Doleac, 2016; Irvin-Erickson et al., 2017), which leads us to expect substantial overlap between incidents falling within the GDT target area and incidents detected by ShotSpotter. Indeed, the 11,517 GDT alerts represent ~ 90% of the gunfire incidents included in the study sample.

NIBIN ballistic evidence was recovered more often for treatment than control incidents for fatal shootings (32.43% vs. 23.23%) and non-fatal shootings (20.15% vs. 16.68%). Guns were recovered in over 3% of cases for both treatment and control fatal shootings. Conversely, non-fatal shootings exhibited gun recovery rates of 2.52% for treatment cases and 5.46% for control cases. Control cases were cleared more often than treatment cases for both fatal shootings (61.38% vs. 53.15%) and non-fatal shootings (55.79% vs. 39.80%). The statistical analysis described below more rigorously tests whether any significant differences exist across the experimental groups.

Entropy balancing

We used the entropy balancing method to conduct a matched 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 sum of the control unit weights equals the total number of cases in the treated group. Unlike other popular matching approaches used in crime and justice research, such as propensity score matching (Apel & Sweeten, 2010), entropy balancing does not require researchers to manually iterate models and check balance until a satisfactory balancing solution is achieved—an approach that 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, across a range of incident-level data and contexts (Black et al., 2020; Parish et al., 2018; Zhao & Percival, 2017). The superior performance of entropy balancing over alternative methods becomes more pronounced as pre-weighted treated and control group samples become more dissimilar (Parish et al., 2018).

A key function of entropy balancing is the retaining of all observations for the analysis. Given their reliance on one-to-one matches between units, alternate balancing approaches commonly drop units when an appropriate match cannot be identified within the pool of control units. This can present potential problems with statistical power and bias 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). Eighteen covariates were used in the entropy matching algorithm. The matching covariates were selected through consultation with prior research on technology and criminal investigations, which have used similar measures to match treated and control cases in quasi-experiments or as control variables in regression models (Guerette & Przeszlowski, 2023; Morgan & Dowling, 2019; Piza et al., 2014; Robin et al., 2021). The covariates measure potentially confounding factors related to police response, officer engagement with suspects, seasonality, on-scene visibility, and socio-demographic neighborhood factors.

1. Outcome measure period total: the total count of the outcome measure on the encompassing street segment during the intervention period. 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.
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 intervention period.
3. Enforcement period total: the total count of arrests and field interviews on the encompassing street segment during the intervention period.
4. Lagged enforcement period total: The average count of arrests and field interviews on the street segments that are spatially contiguous to the encompassing street segment during the intervention period.[11]
5. Nighttime: whether the incident occurred during nighttime, operationalized as before sunrise or after sunset as measured in the *suncalc* package in R (https://github.com/datastorm-open/suncalc).
6. Weekend: whether the incident occurred on a Friday, Saturday, or Sunday.

7-9. 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.

10. CCTV presence: whether a KCPD CCTV camera was installed on the encompassing street segment (coded as 1) or not (coded as 0).
11. 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).
12. Disadvantage index: 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 encompassing census tract (American Community Survey five-year estimates).[12]
13. Demographic index: summed standardized percentages of non-White residents, residents aged 15–29, vacant properties, and renter-occupied properties,

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

[12] American Community Survey 5-year estimates were collected through the *tidycensus* R package (https://walker-data.com/tidycensus/), with estimates available only back to 2009. All incidents occurring earlier were assigned the 2009 5-year (2005–2009) values of all census measures.

as measured in the encompassing census tract (American Community Survey five-year estimates).

14. Population density: standardized average of the number of residents per square mile, as measured in the encompassing census tract (American Community Survey five-year estimates).
15. Geographic mobility: standardized percentage of residents who lived at a different address one year prior, as measured in the encompassing census tract (American Community Survey five-year estimates).
16. Ambient population index: standardized annual ambient population in the surrounding 1.5km^2 grid, as measured in the annual Oak Ridge Laboratory Land Scan data.
17. Daily temperature: standardized average temperature on the date of incident occurrence, as measured in the National Oceanic and Atmospheric Administration's climate database.
18. 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.

Analytic approach

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). Effects are reported as odds ratios, which indicate the proportion to which the independent variable influence the likelihood of a positive dependent variable being observed (i.e., unfounded disposition, collection of ballistic evidence, a gun recovery, and case cleared). Effect sizes are proportional to 1, with values greater than 1 indicating increased likelihood and values less than 1 indicating decreased likelihood.

