



Space-Time Association between Gunshot Detection Alerts, Calls for Service, and Police Enforcement in Chicago: Differences Across Citizen Race and Incident Type

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Abstract

Objectives This study explores the level to which Gunshot Detection Technology (GDT) leads to increased arrests and stops as compared to shots fired calls for service (CFS) in Chicago, Illinois.

Methods A two-process Knox test and point process test are applied to measure the level to which GDT alerts and CFS cluster with arrests and stops in space and time. Both tests are first applied to the aggregate arrest and stops data. We then disaggregate arrests and stops by type as well as suspect race/ethnicity to measure any disproportionate effects across GDT and CFS.

Results Both GDT alerts and CFS are significantly associated with arrests and stops occurring in close spatial and temporal proximity. The relative effect of GDT and CFS was consistent across race in the majority of instances. The small number of instances with disparate effects did not exhibit any clear patterning. For some racial groups and arrest/stop types, GDT was associated with heightened enforcement while CFS had a null effect, with the opposite relationship observed for other racial groups and arrest/stop types.

Conclusions Overall, the results indicate that GDT systems may not generate racial disparities in arrests and stops *above and beyond* what results from the standard police response to gunfire. Racial disparities resulting from police responses to reported gunfire likely relate to aspects of the reporting and dispatch processes generally rather than as they relate specifically to GDT.

Keywords Acoustic gunshot detection · Police enforcement · Racial disparity · Bivariate kxox test · Point process test

Introduction

Policing in the United States can be organized according to distinct historical eras defined by specific social and cultural environments, which broadly influenced the goals and objectives of law enforcement. The political era of the 1800s—largely defined by political influence, inefficiency, corruption, and lack of professional standards—gave way to the professional era focused on improving standards, efficiency, and effectiveness in the early 1900s. Civil unrest of the 1960s and the emergence of research questioning the effectiveness of the standard model of policing led to a tremendous level of change and innovation by the turn of the century. This commenced an era focused on problem-solving, community engagement, and proactive police activities (Jenkins and DeCarlo 2015; Walker and Katz 2022; Weisburd and Braga 2019).

Scholars have recently argued that the current policing model is distinct from the community, problem-solving era most texts identify as the most recent of American policing. Today, police use technology to monitor both public and private places and generate data for crime analysis functions on a daily basis, establishing data and surveillance technology as core components of policing (Gaub and Koen 2021; Hooper 2014). Proponents of technology-driven policing point to the potential benefits that can be realized from improved efficiency and cost-effectiveness of operations (Ariel 2019). Critics argue that heavy reliance on technology can generate an increase in aggressive law enforcement activities and perceived harassment in targeted communities (Chu et al. 2023; Ferguson 2017). Gunshot Detection Technology (GDT) has come to occupy a central role in such debates. Community and activist groups have singled out GDT as a driver of substantially increased-levels of police enforcement, specifically against persons of color (Clayton 2021). This has occurred within the back drop of empirical research that is generally unsupportive of GDT as a crime control tool (Conneally et al. 2024; Doucette et al. 2021; Lawrence et al. 2019; Mares and Blackburn 2012, 2021; Piza et al. 2023d; Vovak et al. 2021), with a small number of notable exceptions (CCSVP, 2023; Mares 2023). This raises an important question: are the benefits of GDT worth potentially exacerbating racial disparities in police enforcement outcomes?

The current study aims to contribute empirical research results to the debate on GDT. Using data provided by the Chicago Police Department, we measure the level to which GDT alerts cluster with arrests and stops (pedestrian and traffic) in space and time through a two-process Knox test (Klauber 1971; Mohler et al. 2021) and a marked point process test (Mohler 2014). Both tests are subsequently applied to shots fired calls for service (CFS) placed to the 9-1-1 emergency line, allowing for the comparison of GDT cases to responses following standard reporting processes. We disaggregate arrests and stops by type, where arrests have types gun, drug, or traffic and stops have types suspect, traffic, investigative, gang, victim, or other. We also disaggregate arrests and pedestrian stops by race/ethnicity to measure any disproportionate effects across GDT and CFS.

Findings indicate a statistically significant association between GDT alerts and each of the arrest and stop types included in the analysis. We also find a statistically significant association between GDT alerts and each of the stop types, with the exception of police-victim contacts, which occur infrequently. We further observe a greater number of arrests and stops of Black individuals, as compared to other races, following GDT alerts. However, similar associations were generally observed between CFS and arrests, and CFS and stops.

We discuss these results in the context of contemporary police technology research, policy, and practice.

Review of Relevant Literature

Policing has become highly reliant on surveillance technologies and the data they generate—arguably ushering in an era of “dataveillance” policing (Gaub and Koen 2021). The move towards data and technology can be traced to the terrorist attacks of September 11, 2001, which made surveillance and data tracking core functions of police agencies around the world. The time since has seen increased emphasis on governmental accountability and the general “informatization” of society, which further institutionalized a model of technology-driven policing, particularly in the United States (Hooper 2014). Technology stands to become even more centered in policing in the near future, as advances in communications devices, information management systems, surveillance camera quality, cloud storage capacity, artificial intelligence, and machine learning continue to push law enforcement towards a paradigm of “big data” policing (Ferguson 2017; O’Brien 2024; Piza et al. 2022).

Data generated by technology systems is key for a number of contemporary policing strategies. Problem-oriented policing, for example, can leverage data generated by dataveillance systems to diagnose the context of crime problems (Gaub and Koen 2021) while hot spots policing necessitates precise geospatial data to identify micro-places experiencing the most disproportionate levels of crime (Santos 2014). In this sense, police technologies are a key component of modern policing strategies in addition to being crime prevention strategies in-and-of themselves. This can create a situation where investment in technology can be justified based upon the support they provide to other evidence-based policing strategies, irrespective of whether research actually finds any empirical support for a given technology.

Despite the reliance on technology in day-to-day policing, the knowledgebase of police technology lags behind the policing field more generally. Lum and Koper (2017) describe police technology as an example of “evidence-based policing playing catch-up,” in the sense that a much smaller scientific literature is available for technological interventions than officer-driven crime control strategies. Police agencies have a history of implementing technology absent much (if any) rigorous analysis or evaluation, essentially giving technology the “benefit of the doubt” in the absence of scientific evidence (Weisburd and Neyroud 2011). For technologies that have been readily evaluated, research tends to focus nearly exclusively on crime control outcomes of interest, largely ignoring metrics related to criminal justice processes (Salvemini et al. 2015) and various aspects of community engagement and equitable distribution of police services (Piza et al. 2022). While featuring prominently in public debates, the level to which police technologies—particularly place-based surveillance technologies—exacerbate racial inequities is a particular issue in need of more empirical attention (Hollis 2019). Such a knowledge gap is damaging to the evidence-based policing movement, as reviews of research indicate that citizen perceptions of and experience with police matter independently of the effectiveness of crime prevention programs (Lum and Nagin 2017).

