ShotSpotter Update

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At this time, we are attempting to solidify our main results. Below is an informal write-up of the setting and basic estimation strategy of our paper. In addition, it also includes some background information, and some ideas for other directions to take the paper.

1 What is ShotSpotter?

ShotSpotter is a gunshot detection software that utilizes external microphones across cities to triangulate the location of gunfire and quickly dispatch police to the area. Shotspotter advertises itself as a colorblind policing technology that is designed to help take firearms off the streets. Given the rise in mass shootings and instances of particularly salient police brutality, cities across the US have installed this gunshot detection software in hopes of better policing outcomes.

1.1 ShotSpotter in Chicago

Chicago's police districts began a staggered rollout of the ShotSpotter technology beginning in 2017. Figure 1 shows the staggered implementation dates of the ShotSpotter technology by police district. Of the 18 Chicago Police districts, 12 (66%) possess ShotSpotter's gunshot detection microphones.

1.2 How Does ShotSpotter Work?

When ShotSpotter is implemented in a police district, microphones are installed across the city on stoplights and buildings to detect, and locate, the sound of gunfire. The instant a gunshot is detected, the following process occurs:

1. The gunshot noise is forwarded to ShotSpotter's "acoustic experts" who check for false-positives. If the noise is percevied to be a gunshot, information including the location and number of rounds fired is forwarded to Chicago Police's Office of Emergency Management. This process typically takes less than 30 seconds.
2. Once the Office of Emergency Management is notified of a gunshot, a dispatcher assigns police officers to immediately head to the location of the gunfire. Shotspotter alerts are given an immediate dispatch priority rating—they are treated with the same level of priority as an active shooter.
3. After police cars are dispatched, police officers are to investigate the area for any potential threats.

1.3 ShotSpotter Criticisms

As of right now, ShotSpotter is heavily criticized as it is claimed to increase the amount of investigatory "stop and frisks" of minorities, create unjust arrests based on ShotSpotter alerts that have questionable accuracy, and be an overly burdensome cost to the taxpayers of Chicago at a 3-year contract of 33 million.

Interestingly, ShotSpotter has yet to be rigorously studied in the economics literature despite the prevalent use of its data for other crime-related work. On the other hand, multiple journalists and law firms have done rough "before and after" statistics to draw the criticisms.

2 This Paper

In this paper, we aim to be the first to rigorously study the effects of ShotSpotter on crime. Our goal is to understand how certain police technologies change the incentives and behaviors of individual officers and how these changes can have real impacts on the communities they serve. These changes, which are chosen by a bureaucratic process, dictate the frequency of police interactions and have the potential to drastically affect the wellbeing of those who are over or under policed. In particular, we have a few research questions:

1. Does ShotSpotter reduce the amount of guns on the street?
2. Does ShotSpotter change policing behavior and cause police to practice "hotspot policing"?

3. Does ShotSpotter take valuable resources away from the police department by sending police officers off on dispatches that could end in nothing? In effect, are other crimes that need attention not being addresed?
4. Does ShotSpotter increase the amount of “stop and frisks”, and if so, does this disproportionally affect people of color?

While we are still in the early stages of this project, we can address some of these questions with our preliminary findings.

3 Data

We have a variety of datasets from Chicago Police Department over a seven-year period (2016-2022):

- *Investigatory Stop Reports Data (ISR)* - This includes all discretionary stops made by police officers. ISR data is a rich data set that includes the race of the suspect, whether a search/pat-down was conducted, whether a firearm was found, and whether an arrest was made. In addition, the ISR data includes information on the police officer(s) that performed the stop.

- *Crimes/Arrests Data* - This data includes all reported crimes and arrests in Chicago. The data includes information on the type of crime/arrest that was made. In particular, we can delineate between crimes/arrests that involved a firearm. This data is used to address our research question (1), of the effects of ShotSpotter on gun obtainment.

- *Calls for Service Dispatch Data* - This data shows the dispatch times for each event in Chicago. The data includes time of reported emergency (think 911 call), the time the dispatcher dispatched the officer, the time the officer arrived on-scene, the final disposition of the event (i.e., did the officer find anything?), and the location of the reported emergency. This data will be used to investigate research question (3) on whether resources are taken away from other crimes/emergencies.

- *Traffic Stops/Citations* - This data contains all traffic stops and citations given by the Chicago Police Department. Our idea for this data is to use it to address research question (2) on hotspot policing. If, for instance, we see that more traffic stops/citations are given around areas where ShotSpotter alerts are common, this may be evidence that police are strategically changing their policing behavior to patrol more frequently in these hotspot areas.

- *Complaints* - This data contains all complaints against the Chicago Police Department. The idea here is to test whether ShotSpotter, given its colorblindness, actually reduces the number of complaints against officers. On one hand, complaints may rise if police officers are performing more stop and frisks or illegal pat-downs in hopes of guns. On the other hand, police may be performing these on suspects that are actually a threat.
- *Police Shifts* - This data contains all shifts worked by police officers in Chicago. There is not a clear use for this data at the moment.

4 Estimation Strategy

Since ShotSpotter is implemented in a staggered adoption, we use a two-way-fixed effects (TWFE) model as our baseline model to understand whether ShotSpotter results in finding more guns. In particular, we estimate the following:

$$Y_{dt} = \beta ShotSpotImplement_{dt} + \gamma_d + \sigma_t + \epsilon_{dt}$$

where Y_{dt} is the outcome of interest in district d at time t, $ShotSpotImplement_{dt}$ is an indicator equal to 1 when ShotSpotter is implemented, γ_d are district fixed effects, σ_t are time fixed effects (day-by-month-by-year), and ϵ_{dt} is the error term.