The jackknife empirical sampling distribution (Quenouille, 1949) was used in the calculation of standard errors and 95% confidence intervals for all models. The jackknife is a cross-validation resampling technique that helps preserve the validity of statistical inferences (Rodgers, 1999). Resampling methods such as jackknife are especially important in statistical analyses incorporating sample weights, specifically to ensure that variance estimators are not inflated (Kolenikov, 2010). The explanatory variable was the aforementioned treated variable, representing incidents occurring in the GDT target area following GDT installation.

Logistic regression models controlled for the operations of the CGIC in Kansas City. Such facilities support the gathering, management, and analysis of intelligence derived from firearms used in crime incidents, and thus may influence investigative outcomes. In Kansas City, the CGIC was established in 2014 and assisted with gun-related cases throughout the city (Novak & King, 2020). As such, all incidents

Table 2 Entropy matching balance, shots fired

Covariates	Treatment		Control (unweighted)		Control (weighted)	
	Mean	Variance	Mean	Variance	Mean	Variance
Outcome period total	22.45	241.10	17.64	2356.00	22.45	1732.00
Lagged outcome period total	13.10	48.96	5.16	61.97	13.09	615.00
Enforcement period total (z)	1.27	59.26	1.17	38.75	1.27	58.98
Darkness	0.78	0.17	0.76	0.18	0.78	0.17
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	4.32	2.04	7.63	3.64	5.74
Demographic index (z)	150.40	497.60	132.70	454.10	150.40	419.90
Population density (z)	−0.15	0.00	1.49	19830.00	−0.15	0.02
Geographic mobility (z)	0.31	0.41	−0.02	0.76	0.31	0.63
Ambient population (z)	1.27	0.48	1.46	3.05	1.27	1.49
Average temperature (z)	0.16	0.83	0.11	0.83	0.16	0.81
Precipitation (z)	−0.02	0.92	0.00	1.03	−0.02	0.89
N treated = 11,518						
N control = 67,642						
N weighted control = 11,518						

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

occurring in 2014 or later were coded as 1 for the CGIC variable, with all other cases coded as 0.[13] A year variable was included to account for any annual trends in the outcome measures. The police division the incident occurred in was also included as a control variable to reflect the fact that different police divisions may have different staffing levels and organizational practices that could influence investigative practices. KCPD division 1 was incorporated as the reference category for this measure.

Results

Results of entropy balancing for shots fired calls for service are presented in Table 2. As expected, the treatment and unweighted control group differ greatly across all of the matching covariates. We succeeded in specifying the *ebalance* algorithm to the

[13] Kansas City's CGIC 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). The CGIC achieved full compliance with BJA operational standards in 2018. Operationalizing the CGIC variable using either 2017 or 2018 instead of 2014 as the CGIC intervention date does not qualitatively alter the logistic regression model findings discussed subsequently.

Table 3 Logistic regression results for unfounded dispositions, shots fired

					95% C.I	
Unfounded	Odds ratio	S.E	*t*	*P*>*t*	Lower	Upper
Treated	1.15	0.04	4.44	0.00	1.08	1.23
CGIC	1.06	0.06	1.05	0.29	0.95	1.19
Year	1.05	0.01	6.10	0.00	1.03	1.07
PD division						
2	1.10	0.04	2.36	0.02	1.02	1.19
3	1.40	0.05	10.32	0.00	1.32	1.50
4	1.42	0.11	4.52	0.00	1.22	1.65
5	1.39	0.08	5.89	0.00	1.24	1.55
6	1.54	0.09	7.32	0.00	1.37	1.73

Standard errors calculated through jackknife resampling. Division 1 set as the reference category for PD division

first moment, resulting in near identical means for all covariates across treated and weighted control groups. While variances differ for many of the covariates, the difference is not nearly as pronounced as what was observed for the unweighted control group.[14]

Table 3 displays the findings of the logistic regression model testing the influence of GDT on unfounded case dispositions for shots fired calls for service. Results indicate that shots fired calls for service in the GDT target area have a 15% increased likelihood of being unfounded as compared to the control group (odds ratio = 1.15; $p < 0.01$).[15]

Table 4 displays entropy balancing results for fatal shootings. We succeeded in specifying the *ebalance* algorithm to the first moment (mean). Variance levels are also very similar across the treatment and weighted control cases for most covariates. Table 5 displays findings of the logistic regression models testing the influence of GDT on ballistic evidence collection (NIBIN), and case clearance for fatal shootings. In each case, GDT treatment was not significantly associated with the dependent variable. In other words, fatal shooting incidents in the GDT target area were no more likely to result in collection of ballistic evidence for NIBIN analysis, or subsequent case clearance, as compared to incidents in the control area. The sparse occurrence of gun recoveries resulted in the logistic regression model not converging for this dependent variable, but the descriptive statistics (Table 2) reflect near identical proportions of gun recoveries across treatment and control incidents.