Hollis (2019, 132) argued that the benefits of technology could be assessed by applying the Rawlsian difference principle: are increased surveillance technologies just if they serve to exacerbate existing inequalities in society? Scholars have recently argued that police

technologies may generate the type of inequalities Hollis alludes to. According to Ferguson (2017), “big data policing” resulting from the mass deployment of surveillance technologies has unintended negative consequences. A wealth of information is now available to police due to the increased ability to collect and analyze crime data, personal data, and environmental data from various surveillance technologies. Although these technologies are designed to target crime, in many instances they can directly result in the oversurveillance of marginalized communities (Chu et al. 2023). When certain areas have been designated as more dangerous, police may be more likely to respond in aggressive ways, which may exacerbate tensions between police and communities of color. Technological police strategies may therefore serve to reinforce racial biases, similar to what has been documented with aggressive policing more generally (Braga et al. 2019; Brunson and Miller 2006).

Racial minority neighborhoods typically experience disparate levels of police enforcement due to high correlation between social disadvantage and crime; such enforcement disparities can be exacerbated when police deploy additional proactive resources into disadvantaged neighborhoods (Wheeler 2020). For example, automated license-plate readers (ALPRs) can compare license plate numbers to information in other law enforcement databases, linking cars and owners by time and location (Kaminski 2015). Facial recognition technology can compare live facial images to mug shots in police databases via the use of CCTV cameras (Wilson 2012). Aerial cameras can record potential criminal and vehicle activity in entire neighborhoods and allow for the footage to be reviewed later by law enforcement (Timberg 2014).

All of these technologies can be beneficial for law enforcement investigations, but they may be considered invasive given that they must also record the activity of many innocent civilians. Communities of color are often disproportionately impacted by these tactics given that their neighborhoods are some of the most heavily surveilled (Chu et al. 2023). Similarly, computer algorithms used in “predictive policing” may amplify racial biases in police enforcement data, leading to biased feedback loops and over-policing of minority neighborhoods (Lum and Isaac 2016). When people of color are disproportionately captured in police databases, it skews future police contacts, as biased data distorts police suspicion (Ferguson 2017). We should note, however, that an evaluation of a predictive policing intervention in Los Angeles found no significant differences in racial-ethnic group differences between control and treatment groups and that general number of arrests declined or remained unchanged at the division level during predictive policing deployments (Brantingham et al. 2018).

Gunshot Detection Technology (GDT) has substantially grown in popularity over the past decade. GDT is comprised of interconnected acoustic sensors that detect the sounds of gunfire and identify the locations of gunfire events in real time (Mares 2022). According to SoundThinking, the manufacturer of the industry-leading ShotSpotter system, the technology has been adopted by over 200 cities worldwide.¹ The technology has recently been criticized by community activists and residents in a number of cities about disproportionate surveillance in communities of color (Contreras 2022). Although ShotSpotter does not use person-based predictive strategies, some argue that it may still perpetuate existing racial biases. If GDT sensors are installed primarily in Black and Latino neighborhoods officers may be deployed more often to those areas, which may lead to disparate enforcement actions in these communities.

¹ <https://web.archive.org/web/20240528171744/https://www.soundthinking.com/company/>.

Increased enforcement can generate and perpetuate social harms. Research has demonstrated having a criminal history can negatively impact future life prospects, such as employment opportunities (Denver and Behlendorf 2022). A recent systematic review and meta-analysis of police stops as a crime reduction tool found pedestrians consistently stopped by police develop significantly higher levels of self-reported crime involvement, mental health issues, and physical health issues, as well as less favorable attitudes towards police as compared to their counterparts (Petersen et al. 2023). Complicating matters is the fact that research findings on the efficacy of GDT as a crime reduction and investigative tool has generated few positive results. Research has generally found that GDT does not reduce gun violence or improve case clearance. For example, Doucette et al. (2021) found no significant impact on county-level firearm homicides, murder arrests, and weapons arrests in an analysis of large metropolitan counties. While evaluations of GDT in St. Louis, MO (Mares and Blackburn 2012, 2021) and Kansas City, MO (Piza et al. 2023) found a negative effect on citizen reports of “shots fired,” no significant effects were found for reported gun crime. Such lack of effect on gun crime reflects the general trend observed in the GDT literature (Connealy et al. 2024; Lawrence et al. 2019; Vovak et al. 2021; see Mares 2023 and CCSVP, 2023 for noteworthy exceptions). Studies also indicate that GDT does not increase clearance rates of gun crimes (i.e., proportion of incidents resulting in arrest) (Choi et al. 2014; Lawrence et al. 2019; Litch and Orrison 2011; Mazerolle et al. 1998; Piza, Arietti, Carter, et al., 2023a; Vovak et al. 2021). Some studies have found procedural benefits of GDT, including reduced response times and increased spatial accuracy (Choi et al. 2014; Lawrence et al. 2019; Piza et al. 2023c). However, an analysis in Camden, NJ found quicker response times resulting from GDT did not reduce gunshot mortality rates (Goldenberg et al. 2019) while a recent study in Chicago found that GDT increased police dispatch and response times (Topper and Ferrazares 2024).

Analyses conducted by the MacArthur Justice Center at Northwestern University revealed that many GDT alerts in Chicago result in officers being deployed to neighborhoods in search of gun crimes that may be unfounded (<https://endpolicesurveillance.com/>), echoing research findings from other jurisdictions (see e.g., Piza, Arietti, Carter, et al., 2023a; Ratcliffe et al. 2019). This could either indicate that the technology is inaccurately identifying false positives, or that it does not improve substantially on officers’ ability to locate evidence, limiting its operational value. A report by the Chicago Inspector General’s Office further suggests that the perceived frequency of gunfire triggered by GDT in Chicago has led police to engage in more stops and searches in these areas (City of Chicago Office of the Inspector General 2021). The culmination of such analyses led to a federal class-action lawsuit being filed against the City of Chicago by the MacArthur Justice Center, which calls for a court order barring the use of the ShotSpotter GDT system in Chicago (Burke and Tarm 2022).

Literature Review Summary and Scope of the Current Study

Law enforcement agencies have increasingly adopted data-driven surveillance technologies in an attempt to maximize efficiency while conserving limited resources. GDT, in particular, has been implemented in hundreds of cities worldwide and is advertised as a means of facilitating the prevention and police response to gun violence. However, critics argue that

if the technology is primarily installed in poor neighborhoods of color it will inevitably lead to greater surveillance of these communities, along with disproportionate police presence and enforcement. Further, research findings generally do not support the efficacy of the technology for crime control (Connealy et al. 2024; Doucette et al. 2021; Lawrence et al. 2019; Mares and Blackburn 2012, 2021; Piza, Arietti, Carter, et al., 2023a; Piza et al. 2023; Vovak et al. 2021; but see CCSVP, 2023; Mares 2023). If GDT does not generate crime control benefits, and has the potential to exacerbate tensions between police and communities of color, it calls into question whether the cost of the technology is a worthwhile investment.

The present study aims to explore whether GDT leads to racially disparate arrests and stops, as compared to police responses initiated by 9-1-1 calls for service (CFS). By comparing the extent to which GDT alerts and shots fired CFS cluster with arrests and stops in space and time, we explore associations with arrestee race. If greater disparity is observed in arrests and stops generated by GDT as compared to CFS, it would indicate a potential disparity effect caused by GDT.