4.1 Other Ideas

While the TWFE model works well in our setting, we also have other forms of variation that we believe can be useful:

- *Police District Boundaries* - As shown in Figure 2, the police districts provide sharp spatial discontinuities where ShotSpotter is implemented/where it is not. Given this, there is a possibility for a spatial RD. Our preliminary findings show that adjacent districts do not pick up effects from ShotSpotter. We believe this may be a situation where we can test the response times of police officers using these lines. Moreover, all of our data contains a spatial element, thus enabling us to match our outcomes to a geographic location.
- *Gunshot Occurrance* - Conditional on ShotSpotter being implemented, a gunshot could be considered a random event. Or, similarly, the number of gunshots fired within a district on a given day may also be random. We are still unsure what to do with this variation, although we believe it will be useful down the line to look at mechanisms.

5 Preliminary Results

Our preliminary results show evidence of the following:

- Table 1 shows ShotSpotter *increases* the number of gun-involved arrests and gun-related crime. While the increase in gun-related crime may seem counterintuitive, this is likely because police are reporting these gun-related crimes more. Hence, we do not know about the underlying distribution of these gun-related crimes. We will try to answer this using 911 data later on. Note that in Panel C and D, other crime and arrests that are unrelated to guns are decreasing. This hints that poice may be substituting away from performing other kinds of stops/arrests, and focusing more on the ShotSpotter cases.
- Table 2 shows that ShotSpotter *decreases* the number of investigatory street reports for all individuals, and more dramatically, Black individuals. Moreover, there appears to be a significant increase in the number of firearms found (Panel C), conditional on a stop.
- Table 3 shows that adjacent police districts have little evidence of Shotspotter effects through spillovers.

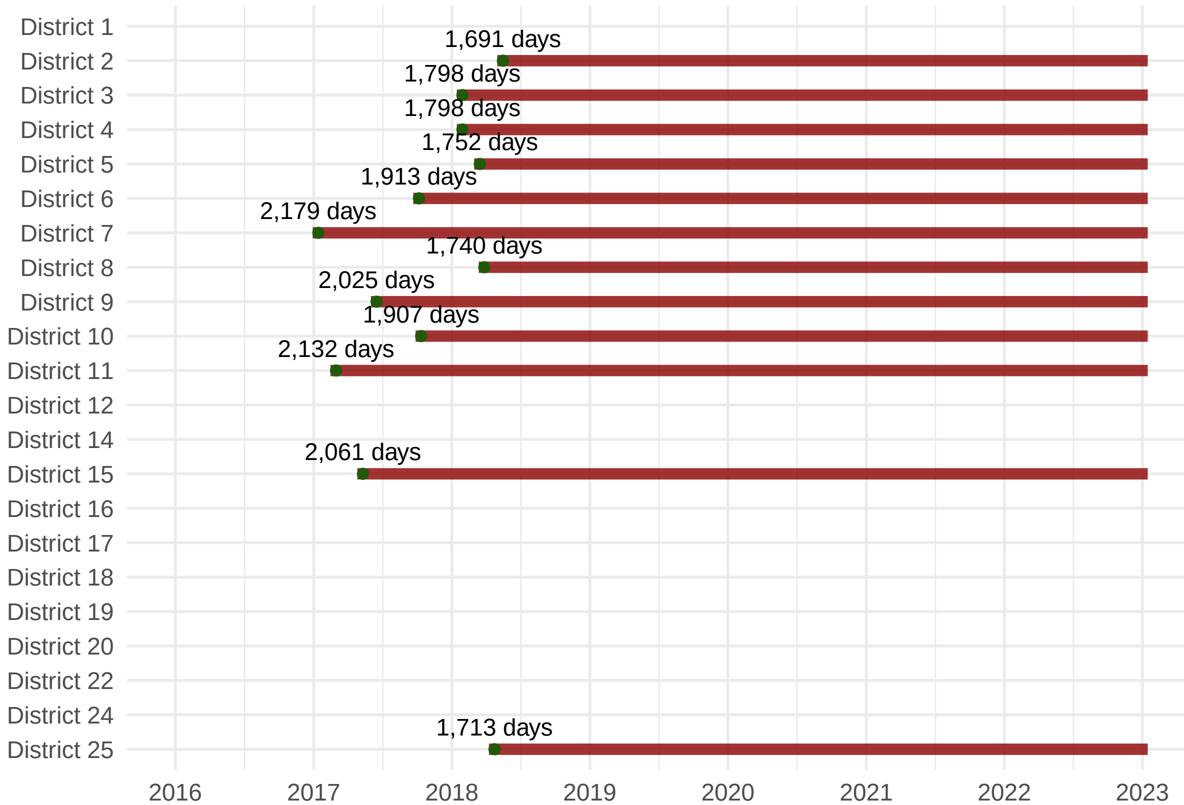

Figure 1: ShotSpotter Rollout Dates by District in Chicago

Note: There are a total of 18 police districts in Chicago, 12 of which get ShotSpotter implemented. Implementation began in early 2017 through late 2018.