[14] The *ebalance* model did not initially converge for shots fired. We increased the maximum number of iterations from 20 to 21 (see Hainmueller & Xu, 2013 p. 15) in order to run the above mentioned *ebalance* model.

[15] While a number of control variables achieved statistical significance across all models, their coefficients have little relevance for the question of whether GDT substantially impacted case outcomes. As to not distract from the primary research question, we do not present a detailed discussion of the control variable results.

Table 4 Entropy matching balance, fatal shootings

	Treatment		Control (unweighted)		Control (weighted)	
Covariates	Mean	Variance	Mean	Variance	Mean	Variance
Outcome period total	1.35	0.39	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)	1.00	2.22	0.69	2.53	1.00	4.94
Darkness	0.66	0.23	0.65	0.23	0.66	0.22
Weekend	0.41	0.24	0.36	0.23	0.41	0.24
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	0.06	0.07	0.07	0.06	0.06
Primary road	0.11	0.10	0.08	0.07	0.11	0.10
Concentrated disadvantage (z)	3.44	2.59	2.47	7.90	3.43	4.23
Demographic index (z)	156.30	358.70	137.10	481.90	156.30	421.20
Population density (z)	−0.15	0.00	−0.07	0.08	−0.15	0.02
Geographic mobility (z)	0.27	0.42	0.04	0.71	0.27	0.59
Ambient population (z)	1.23	0.45	1.47	3.02	1.24	1.18
Average temperature (z)	0.05	1.00	0.13	0.92	0.05	0.96
Precipitation (z)	−0.04	0.58	0.02	1.02	−0.04	0.88
N treated = 100						
N control = 967						
N weighted control = 100						

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

Table 6 displays entropy balancing results for non-fatal shootings. Similar to fatal shootings, we successfully specified the algorithm to the first moment, but both 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 ballistic evidence collection (NIBIN), gun recoveries, or case clearance for non-fatal shootings (see Table 7). In other words, non-fatal shooting incidents in the GDT target area were no more likely to result in collection of ballistic evidence for NIBIN analysis, the recovery of firearms, or subsequent case clearance, as compared to incidents in the control area.

Discussion and conclusion

The current study did not find support for GDT as an investigatory tool for either fatal or non-fatal shooting incidents. The likelihood that responding police officers recovered a firearm or ballistic evidence on scene did not significantly differ between GDT treatment and control incidents during the study period. Perhaps relatedly, the likelihood of case clearance did not significantly differ between GDT and control

Table 5 Logistic regression results, fatal shootings

	Odds ratio	S.E	t	$P>t$	95% C.I Lower	95% C.I Upper
NIBIN						
Treated	1.14	0.37	0.39	0.69	0.60	2.16
CGIC	0.38	0.21	− 1.76	0.08	0.13	1.12
Year	1.31	0.12	3.09	0.00	1.10	1.56
PD division						
2	1.61	0.66	1.16	0.24	0.72	3.58
3	0.99	0.35	− 0.02	0.98	0.50	1.97
4	0.15	0.22	− 1.27	0.20	0.01	2.78
5	1.05	0.52	0.10	0.92	0.40	2.77
6	0.42	0.46	− 0.79	0.43	0.05	3.62
Cleared						
Treated	1.46	0.43	1.26	0.21	0.81	2.62
CGIC	0.73	0.37	− 0.61	0.54	0.27	1.99
Year	0.94	0.07	− 0.86	0.39	0.81	1.09
PD division						
2	1.50	0.52	1.16	0.25	0.76	2.96
3	1.07	0.33	0.23	0.82	0.58	1.98
4	0.56	0.86	− 0.38	0.71	0.03	11.58
5	2.38	1.03	2.01	0.05	1.02	5.57
6	4.30	3.83	1.64	0.10	0.75	24.73

Standard errors calculated through jackknife resampling. Division 1 set as the reference category for PD division

incidents. GDT is thought to detect instances of gunfire that would not otherwise be reported, thus helping police to identify evidence that may enhance case solvability. Given that this study did not find an increase in recovery of firearms or ballistic evidence, the null findings for case clearance are perhaps unsurprising.