Study Setting

Chicago, IL is the third largest city in the United States, with a total population of 2,746,388 according to the most recent decennial census. 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 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 2020). In addition, 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 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. This represents approximately 60% (136.70 of 227.63 square miles) of Chicago’s total land area (see Fig. 1).² Based on annual subscription costs of between \$65K and \$90K per square mile³, Chicago pays between \$8.8 M and \$12.3 M annually for their GDT system.

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

² Square mileage of the GDT target area was measured in ArcGIS Pro version 2.9.3. To total land area of Chicago was determined from the U.S. Census Bureau’s quick facts data: <https://www.census.gov/quick-facts/chicagocityillinois>.

³ https://web.archive.org/web/20240224014239/https://www.shotspotter.com/system/content-uploads/SST_FAQ_January_2018.pdf.

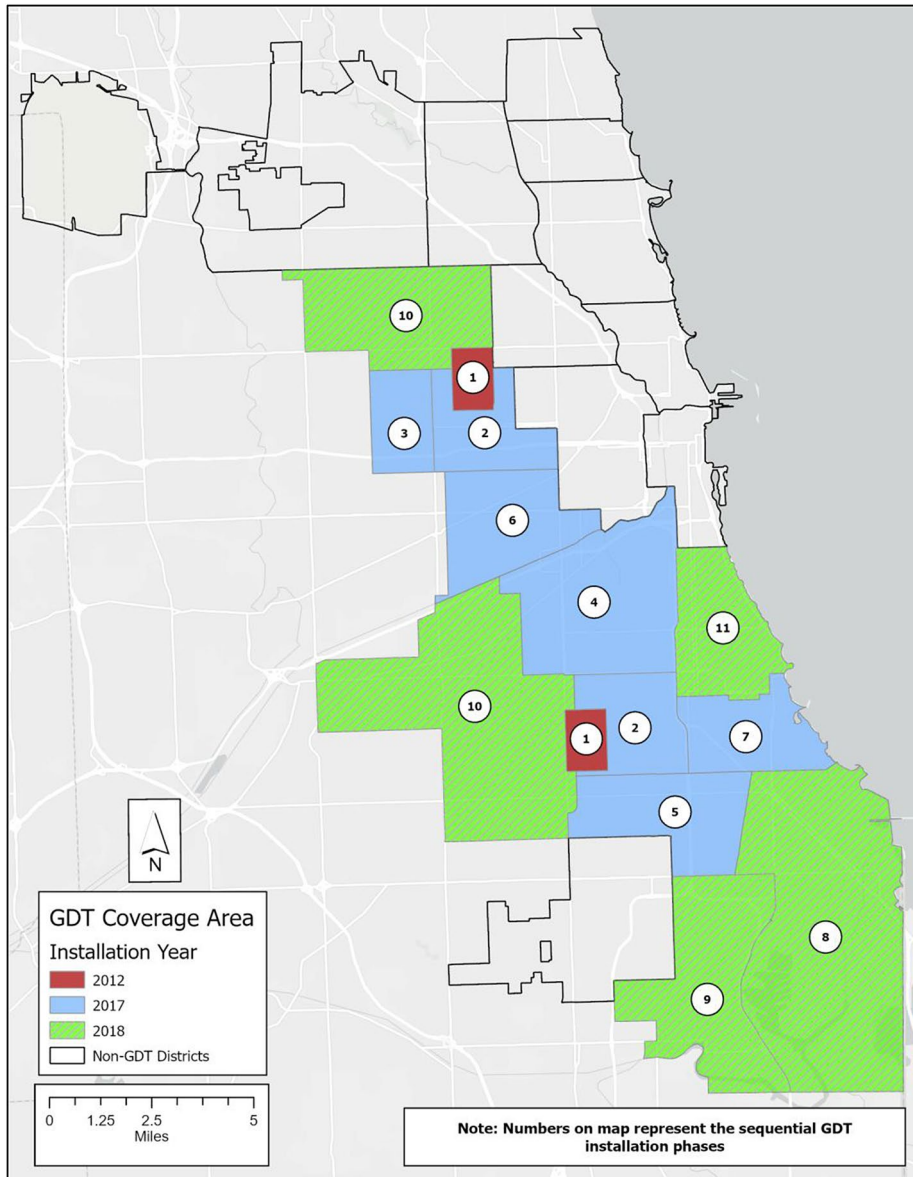


Fig. 1 GDT target area installation dates

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 (see Table 1).

Table 1 Chicago study area characteristics

	GDT AREA		CHICAGO (ALL)		CHICAGO (NON-GDT)	
	Raw Data	Per mi ²	Raw Data	Per mi ²	Raw Data	Per mi ²
Area	136.70 mi ²	-	227.63 mi ²	-	90.93 mi ²	-
Non-white population	67.94	-	49.84%	-	37.02%	-
Poverty rate	23.81	-	18.31%	-	15.45%	-
Shots fired calls for service	48,829	357.20	69,252	304.23	20,423	224.60
Fatal shootings	1,268	9.28	1,578	6.93	310	3.41
Non-fatal shootings	11,034	80.72	14,069	61.81	3,035	33.38
Gun assaults & robberies	18,276	133.69	23,675	104.01	5,399	59.38

Notes 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 and Chicago (non-GDT) target area demographics are measured from the 474 and 367 intersecting Census tracts, respectively, and based on American Community Survey 2019 5-year estimates

While these figures demonstrate the proportional differences GDT area and Chicago, they do not speak to the per capita differences between the GDT area and the rest of the city (i.e., CPD districts without GDT). To facilitate this comparison, Table 1 further reports the outcome measures per square mile. Per capita crime measures are between 1.5 and 2.7 times higher in the GDT target area than the remainder of the city: shots fired calls for service (357.20 vs. 224.60 per mi²), fatal shootings (9.28 vs. 3.41 per mi²), non-fatal shootings (80.72 vs. 33.38 mi²), and gun assaults & robberies (133.69 vs. 59.38 mi²). The non-white population is nearly twice as high (67.94% vs. 37.02%) and the poverty rate ~50% higher (23.81% vs. 15.45%) in the GDT target area than the remainder of the city.

In August 2021, the City of Chicago extended its ShotSpotter contract, heavily committing to GDT as a core component of their public safety strategy. News of the contract was met with community backlash. Activist groups argued that the ShotSpotter system increased needless encounters between police and citizens, subjecting communities of color to over-policing. Calls for deactivating the ShotSpotter system increased in March 2021, after officers responding to a GDT alert fatally shot 13-year-old Adam Toledo in the immediate aftermath of him dropping a firearm while turning towards officers.

Chicago Mayor Brandon Johnson partially campaigned on a promise to terminate the City's ShotSpotter contract considering such community concerns. Johnson delivered on his promise on February 13, 2024 by announcing his decision to discontinue the use of ShotSpotter, with a phasing out of the technology set to begin during September 2024.⁴ The Chicago City Council responded on May 22, 2024 by passing an ordinance by a 34 to 13 margin to override Mayor Johnson's decision.⁵ While the Mayor has veto power over City Council ordinances in Chicago—and Mayor Johnson vowed to move ahead with the cancellation—the fate of the ShotSpotter contract remains unsettled as of the date of this writing.