6 Figures

CPD District	ShotSpotter Alerts
1*	32
2	6,323
3	11,582
4	20,783
5	15,403
6	14,625
7	16,056
8	14,202
9	13,594
10	12,430
11	14,718
12*	311
14*	56
15	8,300
16*	51
17*	23
22*	352
25	10,734

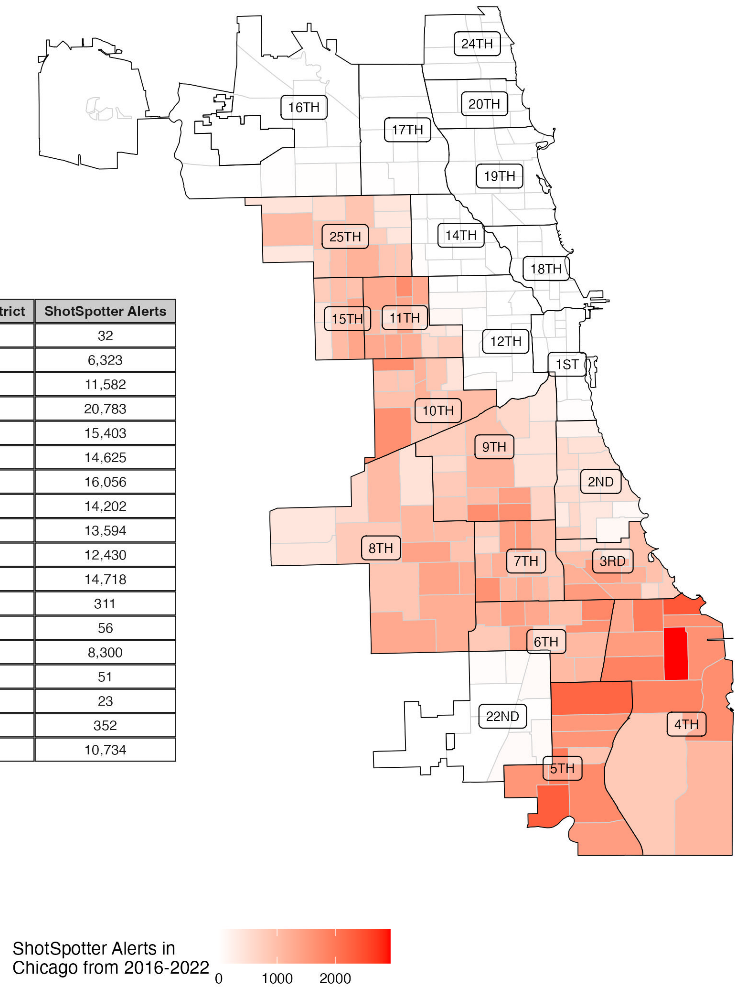

Figure 2: Number of ShotSpotter Alerts in Chicago by Police Beat/District

Note: There are a total of 18 police districts in Chicago. Each of these districts contains beats which are designated by the boxes within the district lines. ShotSpotter began implementation in 2017 and rolled out over the next two years. The table to the left of the map shows the number of ShotSpotter Alerts from 2016-2022. Districts with a star next to them denote districts that do not have ShotSpotter implemented and are therefore likely heard from microphones in neighboring districts.