Clearance rates have remained stable over recent decades (Cook & Mancik, 2024), despite the proliferation of technological tools that entered the policing realm following the September 11, 2001, terrorist attacks (Gaub & Koen, 2021). Research has consistently shown that the presence of eye-witnesses is a strong predictor of case solvability (Braga & Cook, 2023; Wellford & Cronin, 1999). It is fair to question the level to which GDT can increase the availability of eye-witness testimony or other solvability factors out of the control of police. Given that GDT may detect incidents that would otherwise go unreported, shootings in GDT target areas may be even less likely to have witnesses. In this context, the widespread deployment of GDT for case clearance purposes may be an example of what Norris and Armstrong (1999) refer to as technological determinism—the unquestioning belief in technology to solve societal problems. This fits the general history of police giving technology the “benefit of the doubt” in the absence of a well-developed evaluation literature (Weisburd & Neyroud, 2011).

Table 6 Entropy matching balance, non-fatal shootings

	Treatment		Control (unweighted)		Control (weighted)	
Covariates	Mean	Variance	Mean	Variance	Mean	Variance
Outcome period total	3.15	5.44	4.50	165.80	3.15	67.65
Lagged outcome period total	0.56	0.59	0.28	0.48	0.56	2.63
Enforcement period total (z)	0.94	3.84	1.54	30.02	0.94	9.59
Darkness	0.67	0.22	0.68	0.22	0.67	0.22
Weekend	0.53	0.25	0.42	0.24	0.53	0.25
2nd quarter	0.26	0.20	0.28	0.20	0.26	0.19
3rd quarter	0.28	0.20	0.30	0.21	0.28	0.20
4th quarter	0.26	0.20	0.23	0.18	0.26	0.19
CCTV	0.13	0.11	0.11	0.10	0.13	0.11
Primary road	0.10	0.09	0.09	0.08	0.10	0.09
Concentrated disadvantage (z)	3.72	3.45	2.56	6.81	3.72	4.98
Demographic index (z)	154.20	411.30	136.90	394.60	154.20	428.30
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	1.13
Average temperature (z)	0.18	0.92	0.20	0.89	0.18	0.84
Precipitation (z)	0.03	1.46	0.03	1.23	0.03	1.13
N treated = 389						
N control = 3,741						
N weighted control = 389						

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

It is also important to consider the assumed causal mechanisms of GDT. The technology consists of small and inconspicuous microphones unlikely to be noticed by the public. Crime control benefits must exclusively come from the improved response of officers to alerts of gunshots. In the context of case clearance, such improved response is expected to facilitate the collection of on-scene evidence that can help increase case solvability (La Vigne et al., 2019). This did not occur in the current study setting of Kansas City, despite faster and more precise police responses to gunfire detected by GDT being observed in the literature generally (Mares, 2022) as well as within Kansas City itself (Piza et al., 2023a). It is also important to note that in order for evidence collection practices to enhance gun crime investigations, active participation and agency commitment are required (Flippin et al., 2022). King et al. (2013) found that program fidelity varied considerably across NIBIN study sites, with delays in ballistic evidence processing and differing agency standards compromising the promise of the technology. Specifically relating to GDT, officer training and commitment to agency protocols can differ across agencies and wane over time within particular agencies (Lawrence et al., 2018). In this sense, agency leadership and culture are key factors in fostering an operational environment that maximizes GDT effect. The present study did not have access to process measures