Recent quasi-experimental evaluations found that Chicago's ShotSpotter system did not impact levels of gun violence or increase closure of shooting incidents in GDT-covered police districts (Connealy et al. 2024; Piza et al. 2024). However, the level to which the

⁴ https://www.chicago.gov/city/en/depts/mayor/press_room/press_releases/2024/january/city-of-chicago-statement-on-shotspotter-contract.html.

⁵ <https://www.wbez.org/stories/shotspotter-support-ordinance-passes-chicago-city-council/371869c7-2fde-44f4-891f-5f2824521755>.

ShotSpotter system contributed to the over-policing of people of color in Chicago remains an open empirical question.

Methodology

Data

The Chicago Police Department (CPD) provided data for this study as part of a larger National Institute of Justice funded evaluation of the GDT system. All data are recorded at the address-level or with XY coordinates, identifying the precise locations of occurrence as listed in CPD reports.⁶ The data covers the period following the full deployment of the GDT system, from 7/1/2018 to 12/30/2019. This was done to facilitate the Knox separability tests (see Figure A1 in the Appendix), where the assumption of the Knox test is that the intensity of GDT alerts is separable in space and time. Thus, we run the analysis after the staged deployment period, when the assumption of separability of the intensity of GDT alerts was valid. We exclude July 4th, July 5th, December 31st, and January 1st from the analysis, given the unusually high activity of both fireworks and gunshots on these dates.

The datasets needed to facilitate the analysis included shots fired CFS, CPD recorded arrests and stops with a race variable, and GDT alerts. The GDT data included pre-geocoded XY coordinates that were amenable for use in ArcGIS Pro. The calls for service, arrest, and stop data were recorded at the address level and geocoded using a custom-built Chicago area address locator in ArcGIS Pro.⁷ We excluded arrests to the incident types most likely to result from officer search activities following the response to a potential crime scene: gun-related, drug-related, and traffic-related. For the purpose of this analysis, we consider gun-related arrests to be the most appropriate response to a GDT alert given the emphasis on gunfire. Drug- and traffic-related events may occur when officers do not encounter any shooting suspects on scene and respond by engaging in proactive stops and searches, as has been alleged previously (City of Chicago Office of the Inspector General 2021). Each data point was classified as occurring pre or post GDT and whether it occurred in a GDT target area or not. The race variable was used to indicate if an arrest/stop of an individual following a shots fired call for service or GDT activation was disparate across race in the tested space and time bandwidths.

In Fig. 2, we display the spatial density of the four types of events. Moran's I statistics and z-scores confirm statistically significant ($p < 0.01$) clustering for each event. In terms of distance between the observed and expected *I* values, GDT alerts exhibited the greatest level of concentration ($Z = 87.59$), followed by stops ($Z = 71.89$), arrests ($Z = 71.06$), and shots fired CFS ($Z = 60.13$). We measured the relationship between the events through a spearman rank correlation test, using the underlying grid (500ft. x 500ft. cells) for the GDT target area. While all correlations were statistically significant ($p < 0.01$) the strongest relationship was

⁶ While some data are publicly available on the Chicago data portal (<https://data.cityofchicago.org/>), the arrest files do not provide location of arrest and the ShotSpotter alerts aggregate points to the block level. The current study required the more granular, address-level data provided by CPD.

⁷ The arrest data achieved a 99.9% geocoding hit rate, the stops data achieved a 99.8% hit rate, and the calls for service data were above 97.5%. Initially tied and unmatched addresses were manually reviewed by the research team to improve geocoding accuracy.

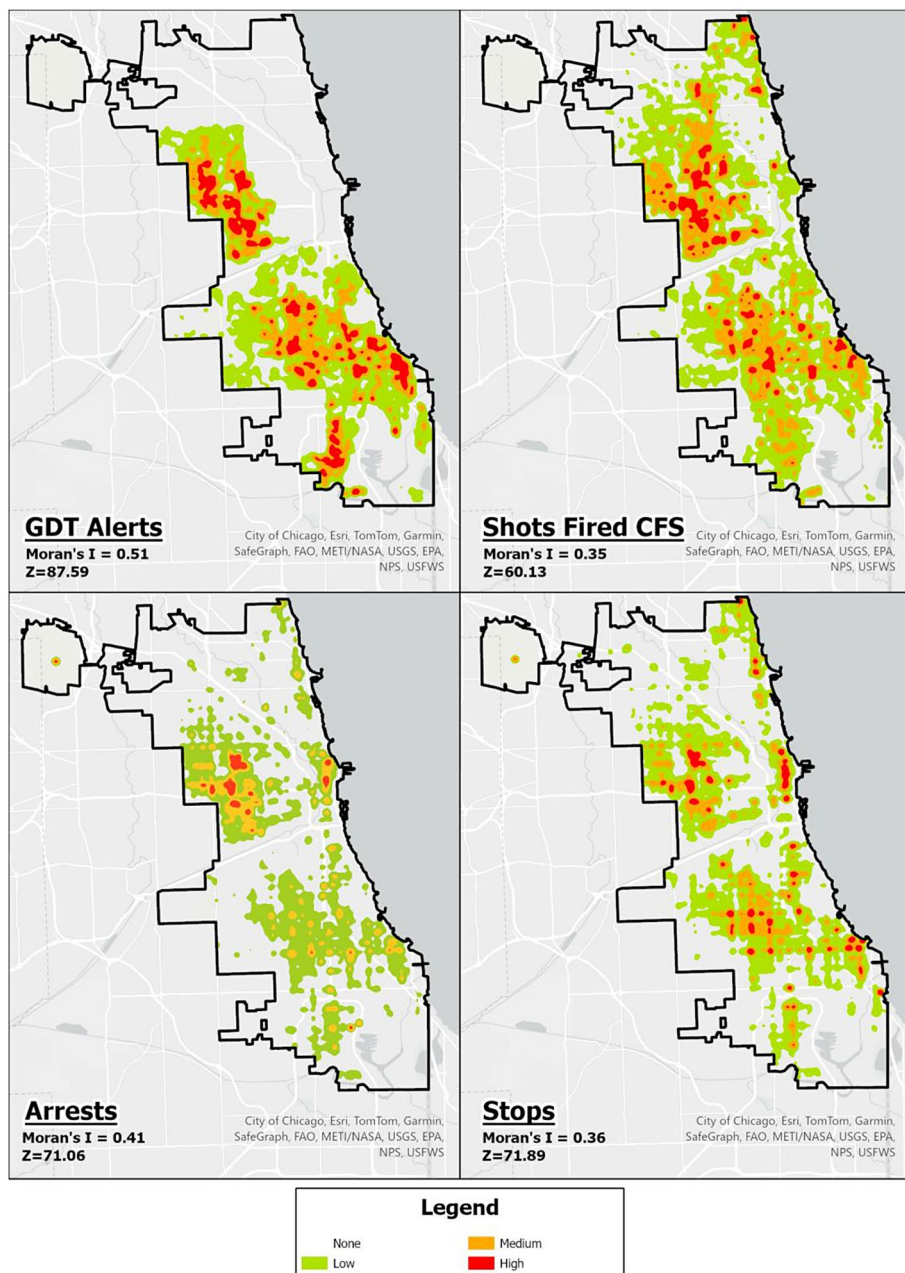


Fig. 2 Density of GDT alerts, citizen initiated shots fired calls for service, arrests, and stops in Chicago: 7/1/2018-12/30/2019