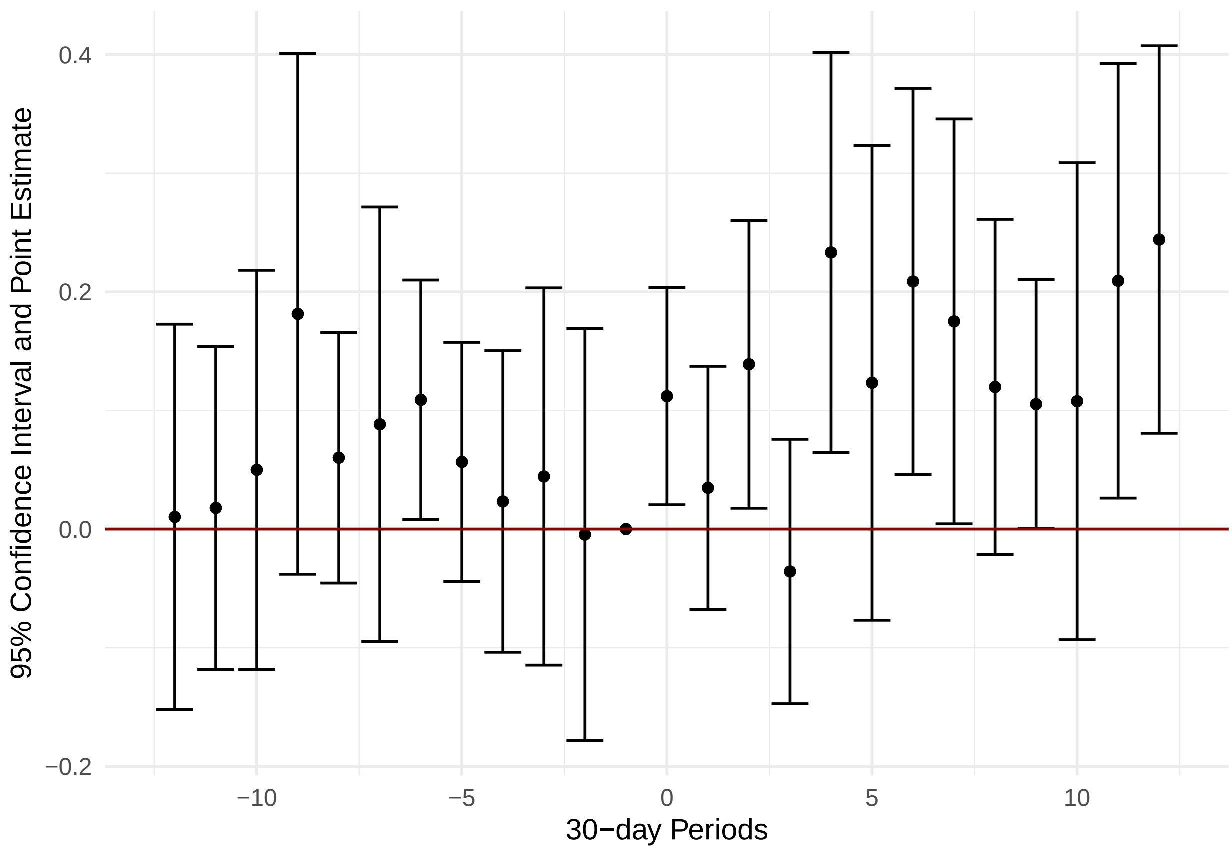

Figure 3: Event Study for Gun Arrests Outcome (OLS)

Note: Each point estimate is a 30-day period. Controls include day-by-month-by-year and district fixed effects. All periods are normalized by the 30-day period before ShotSpotter implementation. Standard errors are clustered by district. The x-axis represents the number of 30-day periods before/after the implmentation of ShotSpotter while the y-axis represents the coefficient estimates and 95 percent confidence intervals.

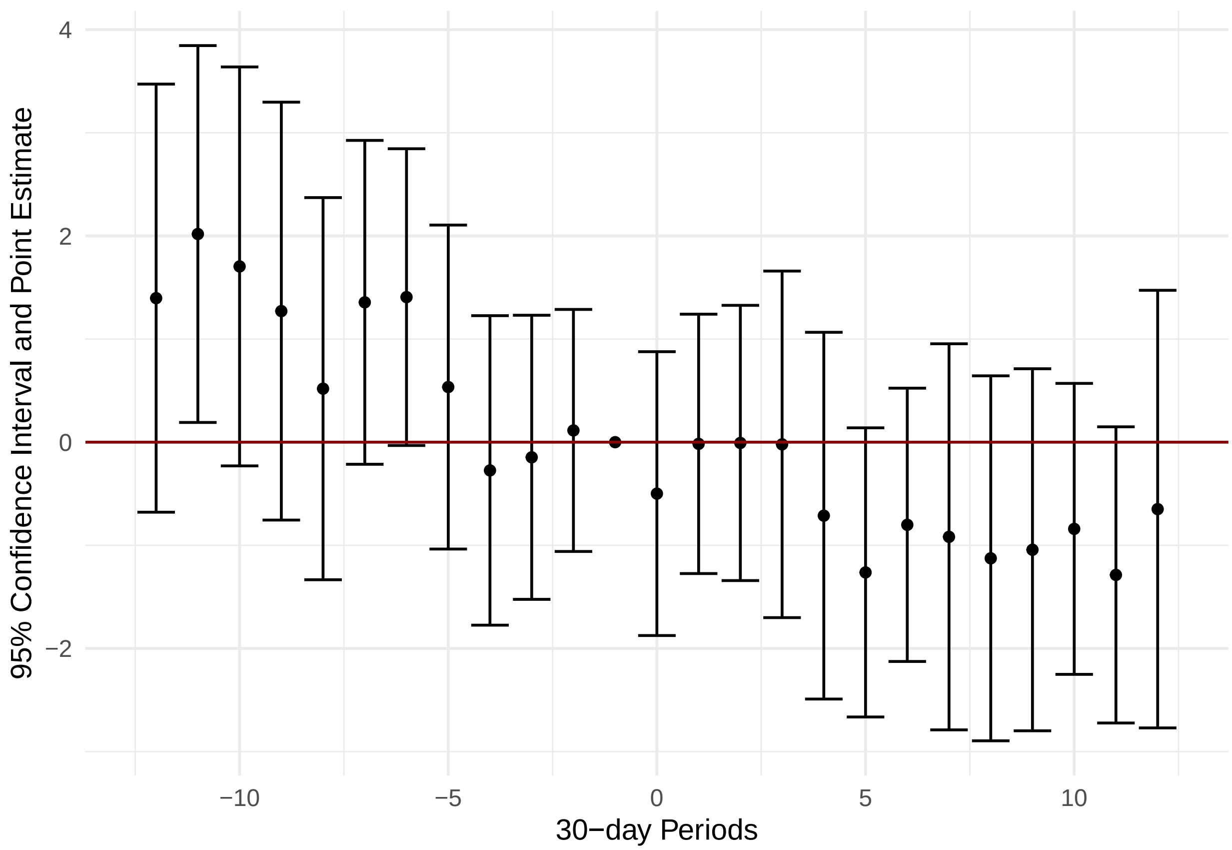

Figure 4: Event Study for All Other Crime Outcome

*Note:*Each point estimate is a 30-day period. Controls include day-by-month-by-year and district fixed effects. All periods are normalized by the 30-day period before ShotSpotter implementation. Standard errors are clustered by district. The x-axis represents the number of 30-day periods before/after the implmentation of ShotSpotter while the y-axis represents the coefficient estimates and 95 percent confidence intervals.