Table 7 Logistic regression results, non-fatal shootings

	Odds ratio	S.E	t	$P>t$	95% C.I Lower	95% C.I Upper
NIBIN						
Treated	0.89	0.16	−0.62	0.54	0.63	1.27
CGIC	1.83	0.54	2.05	0.04	1.03	3.25
Year	1.06	0.05	1.15	0.25	0.96	1.16
PD division						
2	1.25	0.29	0.96	0.34	0.79	1.99
3	0.99	0.20	−0.05	0.96	0.66	1.48
4	0.79	0.52	−0.36	0.72	0.22	2.87
5	1.10	0.35	0.32	0.75	0.60	2.04
6	0.36	0.26	−1.42	0.16	0.09	1.47
Gun recovery						
Treated	0.71	0.28	−0.86	0.39	0.33	1.54
CGIC	0.65	0.37	−0.74	0.46	0.21	2.01
Year	0.98	0.06	−0.25	0.80	0.86	1.12
PD division						
2	1.31	0.54	0.66	0.51	0.59	2.92
3	1.08	0.46	0.18	0.86	0.47	2.50
4	2.32	1.52	1.29	0.20	0.64	8.36
5	0.79	0.36	−0.51	0.61	0.32	1.94
6	2.34	1.46	1.37	0.17	0.69	7.93
Cleared						
Treated	1.05	0.16	0.35	0.73	0.79	1.41
CGIC	0.73	0.18	−1.23	0.22	0.45	1.20
Year	0.76	0.03	−6.86	0.00	0.71	0.82
PD division						
2	0.74	0.14	−1.59	0.11	0.51	1.07
3	0.98	0.16	−0.14	0.89	0.70	1.36
4	1.49	0.70	0.84	0.40	0.59	3.76
5	1.16	0.29	0.59	0.55	0.71	1.90
6	1.60	0.46	1.62	0.11	0.91	2.82

Standard errors calculated through jackknife resampling. Division 1 set as the reference category for PD division

related to evidence collection protocols or officer compliance, which would have provided additional context for the findings.

The causal mechanisms of GDT differ from other crime control technologies such as CCTV, which agencies have begun to integrate with GDT (Mares, 2022; Vovak et al., 2021), especially within the context of CGICs (Flippin et al., 2022; Novak & King, 2020) and real-time crime centers (Guerette & Przeszlowski, 2023; Przeszlowski et al., 2022). Through their visible presence, CCTV cameras communicate an increased risk of detection and apprehension to potential offenders

(Ratcliffe, 2006). In the aftermath of crime occurrence, CCTV footage provides visual evidence that supports investigative efforts, which may better provide a proxy for "eye-witness" testimony than GDT. While the literature is still developing, there are documented cases of CCTV positively impacting offender apprehension (Ashby, 2017; Jung & Wheeler, 2023; Morgan & Dowling, 2019; Piza et al., 2014; Sharp, 2016). This stands in stark contrast to GDT, as most evaluation studies we reviewed found no effect on offender apprehension (Doucette et al., 2021; Lawrence et al., 2019; Litch & Orrison, 2011; Mazerolle et al., 1998), with another finding clearance rates decreased following the deployment of GDT (Vovak et al., 2021). It is possible that the tighter integration of GDT and video surveillance technologies may lead to benefits that the disparate technologies do not provide in isolation (Skogan, 2019). CGICs and Real-Time Crime Centers may provide efficient vehicles for police to achieve such technological integration.

The increased likelihood of unfounded shots fired cases also has important implications for GDT use by police. Shots fired calls for service occurring in the GDT target area were 15% more likely to be classified as unfounded, indicating officers did not find confirmed evidence of gunfire (e.g., shell casings or witnesses) on scene. SoundThinking incorporates incident review processes for the purpose of minimizing the risk of false positive GDT alerts. Gunshot acoustic experts review each GDT alert to confirm whether it is gunfire. This involves both listening to audio recordings and visually analyzing the wave patterns of the acoustic alerts (see Mares, 2022, p. 9). The fact that police officers more often fail to find evidence of shots fired in the GDT target area as compared to the control area, however, suggests the possibility that the ShotSpotter system may generate false positive alerts, despite the aforementioned review process.

We acknowledge that we cannot determine the precise level to which the unfounded dispositions represent false positive alerts. Police officers can fail to find evidence of shots fired for a number of legitimate reasons. For example, the use of a revolver or shots fired from inside a motor vehicle would translate to no shell casings being left on scene. GDT may be more sensitive to gunshots in areas not easily accessible to responding units, limiting the ability to locate evidence. Gun assaults in which gunfire does not strike the intended target may not be discovered if victims or witnesses are not forthcoming with responding officers. Given how often victims of non-fatal shootings do not cooperate with police investigations (Braga & Cook, 2023; White et al., 2021), many assault victims not struck by gunfire would likely be unwilling to engage with police. The CCSVP (2023) study in Winston-Salem, NC, explored why some GDT incidents may be more likely than others to be reported by residents (also see Huebner et al., 2022 for a similar study conducted in St. Louis, MO). They found that higher numbers of rounds fired during an incident, as well as whether the incident was connected to a violent crime, significantly predicted the likelihood of the incident being reported via a citizen 911 call. These findings provide suggestive evidence of why legitimate shots fired incidents not called in by residents may be less likely to yield physical evidence due to fewer gunshots being fired, thus resulting in unfounded case dispositions.