Table 2 Spearman rank correlation of event types in the GDT target area

	GDT	CFS	Arrests	Stops
GDT	1.00	-	-	-
Shots Fired CFS	0.52	1.00	-	-
Arrests	0.64	0.63	1.00	-
Stops	0.61	0.62	0.86	1.00

Table 3 Event descriptive statistics (7/1/2018–12/30/2019)

Event	Frequency
GDT Alerts	28,302
Shots Fired Calls for Service	26,687
Arrests	34,799
<i>Gun</i>	504
<i>Drug</i>	16,537
<i>Traffic</i>	17,758
Stops	243,704
<i>Suspect</i>	38,423
<i>Traffic</i>	20,419
<i>Investigation</i>	111,544
<i>Other</i>	59,627
<i>Gang</i>	13,261
<i>Victim</i>	430

Note 24,706 GDT alerts were also included in the shots fired calls for service database, and classified as “ShotSpotter” to denote their source. These incidents were considered as GDT alerts in the analysis. This ensures the GDT alerts and shots fired calls for service datasets are mutually exclusive

observed between arrests and stops ($\rho=0.86$). GDT alerts exhibited strong associations with arrests ($\rho=0.64$) and stops ($\rho=0.61$) and a moderate association with shots fired CFS ($\rho=0.52$).

Table 3 presents descriptive statistics of the point data used in the analysis. A total of 28,302 GDT alerts and 53,112 shots fired calls for service occurred during the study period. 34,799 arrests occurred, with the highest proportion related to traffic-related incidents ($n=17,758$) followed by drug charges ($n=16,537$) and gun offenses ($n=504$). 243,704 stops occurred during the study period. The most common stop type was investigation related ($n=111,544$) followed by other ($n=59,627$), which did not fit the premise of any alternative category type. 38,423 stops related to officer suspicion the stopped person was a crime suspect with traffic stops ($n=20,419$) the fourth most common category. Gang-related ($n=13,261$) and stops enacted due to officer suspicion the stopped person was a crime victim ($n=430$) were the categories appearing most sparsely in our data. Over 71% of arrests and 68% of stops were of Black persons (see Table 4).

Knox Test

We consider a two-process Knox test (Klauber 1971; Wyant et al. 2012) to detect excess clustering of arrests and stops nearby GDT alerts and shots fired calls for service in space and time. In particular, given a time cutoff τ and spatial distance cutoff δ , the Knox statistic (Knox and Bartlett 1964) $\kappa(\tau, \delta)$ is given by,

$$\kappa(\tau, \delta) = \frac{1}{N_s} \sum_{i,j} 1\{\|\vec{x}_i^a - \vec{x}_j^s\| \leq \delta, |t_i^a - t_j^s| < \tau\}$$

Table 4 Event descriptive statistics by Race (7/1/2018–12/30/2019)

Event	Frequency
Arrests	34,799
<i>American Indian/Alaskan Native</i>	9
<i>Asian/Pacific Islander</i>	162
<i>Black</i>	24,845
<i>Black/Hispanic</i>	240
<i>White</i>	2,449
<i>White/Hispanic</i>	7,053
<i>Unknown/Refused</i>	41
Stops	243,704
<i>American Indian/Alaskan Native</i>	333
<i>Asian/Pacific Islander</i>	2,177
<i>Black</i>	166,080
<i>Black/Hispanic</i>	7
<i>White</i>	59
<i>White/Hispanic</i>	54,166
<i>Unknown/Refused</i>	4
<i>Missing</i>	20,878

Here the parent process, $\mathcal{D}^s = (\vec{x}_j^s, t_j^s)$, consists of the space-time shots fired events and the dependent process, $\mathcal{D}^a = (\vec{x}_j^a, t_j^a)$, consists of the space-time arrest events. The Knox statistic is the average number of arrest events within a radius δ and within τ days of a shots fired call for service (where N_s is the number of shots fired calls). In the main analysis, we incorporate a temporal cutoff of 30 min and spatial cutoff of 100 m to reflect the spatiotemporal signature of GDT alerts as measured in prior empirical research (Irvin-Erickson et al. 2017).

To determine excess clustering, the Knox statistic can be compared to a null distribution for the statistic that corresponds to the two processes being independent. If the parent process, $\mathcal{D}^s$, is Poisson or separable in time, then the process is invariant under a random permutation of the event times. Thus, the null Knox statistic and its uncertainty can be computed through multiple realizations of,

$$\tilde{\kappa}(\tau, \delta) = \frac{1}{N_s} \sum_{i,j} 1\{\|\vec{x}_i^a - \vec{x}_j^s\| \leq \delta, |t_i^a - \tilde{t}_j^s| < \tau\},$$

where $\tilde{t}_i^s$ are a random permutation of the event times of the shots fired events.

Marked Point Process Test

We build upon the Knox tests through a point process to model the space-time intensity of arrests or stops. This analysis builds upon the Knox tests by directly comparing the excess events caused by GDT and shots fired CFS. The point process incorporated the following formula:

$$\begin{aligned}\lambda(t, x, y) = & \mu_t(t) \mu_s(x, y) \\ & + \sum_{t > t_i} K_0 g(t - t_i; \omega) h(x - x_i, y - y_i; \sigma) \\ & + \sum_{t > u_j} K_{m(j)} g(t - u_j; \theta) h(x - v_j, y - z_j; \eta)\end{aligned}$$

The first term in the model, $\mu_t(t) \mu_s(x, y)$, captures Poisson variation across space and time, where we use a monthly histogram estimator in time and a histogram estimator in space with bandwidth 0.01 degrees (and we assume separability). In Chicago 0.01 degrees is approximately 0.83 km. The second term models self-excitation, where K_0 is the expected number of arrests or stops triggered by a previous arrest or stop at time and location (t_i, x_i, y_i) , g is an exponential kernel with parameter ω (in units of inverse days) and h is a Gaussian kernel with parameter σ (in units of degrees). While the bandwidths for the background intensity are fixed, we estimate ω and σ using maximum likelihood. These first two terms provide a non-stationary, non-parametric estimate of the intensity of arrests/stops in the absence of police responses to GDT or CFS. The third term then models the contribution of police responses to the overall intensity of arrests/stops, where on average a police response at time and location (u_j, v_j, z_j) , causes $K_{m(j)}$ excess arrests/stops. Here we allow $K_{m(j)}$ to depend on the response type, where $m(j) = 1$ if the response is from a GDT alert and $m(j) = 2$ if the response is from a shots-fired CFS (again the kernels are assumed to be exponential and Gaussian). The model can be viewed as a mixture model where the exponential-Gaussian kernels are centered at the locations of arrests and shots-fired detections/calls. The mixture model parameters are estimated using an Expectation-Maximization algorithm as is done in Mohler (2014). We fit the model separately to each of eight arrest/stop event types.