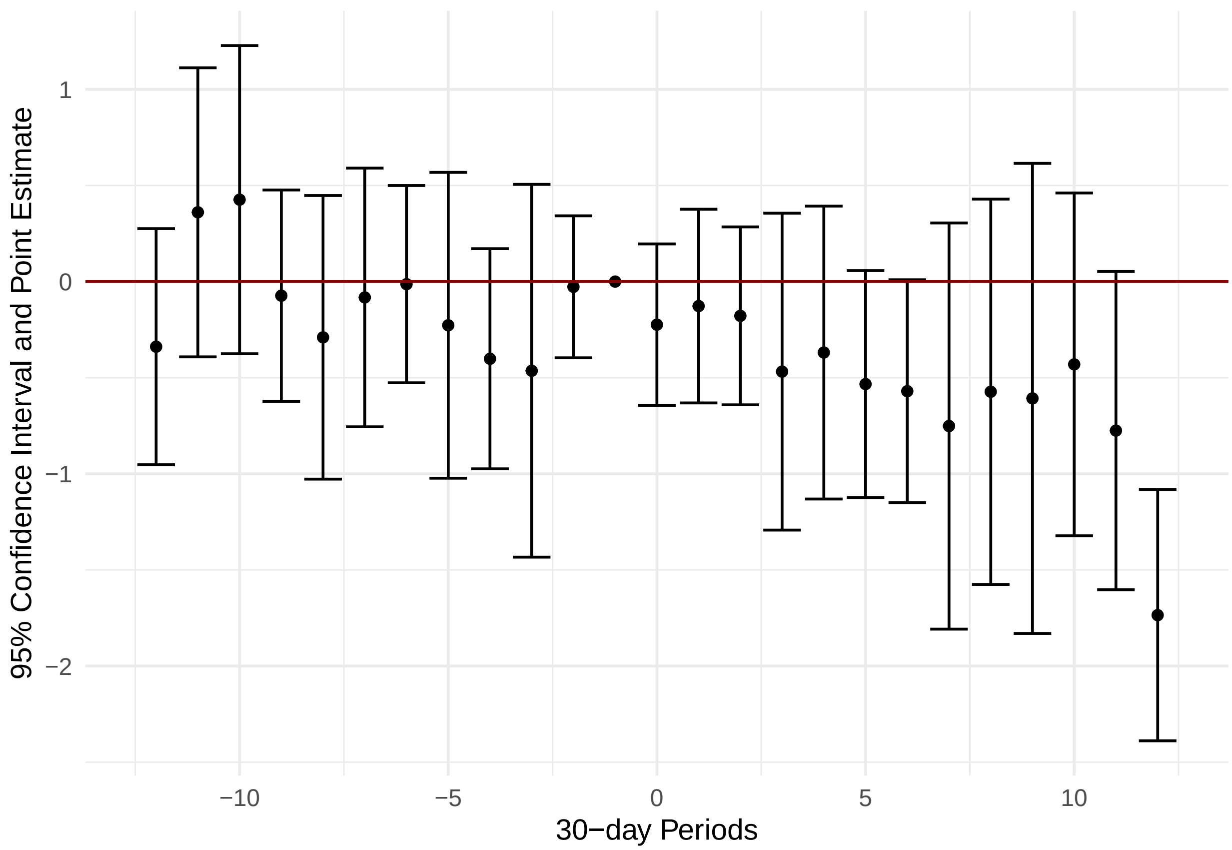

Figure 5: Event Study for All Other Arrests Outcome

Note: Each point estimate is a 30-day period. Controls include day-by-month-by-year and district fixed effects. All periods are normalized by the 30-day period before ShotSpotter implementation. Standard errors are clustered by district. The x-axis represents the number of 30-day periods before/after the implmentation of ShotSpotter while the y-axis represents the coefficient estimates and 95 percent confidence intervals.