Regardless of the source of the unfounded dispositions, the shots fired finding reflects increased workload of police responding to incidents where gunfire was not confirmed. Prior research has highlighted this as a potential issue with GDT, given that the regular deployment of officers to incidents misclassified as gunfire can reduce officer enthusiasm for responding quickly to the scene of GDT alerts (Ratcliffe et al., 2019) and may divert police resources from potentially higher priority calls. Moving beyond fatigue of responding officers, workload has long been a challenge to improving case clearance of gun crimes (Carter, 2013; Prince et al., 2021). In their analysis of gun murders versus non-fatal gunshot assaults, Cook et al. (2019) observed non-fatal assaults to have a 24% lower clearance rate—a finding largely attributed to the lack of investigative time and resources dedicated to non-fatal case clearance.

KCPD is a formal CGIC, which operate under investigative processes and best practices articulated by the U.S. Department of Justice, Bureau of Justice Assistance (BJA) which emphasize comprehensive evidence collection, utilization of NIBIN/eTrace, and committed investigative teams (Police Foundation, 2017). However, in their evaluation of the KCPD CGIC Novak and King (2020) noted that while KCPD made strategic changes to the CGIC in 2017, they did not achieve compliance with the CGIC business model outlined by BJA until September 2018, in the latter stage of our study period and 4 years after the CGIC's implementation. In addition, Novak and King (2020) noted, among other issues, that investigators self-reported to be waiting on additional information from other sources or that an investigative case was inactive due to a lack of further information. This suggests that purely collecting additional ballistic evidence in itself may not generate investigative benefits. While the current study uncovered null effects of GDT on case closure, it is possible that earlier compliance of the CGIC with BJA standards may have accentuated the effect of the GDT system. We recommend that future research attempt to more directly measure the coupling between CGIC efficiency and GDT effect.

Despite its implications for both research and practice, this study suffers from some specific limitations the reader should be aware of. As mentioned previously, the lack of case numbers in the ShotSpotter data precluded us from identifying the specific incidents in our sample that were detected by GDT. However, observations from prior research (Carr & Doleac, 2016; Irvin-Erickson et al., 2017) as well as the proportion of ShotSpotter detections to treated incidents in our sample indicates a substantial level of overlap between incidents falling within the GDT target area and incidents identified by GDT. The use of the jackknife resampling method further protects against biased estimates by randomly assigning cases between the treatment and control conditions. Nonetheless, we acknowledge the absence of incident-level treatment data as a limitation. We did not have access to individual-level data, which prevented us from including victim race and gender as matching covariates in the entropy balancing algorithm. We further lacked insight into the investigative processes of KCPD. Our process measures (ballistic evidence and gun recoveries) reflected on-scene collection by responding patrol officers. Any firearms recovered by detective units during arrests resulting from a retroactive investigation were not reflected in our data. While causal mechanisms undergirding GDT relate to improved response to shooting scenes—providing construct validity to our process measures—including guns recovered as a result of retroactive investigations would have provided a more complete accounting of evidence collection in Kansas City. We also did not have any measures of investigative unit activity, training, or detective adherence to standard operating procedures, which may relate to case clearance given the documented importance of strategic and tactical agency functions for case clearance (Carter & Carter, 2016; Lawrence et al., 2018). For example, prior research has demonstrated that CGIC practices including comprehensive ballistic evidence collection and analysis can help to generate investigative leads in gun crime investigations, thus enhancing case solvability (Flippin et al., 2022; Novak & King, 2020). In this sense, understanding specific detective actions taken during specific shooting cases would have provided important insight.

While acknowledging these limitations, we believe our study positively contributes to the literature. It contributes to the underdeveloped research on GDT's case clearance capacity and is the first such study to use a matched-quasi experimental design, which helps maximize internal validity (Farrington et al., 2006). Future research on GDT should build upon our approach.

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Data Availability Data and code to replicate the analysis are available at http://hdl.handle.net/2047/D20616273.

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