We note that the Knox test and the point process analysis have different interpretations. The Knox test is an interaction test, with the null hypothesis being that the two point processes under consideration are independent. However, the Knox test statistic is not an interpretable measure of interaction size. Here the point process analysis is useful, as $K_{m(j)}$ is a measure for how many excess arrests are attributable to each GDT alert or CFS (and the size of K_1 can be compared to K_2).

Results⁸

We apply the bivariate Knox test to both GDT alerts and shots fired CFS in order to test for a space-time association with arrests and stops. We apply the test separately to arrests disaggregated by gun violence, drug arrests and traffic arrests for temporal cutoffs of 30 min and a spatial cutoff of 100 m.⁹ In Table 5, we display the data Knox statistic κ , mean Knox statistic for the null permutation distribution $\tilde{\kappa}$ (using 200 permutations), 95% range for the null Knox statistic, and p-value.

⁸ R and MATLAB code used to Conduct the Knox and Point Process Tests are Available at: <http://hdl.handle.net/2047/D20661301>

⁹ We also conducted the Knox test for 60 min/250 meter and 120 min/500 meter cutoffs. Findings of these models were not qualitatively different from the 30 min/100 meter models. Results of these models are presented in the appendix 1.

Table 5 Knox test results disaggregated by arrest and call type

κ	$\tilde{\kappa}$	$\tilde{\kappa}_{0.5}$	$\tilde{\kappa}_{0.95}$	p	τ	δ	arrest type	call type
0.00042	0.00001	0.00000	0.00004	0.00000	30	100	gun	gdt
0.00041	0.00001	0.00000	0.00004	0.00000	30	100	gun	cfs
0.00120	0.00027	0.00011	0.00053	0.00000	30	100	drug	gdt
0.00090	0.00031	0.00011	0.00052	0.00000	30	100	drug	cfs
0.00074	0.00027	0.00011	0.00046	0.00000	30	100	traffic	gdt
0.00112	0.00031	0.00007	0.00056	0.00000	30	100	traffic	cfs

Notes Columns include data kxox statistic κ , mean kxox statistic for the null permutation distribution $\tilde{\kappa}$, 95% range for the null kxox statistic, p-value, temporal cutoff τ (minutes) and spatial cutoff δ (meters)

Table 6 Knox test results disaggregated by race/ethnicity, arrest and call type

κ	$\tilde{\kappa}$	$\tilde{\kappa}_{0.5}$	$\tilde{\kappa}_{0.95}$	p	τ	δ	race/eth.	arrest type	call type
0.00025	0.00001	0.00000	0.00004	0.00000	30	100	Black	gun	gdt
0.00037	0.00001	0.00000	0.00004	0.00000	30	100	Black	gun	cfs
0.00099	0.00023	0.00007	0.00046	0.00000	30	100	Black	drug	gdt
0.00064	0.00025	0.00007	0.00041	0.00004	30	100	Black	drug	cfs
0.00057	0.00021	0.00007	0.00039	0.00006	30	100	Black	traffic	gdt
0.00079	0.00022	0.00004	0.00041	0.00000	30	100	Black	traffic	cfs
0.00018	0.00000	0.00000	0.00000	0.00000	30	100	Hispanic	gun	gdt
0.00000	0.00000	0.00000	0.00000	0.87310	30	100	Hispanic	gun	cfs
0.00014	0.00003	0.00000	0.00011	0.00154	30	100	Hispanic	drug	gdt
0.00022	0.00004	0.00000	0.00011	0.00000	30	100	Hispanic	drug	cfs
0.00018	0.00005	0.00000	0.00018	0.00579	30	100	Hispanic	traffic	gdt
0.00019	0.00008	0.00000	0.00019	0.04794	30	100	Hispanic	traffic	cfs
0.00000	0.00000	0.00000	0.00000	--	30	100	White	gun	gdt
0.00004	0.00000	0.00000	0.00000	0.00000	30	100	White	gun	cfs
0.00007	0.00001	0.00000	0.00004	0.00052	30	100	White	drug	gdt
0.00004	0.00002	0.00000	0.00011	0.52801	30	100	White	drug	cfs
0.00000	0.00000	0.00000	0.00004	0.72479	30	100	White	traffic	gdt
0.00015	0.00001	0.00000	0.00007	0.00000	30	100	White	traffic	cfs

Notes Columns include data kxox statistic κ , mean kxox statistic for the null permutation distribution $\tilde{\kappa}$, 95% range for the null kxox statistic, p-value, temporal cutoff τ (minutes) and spatial cutoff δ (meters)

We observe a statistically significant association between GDT alert events and arrests across the three spatial and temporal scales and arrest types. For example, we observe an average of 0.00042 gun arrests within 100 m and 30 min of a GDT alert, where we would expect to observe between 0.00000 and 0.00004 by random chance (95% null distribution range). We observe similar Knox statistics when the test is applied to CFS. For example, on average there were 0.00041 gun arrests within 100 m and 30 min of a citizen initiated shots fired call, nearly identical to the Knox value for GDT.

In Table 6, we display Knox test results disaggregated by race/ethnicity, arrest and call type, where we again find statistically significant space-time associations across race/ethnicity, arrest type, and spatial-temporal scales. We do find greater number of arrests for Black individuals, followed by Hispanic individuals, in comparison with White individuals. For example, we observe an average of 0.00025 gun arrests of Black individuals within

100 m and 30 min of a GDT alert, compared to 0.00018 arrests of Hispanic individuals and 0 arrests of white individuals. Relative effects of GDT alerts and CFS, however, were consistent across race and arrest types. For gun arrests, drug arrests, and traffic arrests both GDT ($k=0.00025$) and CFS ($k=0.00037$) were significantly associated with arrests of Black suspects. Disparate effects were observed for Hispanic and White suspects in some cases. While GDT alerts were significantly associated with gun-arrests of Hispanic suspects ($k=0.00018$) CFS showed no significant effects. For drug arrests, GDT alerts were significantly associated with arrests of White suspects ($k=0.00007$) while CFS exhibited no significant association. The opposite effect was observed for traffic arrests, with CFS associated with arrests of White suspects ($k=0.00015$) while GDT alerts exhibited no significant association.

In Table 7, we display Knox test results across disaggregated stop and call type, where we again find statistically significant space-time associations across stops and spatial-temporal scales (with the exception of victim stops, which are sparsely represented in the data). For example, we observe an average of 0.00406 suspect stops within 100 m and 30 min of a GDT alert, where we would expect to observe between 0.00018 and 0.00089 by random chance (95% null distribution range). We observe similar Knox statistics when the test is applied to shots fired CFS. For example, on average there were 0.00430 suspect contacts within 100 m and 30 min of a shots fired call. The exception is victim stops, with GDT alerts exhibiting a significant association ($k=0.0004$) but at a markedly higher p-value than the other significant associations observed ($p=0.03$). CFS did not achieve statistical significance for victim stops. It should be noted, however, that victim stops are sparsely represented in the data, which may explain the lack of statistical significance.