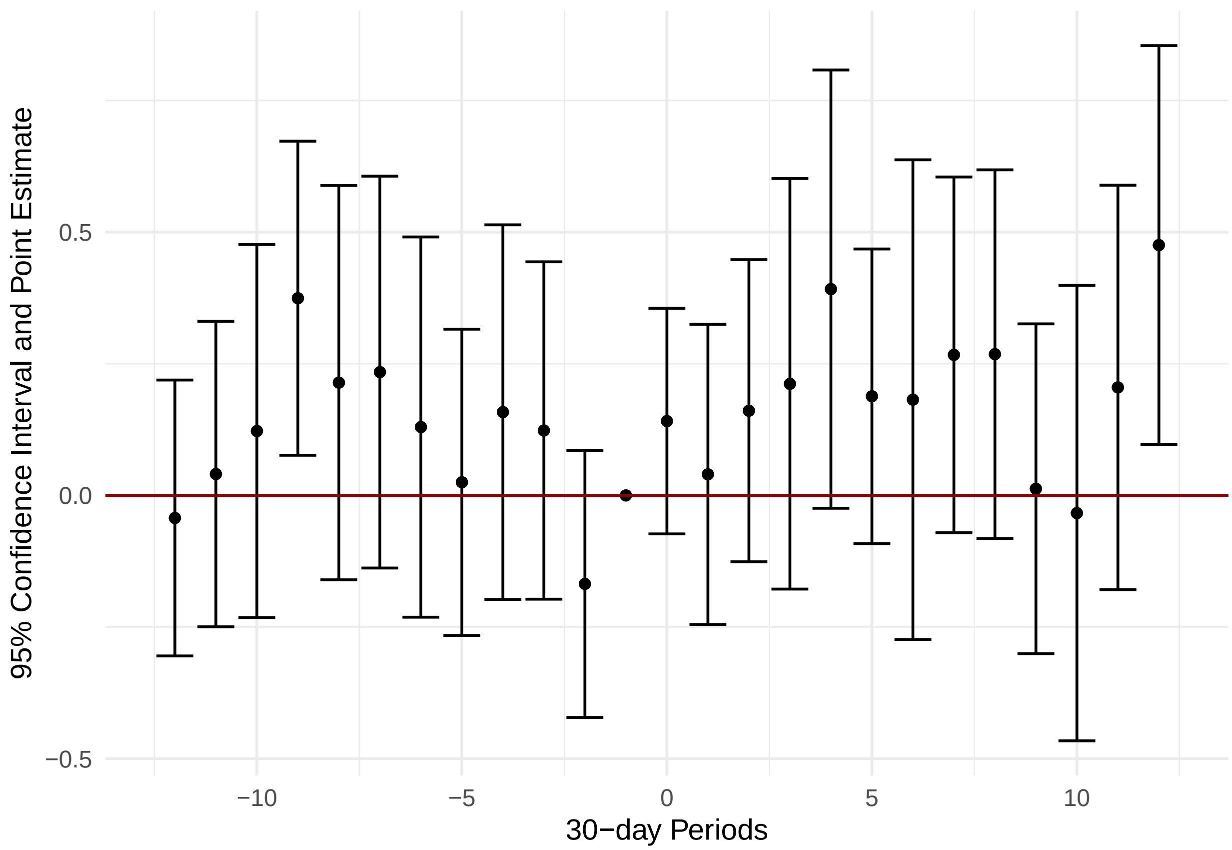

Figure 6: Event Study for Gun Involved Outcome

Note: Each point estimate is a 30-day period. Controls include day-by-month-by-year and district fixed effects. All periods are normalized by the 30-day period before ShotSpotter implementation. Standard errors are clustered by district. The x-axis represents the number of 30-day periods before/after the implmentation of ShotSpotter while the y-axis represents the coefficient estimates and 95 percent confidence intervals.

