THE IMPACT OF SHOTSPOTTER ON VIOLENT CRIME: A STUDY ON THE EFFECTIVENESS OF IMPLEMENTING ACOUSTIC GUNSHOT DETECTION TECHNOLOGY TO IMPROVE POLICING

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RESEARCH COMPLIANCE CERTIFICATION

Research activities involving the use of human subjects, vertebrate animals, and/or biohazards must be reviewed and approved by the appropriate Texas A&M University regulatory research committee (i.e., IRB, IACUC, IBC) before the activity can commence. This requirement applies to activities conducted at Texas A&M and to activities conducted at non-Texas A&M facilities or institutions. In both cases, students are responsible for working with the relevant Texas A&M research compliance program to ensure and document that all Texas A&M compliance obligations are met before the study begins.

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This project did not require approval from the Texas A&M University Research Compliance & Biosafety office.

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ABSTRACT

The Impact of ShotSpotter on Violent Crime: A Study on the Effectiveness of Implementing Acoustic Gunshot Detection Technology to Improve Policing

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This study will seek to examine the relationship between ShotSpotter technology and the rate of violent crimes within cities across the United States. In recent years, the ShotSpotter technology has become more prevalent as it has been implemented in over 100 cities and counties in an effort to combat crime. Developers sought to more effectively identify, investigate, and prosecute gun-involved crimes, as well as fix the traditional issues of underreporting and the lack of accurate and timely information associated with crime. This paper analyzes the effectiveness of the technology in measuring its observable effects on violent crime rates. Utilizing a generalized difference-in-difference model, the study examines the violent crime rates pre- and post-ShotSpotter and compares the variation to the cities that never utilized the technology. The effect of ShotSpotter, as implemented in each city, was found to have a significant negative effect on violent crime rates.

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Contributors

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The data analyzed for "The Impact of ShotSpotter on Violent Crime" was provided by the Justice Tech Lab at Texas A&M and Claire Risher. The analyses depicted in "The Impact of ShotSpotter on Violent Crime" was conducted in full by Samantha Kim and this data is currently unpublished.

All other work conducted for the thesis was completed by the student independently.

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1. INTRODUCTION

1.1 Introduction and Motivation

In today's world, especially given the recent current events, one of the most important responsibilities and challenges of police departments is to invest in the technology that will best help policing become more efficient and effective. In order to do so, they must sort through the multitude of technologies that are available. One technology that has come to the scene in the 21st century is acoustic gun detection systems. This study will look at one system in particular called ShotSpotter. ShotSpotter is a technology that detects and conveys the location of the gunfire (or other weapon fire) using sensors. The technology aims to provide "precision policing solutions that help save lives, deter crime, and make communities safer" (ShotSpotter, 2020). The current study seeks to get insight on the efficacy of ShotSpotter by analyzing whether there is an impact on violent crime rates with its implementation.

1.2 Background and Literature Review

1.2.1 ShotSpotter Background

ShotSpotter is an auditory system using locally installed audio sensors to record the exact time and location of shots fired. This system uses a network of audio devices installed strategically on lampposts and traffic lights to pick up the audio signal of gunshots fired. They then use a system of algorithms, AI, as well as human audio analysts to triangulate the location and verify the gunshot from other loud noises. ShotSpotter does all this within 60 seconds of shots fired and instantly notifies police departments through a mobile and desktop app. Specifically, the service provides data on the location of the shot (longitude, latitude), the exact time of the shot and whether single or multiple shots were fired. The system has been deployed in over 100 cities as well as by the US Secret Service (ShotSpotter, 2017). The Colombia Police Chief Skip Holbrook also commented that qualitative improvements in response are easy to implement when information is fast and exact as "[officers] can figure out the best response strategy in terms of how they'll approach the area". He additionally notes that "about 75% of gunshots in the city go unreported by residents" and "as many as 150 crime scenes that might have been otherwise ignored because no one in the area called 911" (Trainor, 2019).

1.2.2 Pricing of the Technology

The company owning ShotSpotter is currently privately owned, making the technology very expensive. In Sacramento, on June 16, 2020, the city council passed the motion to fund the gunshot detection system for the next 5 years, costing them $2,544,008 total ($505,608 for the first two years and $509,600 the following three years). According to the Council Report, on average, it costs around $65,000 per square mile. In the city's proposed fiscal year budget for 2019/20, the police department is allocated $5,289,372 out of its total $1.2 billion budget (City of Sacramento, 2019). The ShotSpotter technology therefore costs around 9.6% per year of the police departments allocate budget. The rest of the budget is spent on urban are security initiatives, public safety programs, hiring police officers, gang violence suppression, and a selective traffic enforcement program. With budgets getting tighter in 2019, the Sacramento County Sherriff's Office decided to keep the technology (City of Sacramento, 2020). However, they decided to get rid of deputies specifically assigned to respond to gunshot alerts, saying that they will still send a patrol unit when available (Giles, 2019). As seen in the recent political climate, there has been a call for defunding the police and with less funding, it is of greater importance to see whether the technologies used by the departments are positively impactful in their ability to reduce crime.