In Table 8, we display Knox test results disaggregated by race/ethnicity¹⁰, stop and call type. We again find statistically significant space-time associations across race/ethnicity, stop type, and spatial-temporal scales. We do find greater number of contacts for Black individuals, followed by White/Hispanic and then Asian individuals. For example, we observe an average of 0.00344 suspect contacts of Black individuals within 100 m and 30 min of

Table 7 Knox test results disaggregated by contact and call type

κ	$\tilde{\kappa}$	$\tilde{\kappa}_{0.5}$	$\tilde{\kappa}_{0.95}$	p	τ	δ	stop type	call type
0.00406	0.00047	0.00018	0.00089	0.00000	30	100	suspect	gdt
0.00430	0.00061	0.00025	0.00114	0.00000	30	100	suspect	cfs
0.00245	0.00028	0.00007	0.00047	0.00000	30	100	traffic	gdt
0.00252	0.00034	0.00011	0.00061	0.00000	30	100	traffic	cfs
0.02645	0.00121	0.00036	0.00198	0.00000	30	100	invstg	gdt
0.01889	0.00152	0.00057	0.00286	0.00000	30	100	invstg	cfs
0.00668	0.00064	0.00019	0.00126	0.00000	30	100	other	gdt
0.00524	0.00089	0.00031	0.00154	0.00000	30	100	other	cfs
0.00276	0.00027	0.00007	0.00053	0.00000	30	100	gang	gdt
0.00274	0.00035	0.00011	0.00064	0.00000	30	100	gang	cfs
0.00004	0.00001	0.00000	0.00004	0.03264	30	100	victim	gdt
0.00004	0.00001	0.00000	0.00004	0.13381	30	100	victim	cfs

Notes Columns include data kxox statistic κ , mean kxox statistic for the null permutation distribution $\tilde{\kappa}$, 95% range for the null kxox statistic, p-value, temporal cutoff τ (minutes) and spatial cutoff δ (meters)

¹⁰ Unlike arrests, the stops data do not have mutually exclusive White and Hispanic race categories. Instead, White/Hispanic is included as a single race category. Asian is an additional race category included in the stops data that is absent from the arrests data.

Table 8 Knox test results disaggregated by race/ethnicity, stop type and call type

κ	$\tilde{\kappa}$	$\tilde{\kappa}_{0.5}$	$\tilde{\kappa}_{0.95}$	p	τ	δ	race/eth.	stop type	call type
0.00344	0.00038	0.00017	0.00062	0.00000	30	100	Black	suspect	gdt
0.00282	0.00048	0.00018	0.00075	0.00000	30	100	Black	suspect	cfs
0.00000	0.00000	0.00000	0.00000	0.87310	30	100	Asian	suspect	gdt
0.00000	0.00000	0.00000	0.00004	0.78255	30	100	Asian	suspect	cfs
0.00110	0.00008	0.00000	0.00025	0.00000	30	100	White/His	suspect	gdt
0.00109	0.00012	0.00000	0.00034	0.00000	30	100	White/His	suspect	cfs
0.00216	0.00023	0.00007	0.00042	0.00000	30	100	Black	traffic	gdt
0.00202	0.00026	0.00007	0.00052	0.00000	30	100	Black	traffic	cfs
0.00000	0.00000	0.00000	0.00000	0.92014	30	100	Asian	traffic	gdt
0.00000	0.00000	0.00000	0.00004	0.84777	30	100	Asian	traffic	cfs
0.00032	0.00004	0.00000	0.00014	0.00000	30	100	White/His	traffic	gdt
0.00045	0.00006	0.00000	0.00019	0.00000	30	100	White/His	traffic	cfs
0.02162	0.00093	0.00024	0.00165	0.00000	30	100	Black	invstg	gdt
0.01040	0.00110	0.00038	0.00201	0.00000	30	100	Black	invstg	cfs
0.00000	0.00000	0.00000	0.00004	0.73151	30	100	Asian	invstg	gdt
0.00026	0.00001	0.00000	0.00011	0.00000	30	100	Asian	invstg	cfs
0.00789	0.00024	0.00004	0.00056	0.00000	30	100	White/His	invstg	gdt
0.00735	0.00034	0.00009	0.00074	0.00000	30	100	White/His	invstg	cfs
0.00483	0.00050	0.00013	0.00089	0.00000	30	100	Black	other	gdt
0.00337	0.00064	0.00027	0.00115	0.00000	30	100	Black	other	cfs
0.00004	0.00000	0.00000	0.00000	0.00000	30	100	Asian	other	gdt
0.00000	0.00001	0.00000	0.00004	0.75990	30	100	Asian	other	cfs
0.00173	0.00011	0.00000	0.00028	0.00000	30	100	White/His	other	gdt
0.00161	0.00017	0.00000	0.00037	0.00000	30	100	White/His	other	cfs
0.00216	0.00021	0.00004	0.00039	0.00000	30	100	Black	gang	gdt
0.00157	0.00026	0.00007	0.00049	0.00000	30	100	Black	gang	cfs
0.00007	0.00000	0.00000	0.00000	0.00000	30	100	Asian	gang	gdt
0.00000	0.00000	0.00000	0.00004	0.82558	30	100	Asian	gang	cfs
0.00053	0.00005	0.00000	0.00014	0.00000	30	100	White/His	gang	gdt
0.00105	0.00007	0.00000	0.00022	0.00000	30	100	White/His	gang	cfs
0.00004	0.00000	0.00000	0.00004	0.00207	30	100	Black	victim	gdt
0.00000	0.00001	0.00000	0.00004	0.62849	30	100	Black	victim	cfs
0.00000	0.00000	0.00000	0.00000	--	30	100	Asian	victim	gdt
0.00000	0.00000	0.00000	0.00000	--	30	100	Asian	victim	cfs
0.00000	0.00000	0.00000	0.00004	0.80983	30	100	White/His	victim	gdt
0.00004	0.00000	0.00000	0.00004	0.00003	30	100	White/His	victim	cfs

Notes Columns include data knox statistic κ , mean knox statistic for the null permutation distribution $\tilde{\kappa}$, 95% range for the null knox statistic, p-value, temporal cutoff τ (minutes) and spatial cutoff δ (meters)

a GDT alert, compared to 0.001101 suspect contacts with white/Hispanic individuals and 0 suspect contacts with Asian individuals. Again, this reflects the general pattern observed in the CFS data with an average of 0.00282 stops of Black individuals within 100 m and 30 min of a GDT alert, compared to averages of 0.00110 and 0 for white/Hispanic and Asian, respectively. A GDT/CFS disparity was observed in five instances, three of which involved Asian individuals. CFS were significantly associated with investigative stops of Asian individuals ($k=0.00026$) while GDT alerts were not. GDT alerts were significantly

Table 9 Estimated model parameters capturing the influence of GDT alerts and shots fired calls for service on arrests and contacts

	θ	η	K_1	$K_1 95_{low}$	$K_1 95_{up}$	K_2	$K_2 95_{low}$	$K_2 95_{up}$
drug arrest	45.49	0.0013	0.0020	0.0015	0.0025	0.0017	0.0012	0.0022
gun arrest	38.66	0.0008	0.0007	0.0004	0.0010	0.0008	0.0004	0.0011
traffic arrest	16.99	0.0032	0.0032	0.0026	0.0039	0.0089	0.0078	0.0100
gang contact	125.2	0.0011	0.0033	0.0027	0.0040	0.0031	0.0025	0.0038
traffic contact	80.82	0.0021	0.0056	0.0047	0.0065	0.0052	0.0043	0.0061
suspect contact	109.8	0.0011	0.0060	0.0051	0.0069	0.0046	0.0038	0.0054
other contact	98.55	0.0014	0.0092	0.0081	0.0103	0.0071	0.0061	0.0081
victim contact	102.8	0.0012	0.0001	0.0000	0.0002	0.0000	0.0000	0.0001