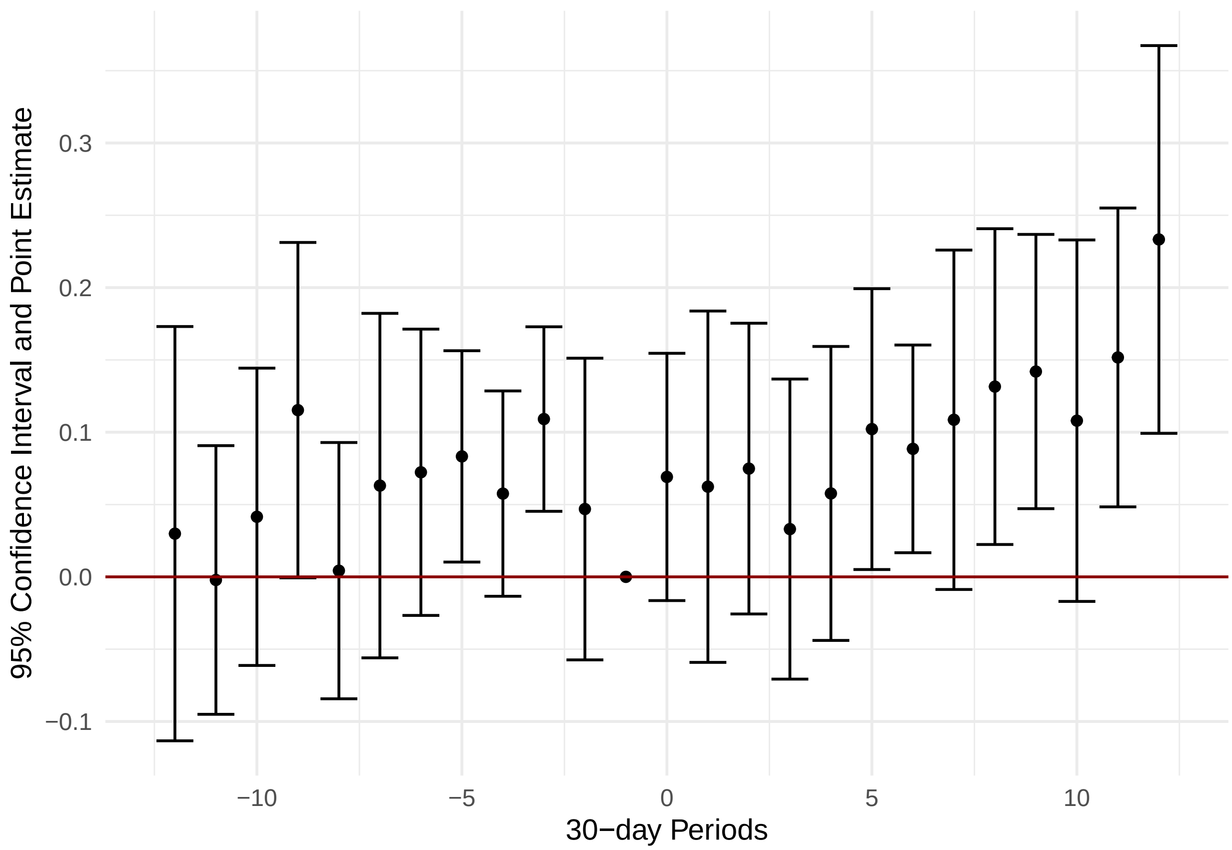

Figure 7: Event Study for Number Firearms Found

Note: Each point estimate is a 30-day period. Controls include day-by-month-by-year and district fixed effects. All periods are normalized by the 30-day period before ShotSpotter implementation. Standard errors are clustered by district. The x-axis represents the number of 30-day periods before/after the implmentation of ShotSpotter while the y-axis represents the coefficient estimates and 95 percent confidence intervals.

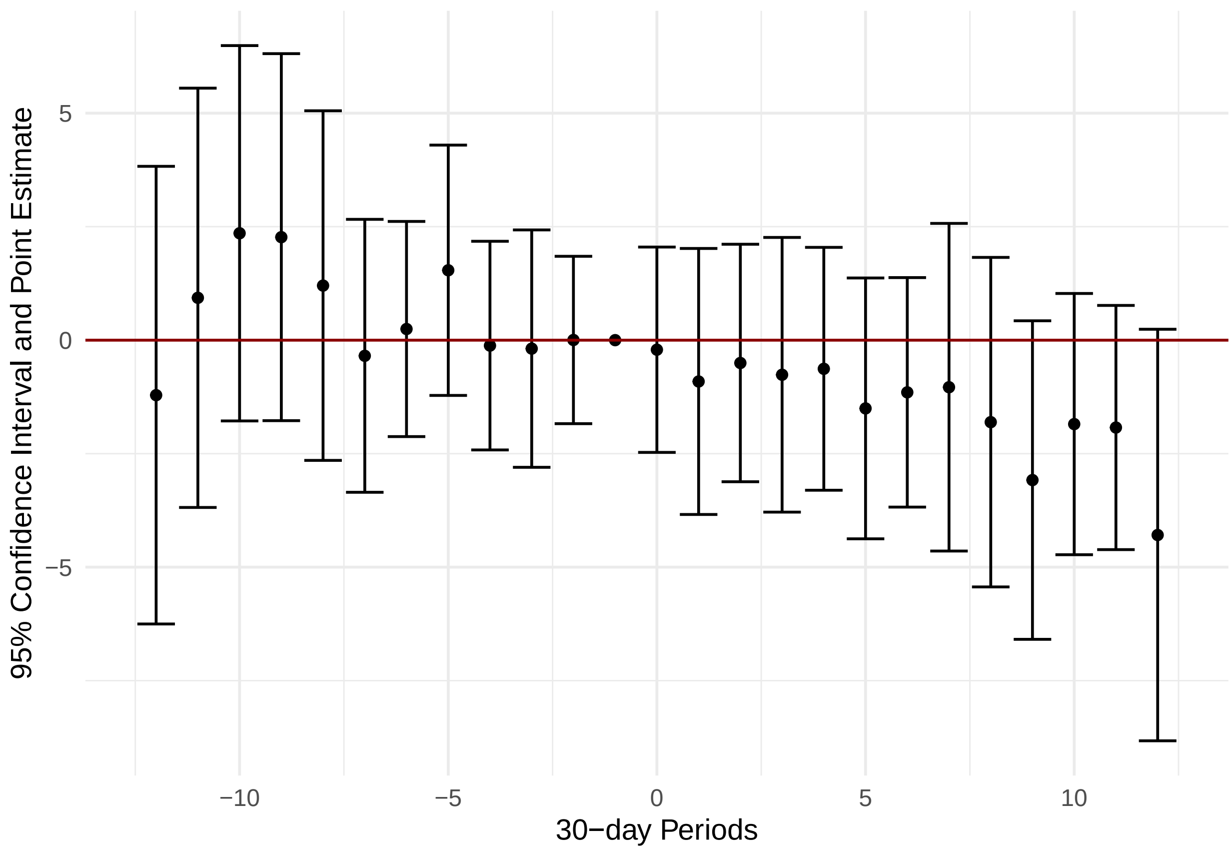

Figure 8: Event Study Number of Black Stops

Note: Each point estimate is a 30-day period. Controls include day-by-month-by-year and district fixed effects. All periods are normalized by the 30-day period before ShotSpotter implementation. Standard errors are clustered by district. The x-axis represents the number of 30-day periods before/after the implmentation of ShotSpotter while the y-axis represents the coefficient estimates and 95 percent confidence intervals.