1.3 Policing Technology

Innovations and technology are transforming the way policing and law enforcement operate. From the adoption of social media, cameras, license plate readers, security cameras, and gunshot detection systems, police departments are adding a growing number of tools to aid them in crime solving and prevention. It has been shown in previous studies that if the level of technology used in combating social crimes increases, the equilibrium density of crime burden decreases (J. Shukla, Goyal, Agrawal, Kushwah, A. Shukla, 2013). This finding speaks positively in the favor of implementing ShotSpotter, however, it takes into account only the general effect of technology on crime. Within policing technology, it can be further categorized and defined into two different types. According to Byrne and Marx (2011), material-based technology (hard technology) and information-based technology (soft technology). Examples of hard technology include CCTV's, body armor, etc., while soft technology includes crime mapping, gunshot location devices, security cameras, etc. ShotSpotter is categorized as soft technology. In general, soft technologies are used for crime prevention, along with risk and threat assessment. Additionally, they are often privately owned, making the technology quite costly to obtain and maintain. Many of these technologies, like facial recognition software and communications monitoring, raise ethical concerns of surveillance, however, this study will not delve into the ethics of the usage of gun detection technology and will focus solely on its efficacy. Byrne and Marx (2011) pointed out that when searching for the direct impact of soft technology on crime, it is often challenging since there are many other factors that are not fully accounted for. Ideally, the technology would be used in conjunction with other programs and training. Even so, the technology system may be put into place but may not be utilized to its greatest capacity, and in turn, will not yield the highest desired result. The fault is on the supporting factors rather than the technology itself, making its effect on crime difficult to measure. Still, as pointed out by Nunn (2001), these technologies are used to in an effort to keep social order through surveillance. Subsequently, surveillance technologies highlight differences in behavior and uncover patterns to aid law enforcement in solving crimes, which can only be observed by analyzing data. Gunshot detection technology provides a more accurate picture and dataset of gun violence which would have otherwise gone unreported.

1.4 Crime Drop

It is important to bear in mind that violent crime rate has fallen since the 1990s. It briefly stalled in during the 2008 recession, yet overall, violent crime has continued to decline in the United States by nearly 50% (Farrell, Tilley, Tsleoni, 2014). Many different explanations have been offered by previous studies, including changing demographics, mass incarceration, and even lead poisoning. Most of the explanations have failed to provide evidence. The strongest explanation that has the strongest evidence is the security hypothesis (Farrell, Tilley, Tsleoni, 2014). Though the regression mitigates the crime drop effect, the graphs will not be able to account for the overall decrease which will minimize the actual effect.

1.5 Comparing to Foot Patrol Experiment

In a study by Ratcliffe, Taniguchi, Groff, and Wood (2011), they found that an increase police patrol acted as a deterrent to committing crimes. In their experiment, they mapped out the areas with higher violent crime rates and, for the next six months, a pair of officers patrolled the area. Violent crime rates before the experiment were then compared to those after the patrol had concluded. The researchers found that patrolled hotspots had a decrease in violence of 90 offenses which was 23 percent more offenses than the equivalent control areas. However, 37 of those 90 reduced offenses ended up occurring in neighboring areas; overall, there was a net reduction of 53 offenses. The theory behind the reasoning is that potential criminals will observe increased police presence and bet deterred from committing a crime in that area of the fear of getting caught. ShotSpotter claims that with their technology, it can "detect gunshots for consistent, rapid, precise police response" and "detect highest crime risk areas for directed patrols to maximum crime deterrence" (ShotSpotter, 2020). I expect that the results between ShotSpotter and violent crime rates will have a similar effect since, the idea behind the by Ratcliffe, Taniguchi, Groff, and Wood (2011) study is that potential criminals will observe increase police presence and be deterred from committing a crime in that area out of fear of getting caught. However, it is important to note that in the case of Sacramento County, with their reduction in police officers reacting to gunshot detection alerts, the technology will inherently not have the same positive effect on violent crime since the police officers' physical presence will be limited.

1.6 Hypothesis

With the faster response rates and the ability to track where the gun fire is located, I hypothesize that the technology will have a significant impact in reducing violent crime rates. However, given that there is little evidence of similar technologies having a visible impact, I predict that ShotSpotter will have a negative correlation with violent crime rates but with a smaller correlation coefficient.