Note K_1 =GDT alert, K_2 =Shots fired CFS

Table 10 Estimated number of excess arrests/stops attributed to Shotspotter detections and calls for service (total and disaggregated by race/ethnicity)

	GDT Alerts				Calls for Service			
	Total	White	Black	Hispanic	Total	White/ Hisp.	Black	other
drug arrest	56.95	3.23	43.59	10.13	45.32	3.83	27.68	13.82
gun arrest	18.63	0.00	15.64	2.99	20.37	1.00	18.32	1.04
traffic arrest	91.63	1.94	63.19	26.50	237.80	19.34	135.00	83.44
gang contact	94.54	24.88	67.03	2.63	83.49	36.73	41.51	5.25
traffic contact	158.80	24.89	129.10	4.85	139.00	33.17	99.66	6.21
suspect contact	170.40	42.93	124.70	2.78	123.50	40.64	74.35	8.49
other contact	259.90	70.23	180.70	9.02	189.50	59.67	116.50	13.38
victim contact	1.85	0.01	1.85	0.00	1.16	0.00	1.16	0.00

associated with gang-related ($k=0.00007$) and “other” ($k=0.00004$) stops involving Asian individuals. CFS were not associated with stops of Asian individuals in either case. GDT alerts were associated with victim-related stops of Black individuals ($k=0.00004$) while CFS were not significantly associated. CFS were associated with victim-related stops of White/Hispanic individuals ($k=0.00004$) while GDT alerts were not significantly associated.

In Table 9 we report the estimated parameters from the point process model of the space-time intensity of arrests or contacts. For example, we estimate that a GDT alert on average leads to 0.002 additional drug arrests (95% CI 0.0015–0.0025). The timescale parameter in this case is 45.49, indicating that the arrest on average happens quickly after the detection occurs (approximately 1.5 min later). A similar effect was observed for CFS, with each CFS leading to 0.0017 additional drug arrests. We find similar effect sizes between GDT alerts and CFS for each of the additional enforcement categories.¹¹

Through the Expectation-Maximization algorithm, a branching structure graph is estimated that provides a probability that each arrest is caused by a prior GDT alert or shots fired CFS. We then aggregate these probabilities to estimate the total number of arrests attributed to GDT alerts and CFS, which we display in Table 10. For example, we estimate that 57 additional drug arrests were due to GDT alerts and 45 additional drug arrests were

¹¹ We identified 1,325 events where the GDT alerts and citizen call were within 10 min and 100 m of on another. Given the possibility these incidents may be related, we conducted an alternative Hawkes process specification where these incidents are considered a third treatment group. The findings of this analysis are reported in the appendix 1. They do not qualitatively differ from the main analysis.

due to CFS, 19 additional gun arrests were due to GDT alerts and 20 additional gun arrests were due to CFS, and 92 additional traffic arrests were due to GDT alerts and 238 additional traffic arrests were due to CFS. We also provide estimates of excess police contacts due to GDT and CFS in Table 10.

Discussion and Conclusion

As police agencies continue to deploy GDT systems to combat gun violence, research on potential unintended negative consequences is paramount (Ratcliffe et al. 2019). A primary concern advanced by critics is that GDT disproportionately targets disenfranchised communities, while law enforcement officials purport that GDT coverage areas reflect gun violence levels. Descriptive statistics in Chicago lend credence to both perspectives. Per capita gun crime levels were upwards of 1.5 times higher in the GDT target area than the remainder of the city, with the non-white population and poverty rate over twice as high and ~50% higher, respectively (see Table 1). An important question is whether the context of GDT deployment translates into enhanced enforcement, specifically against people of color.

Overall, we find that higher numbers of Black individuals are arrested and stopped closely following (in space and time) GDT alerts compared to individuals of other races. However, for the vast majority of arrest/stop types, the effect of GDT and CFS was similar and consistent across racial categories. In other words, when GDT was significantly associated with arrests/stops, CFS generated similar effects.

Disparities between GDT and CFS findings occurred in a small number of instances, which warrant closer examination. In the Knox tests, GDT alerts were significantly associated with gun-arrests of Hispanic suspects, drug arrests of White suspects, and both gang-related and “other” stops of Asian individuals, with CFS showing no such effects. The point process analysis further found that over 70% of excess gang-related stops generated by GDT were of Black individuals, as compared to 49.7% of the excess gang-related stops generated by CFS. However, there were a number of instances where CFS exhibited more enforcement-generating effects than GDT. CFS was associated with traffic arrests of White suspects, investigative stops of Asian individuals, and victim-related stops of White/Hispanic individuals with GDT not exhibiting significant effects in any of these cases. These findings do not exhibit a clear pattern, with GDT and CFS exhibiting significant and null effects, respectively, in some instance with the opposite relationships observed in others.

Overall, the results indicate that GDT systems may not generate racial disparities in arrests and stops *above and beyond* what results from the standard police response to gunfire. This suggests that racial disparities resulting from police responses to reported gunfire likely relate to aspects of the reporting and dispatch processes generally rather than as they relate specifically to GDT. We note, however, that the nature of the data does not allow us to speak to any biases inherent in how the individual arrests and stops are carried out by officers. A primary accusation raised by community activists is that the Chicago PD used GDT alerts as a preemptive reason to arbitrarily stop persons not engaged in reasonably suspicious behavior. Such actions would clearly violate legal search-and-seizure standards established by the Fourth Amendment of the U.S. Constitution. Exploring this question would require data outside our current access, such as report narratives outlining the context in which police stops and/or arrests of citizens occurred or visual data of police-citizens interactions,

such as body-worn camera video footage (Piza, Connealy, Sytsma, et al., 2023a; Terrill et al. 2023). Furthermore, critics argue GDT alerts provide unreliable criminal evidence for court proceedings, which can lead to wrongful convictions (see, e.g., Burke and Tarm 2022). Again, court data needed to explore this aspect of GDT alerts was outside the scope of the current study. We encourage social scientists to establish the practitioner partnerships and collect the data needed to rigorously analyze these aspects of GDT.

Lastly, in the context of the current debate around GDT, our findings should not be considered as an endorsement of the technology. While this study's results suggest GDT may not inherently lead to racially biased policing to the level suggested previously, they do not speak to whether the technology delivers the intended crime control benefits. As discussed previously, the cumulative research evidence suggests GDT does not consistently deliver crime control benefits. Given the debate surrounding the racial impacts of GDT in Chicago, we felt an important consideration in assessing the technology was to empirically determine the level to which such racial biases exist. This is especially the case given that much prior research indicates the presence of racial bias can inhibit the level of community support necessary for police to implement the type of focused interventions needed to effectively prevent crime (Braga et al. 2019).

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