7 Tables

Table 1: Effect of ShotSpotter Activations on Various Outcomes (OLS/Poisson)

			Omitting 2020	
	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)
Panel A: Number Gun Crimes				
ShotSpotter Activated	0.324***	0.050	0.286***	0.038
	(0.091)	(0.046)	(0.090)	(0.045)
Mean of Dependent Variable	2.018	2.018	1.991	1.991
Observations	56254	56254	48202	48202
Panel B: Number Gun Arrests				
ShotSpotter Activated	0.165***	-0.053	0.153***	-0.046
	(0.048)	(0.077)	(0.044)	(0.076)
Mean of Dependent Variable	0.636	0.636	0.614	0.615
Observations	56254	56232	48202	48180
Panel C: Number Non-Gun Crimes				
ShotSpotter Activated	-1.615**	-0.027	-1.973***	-0.045**
	(0.670)	(0.018)	(0.578)	(0.018)
Mean of Dependent Variable	28.686	28.686	29.442	29.442
Observations	56254	56254	48202	48202
Panel D: Number Non-Gun Arrests				
ShotSpotter Activated	-1.095***	-0.071**	-1.044***	-0.075**
	(0.217)	(0.025)	(0.207)	(0.026)
Mean of Dependent Variable	4.753	4.753	4.968	4.968
Observations	56254	56254	48202	48202
FE: Day-by-Month-by-Year	X	X	X	X
FE: District	X	X	X	X

Note:
* p < 0.1, ** p < 0.05, *** p < 0.01
Standard errors are clustered by district. Shotspotter is activated in 12 of the 22 police districts in Chicago. Number Gun Crimes refers to all crimes that have a gun involved. For instance, this can include a burglary or aggrevated assault with a firearm. Number of Gun Arrests are the number of gun crimes that end in an arrest. Number of Non-Gun Crimes are all crimes that have no firearm involved. Similarly, not all of these end in arrests. Columns 3 and 4 omit year 2020 (Covid-19).

Table 2: Effect of ShotSpotter Activations on Investigatory Street Stops (OLS/Poisson)

			Omitting 2020	
	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)
Panel A: All Stops				
ShotSpotter Activated	-3.762***	-0.257***	-3.458***	-0.248***
	(1.114)	(0.085)	(1.063)	(0.078)
Mean of Dependent Variable	12.986	12.986	13.373	13.373
Observations	56254	56254	48202	48202
Panel B: Black Stops				
ShotSpotter Activated	-3.107***	-0.295***	-2.703***	-0.271***
	(0.871)	(0.088)	(0.861)	(0.085)
Mean of Dependent Variable	8.973	8.973	9.285	9.285
Observations	56254	56254	48202	48202
Panel C: Firearms Found				
ShotSpotter Activated	0.138***	-0.160	0.141***	-0.134
	(0.038)	(0.102)	(0.038)	(0.103)
Mean of Dependent Variable	0.302	0.308	0.293	0.300
Observations	56254	55220	48202	47168
FE: Day-by-Month-by-Year	X	X	X	X
FE: District	X	X	X	X

Note:
* p < 0.1, ** p < 0.05, *** p < 0.01
Standard errors are clustered by district. Shotspotter is activated in 12 of the 22 police districts in Chicago. Stops refer to footstops that have an investigatory stop report (ISR). Note that these stops do not include juveniles. Columns 3 and 4 omit year 2020 (Covid-19).

Table 3: Effect of ShotSpotter Activations with Bordering Districts (OLS/Poisson)

			Omitting 2020	
	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)
Panel A: Number Gun Crimes				
ShotSpotter Activated	0.318***	0.049	0.283***	0.038
	(0.089)	(0.044)	(0.088)	(0.044)
ShotSpotter Border Activated	0.038	0.017	0.020	0.003
	(0.070)	(0.049)	(0.070)	(0.050)
Mean of Dependent Variable	2.018	2.018	1.991	1.991
Observations	56254	56254	48202	48202
Panel B: Number Gun Arrests				
ShotSpotter Activated	0.156***	-0.053	0.144***	-0.047
	(0.046)	(0.075)	(0.042)	(0.075)
ShotSpotter Border Activated	0.059	-0.004	0.058	0.004
	(0.056)	(0.095)	(0.051)	(0.090)
Mean of Dependent Variable	0.636	0.636	0.614	0.615
Observations	56254	56232	48202	48180
Panel C: Number Non-Gun Crimes				
ShotSpotter Activated	-1.391**	-0.019	-1.717***	-0.036**
	(0.620)	(0.016)	(0.508)	(0.015)
ShotSpotter Border Activated	-1.510**	-0.058***	-1.698***	-0.064***
	(0.681)	(0.019)	(0.589)	(0.020)
Mean of Dependent Variable	28.686	28.686	29.442	29.442
Observations	56254	56254	48202	48202
Panel D: Number Non-Gun Arrests				
ShotSpotter Activated	-1.067***	-0.069***	-1.011***	-0.071***
	(0.227)	(0.024)	(0.212)	(0.024)
ShotSpotter Border Activated	-0.188	-0.018	-0.215	-0.028
	(0.299)	(0.035)	(0.282)	(0.037)
Mean of Dependent Variable	4.753	4.753	4.968	4.968
Observations	56254	56254	48202	48202
FE: Day-by-Month-by-Year	X	X	X	X
FE: District	X	X	X	X

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered by district. ShotSpotter Border Activated refers to a district that is adjacent to a treated district. A bordering district is considered treated if any of its adjacent districts are treated. Shotspotter is activated in 12 of the 22 police districts in Chicago. Number Gun Crimes refers to all crimes that have a gun involved. For instance, this can include a burglary or aggrevated assault with a firearm. Number of Gun Arrests are the number of gun crimes that end in an arrest. Number of Non-Gun Crimes are all crimes that have no firearm involved. Similarly, not all of these end in arrests. Columns 3 and 4 omit year