2. DATA

2.1 Violent Crime Data

The violent crime data for this paper comes from the Federal Bureau of Investigation (FBI) for the period of January 1995 through December 2018 in the Uniform Crime Report (UCR). The UCR data included violent crimes (criminal homicide, forcible rape, robbery, and aggravated assault) and measures of property crime (burglary, larceny-theft, and motor vehicle theft). The file was procured from Jacob Kaplan, a PhD candidate at the University of Pennsylvania, who concatenated UCR data (Offenses Known and Clearances by Arrest) from 1960 through 2018 (Kaplan, 2020). Crime was standardized by city population as monthly crimes per 10,000 people. The timeline used was from 1995-2018, as 1995 predated the first known implementation of ShotSpotter in Redwood City, CA, by 5 years (based on data from JTL) and 2018 is the most recent crime data currently available. Cities without full and complete data on total violent crime during this time period were excluded from the analysis. Within UCR data, there is a limitation where a handful of cities that do not report and instead recorded crime as a zero. However, the likelihood of no crime being committed is incredibly low, so instead of leaving the value "0", I counted the data as missing.

2.2 ShotSpotter Data

Data for the start and end dates for the contracts of the cities that implemented ShotSpotter was acquired from both the Justice Tech Lab database and from public news articles. The data included the month and year of when ShotSpotter was contracted to start and, in some cases, end, which I aggregated the data to the city month level. Originally, I had a dataset of 46 ShotSpotter cities with the data from JTL. With cities that were known to have had ShotSpotter at some point in time, data was gathered through news articles and city contracts to find the start month and year, along with the end month and year. If the start year was available but not the start month, the city was coded as having started in December (Baton Rouge, LA and Glendale, AZ). Further, there were many cities that signed a contract with ShotSpotter post-2018 (2019: 11 Cities, 2020: 2 Cities). Cities that started their usage of the technology too early were omitted from the analysis leaving a total of 73 cities. I also chose to omit cities that started in 2018 in order to give at least a one-year post-treatment (2018=8 cities). While excluding cities with incomplete violent crime data, the complete dataset had 70 cities that had ShotSpotter, 6 of which terminated its usage of ShotSpotter at some point in time (reference Table A.1 and Table A.2).

2.3 Control Variables

For the control variables, I chose to use unemployment, poverty rates, average household income, demographics and population. Historically, it was found that there was a decline in property crimes rates during the 1990's due to the decline of unemployment rates (Raphael and Winter-Ebmer, 2001). The impact of violent crime rates is significantly less than property crime rates, however, there was still a statistically significant affect. Additionally, in the literature by Fleisher (1966) and Ehrlich (1973), they both found that there was a significant impact on crime with the rate of unemployment and income inequality. Following up with income inequality, Hsieh and Pugh (1993) also discovered that poverty and income inequality are associated with violent crime. In terms of population, Harries (2006) demonstrated that violent crime was moderately correlated with population density and that crime generally affected the same street blocks. For my study, I will be using city fixed effects which inherently, since it is not time-varying, will account for population. Within the analysis, originating agency identifier (ori) will uniquely identify each city. Lastly, I will be including demographic data as a control. It is widely known that racial inequality in socioeconomic conditions correlate with violent crime (Blau and Blau, 1982) and is also later reaffirmed in the research done by Liska, Logan, and Bellair (1998) where they concluded that crime rates are impacted positively by racial composition. Data for the controls were attained by using various governmental sources. Poverty and income data, along with demographic data, was gathered from the United States Census. Unemployment data was obtained from the Bureau of Labor Statistics.

2.4 Limitations

Within this study, there are a few limitations to take into consideration. Firstly, as indicated in the Doleac and Carr (2016) paper, traditional crime data collection is flawed for a number of reasons, especially as it pertains to crime data on gun violence. Data concerning shots fired or guns wielded is greatly underreported, since individuals involved in gun violence may be wary to report shots or seek medical attention for fear of potential arrest or other legal consequences. With the implementation of ShotSpotter, violent crime rates could potentially increase due to the fact that they were previously underreported. With them now being accounted for, it could therefore impact the outcome of the regression. However, in all the treatment cities, there was no sudden increase of violent crime being reported.

Another limitation is that there may be a lag present in the effectiveness of ShotSpotter. As stated before, the physical prevention of gun violence is largely determined by the policy development, training, and community engagement. Only then will the outcome reflect a more accurate depiction of whether ShotSpotter is indeed impactful in reducing violent crimes. However, since the effectiveness is dependent on other factors, it may take time for the data to become useful in its implementation. Though this limitation is hard to account for, within the treatment cities, only cities that started in pre-December 2017 were included to give a full year lag time.

The third limitation concerns the coverage of the ShotSpotter technology. Cities and counties normally sign a contract with ShotSpotter for ranging from 1-5 years and once they renew, which the majority do, they will sometimes expand the square mileage reach of the technology. According to their website, 18 cities expanded their serve after the initial deployment of the technology, with some expanding more than once (ShotSpotter, 2020). Therefore, the data from ShotSpotter only represents a portion of the entire city or county. As a general guideline, cities will choose its placement the sensors in high crime areas. Therefore, the expansion, though helpful in gathering data, may not have as big of an impact. However, it is a factor that may affect the overall measurement of its effectiveness. Unlike the first limitation, this limitation cannot be resolved currently given the constraints of the data available.

3. METHODOLOGY

3.1 Difference-in-Difference

For the baseline specification, I used a generalized difference-in-difference model to assess the effect of ShotSpotter on violent crime trends within cities throughout the United States over time. The treatment group consisted of those who purchased ShotSpotter while the cities who never had ShotSpotter were the control group. I constructed a panel of data on reported violent crimes, by month, by year, and by location. The difference in differences regression takes the following form:

$$\begin{aligned} Outcome_{it} = \beta_0 + \beta_1 ShotSpotter + \beta_2 UnemploymentRate + \beta_3 PovertyPercentage + \\ \beta_4 MedianHouseholdIncome + \beta_5 Gender + \beta_6 Race + \alpha_i \\ + \Upsilon_t + e_{it\,t} \end{aligned} \tag{3.1}$$

In Equation 3.1, the $Outcome_{it}$ represents the violent crime rate for the outcome of interest at a given month t for city i, where the outcomes of interest are actual all violent crimes. The intercept, β_0 , is the crime rate for city i in January 1995. *ShotSpotter* is the dummy variable, 1 if ShotSpotter is present (post-treatment) and 0 if it is not (pre-treatment). The *Treatment* variable, which represents whether the city is a treatment city, 1, or a control city, 0 is not included in the equation since the fixed effects eliminates any variation between the two groups. Additionally, *Treatment* is the same as the interaction term (*Treatment* * *ShotSpotter*). The fixed effects consist of controlling for the city, α_i, and the year, Υ_t, with our last variable, e_{it}, as the error term, while clustering at the city level. I will also control for unemployment rate, poverty percentage, median household income, race demographics and gender demographics. The coefficient of interest is β_2.

Therefore, in our null hypothesis,

If H0: $\beta_2 = 0$, then I accept the null hypothesis.

If H1: $\beta_2 \neq 0$, then I reject the null hypothesis.

Table 3.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Ori	955160	2209.96	1299.956	1	4430
Month	955160	6.485	3.451	1	12
Year	988499	2007.277	6.874	1995	2018
Violent Crime Rate	923736	3.042	6.36	0	608.89
Treatment Cities	955160	.019	.135	0	1
Population	923739	54269.464	195924.58	10000	8616333
Unemployment Rate	972532	212.439	60.514	1	280
Poverty Percentage	891625	4.247	10.819	.025	178.386
Median Household Income	937542	52669.301	15548.776	0	140382
Male Percentage	970683	.491	.012	.426	1
White Percentage	970683	.817	.129	.026	1
Black Percentage	970683	.11	.115	0	.869
American Indian & Alaska Native Percentage	970683	.013	.048	0	.965
Asian Percentage	970683	.043	.051	0	.92
Hispanic Percentage	970683	.132	.152	0	.978

In Table 3.1, the summary statistics show that there are a little less than 1 million observations for each variable. The only control variable that is significantly different in observation size is poverty percentage. This is due to the fact that data on the year 1996 was not available in the full dataset. Another point to note is that, since the smallest treatment city had 14,536 people, I chose to only include cities that had above 10,000 people, which is why 10,000 is the minimum population shown in the summary statistics.

I also included a separate regression for the treatment cities that decided to end their contract with ShotSpotter pre-2018. There were a total 6 cities (Beloit, WI; Brockton, MA; Canton, OH; Charlotte, NC; Detroit, MI; San Antonio, TX) that discontinued their usage of ShotSpotter. Therefore, I made another regression using the time ShotSpotter was implemented as the pre-treatment and its cancellation as the post-treatment. I will use the same controls and fixed effects as the previous regression.

$$Outcome_{it} = \beta_0 + \beta_1 ShotSpotter + \beta_2 UnemploymentRate + \beta_3 PovertyPercentage + \beta_4 MedianHouseholdIncome + \beta_5 Gender + \beta_6 Race + \alpha_i + \Upsilon_t + e_{it\,t} \tag{3.2}$$

In this case, as displayed in Equation 3.2, ShotSpotter is the dummy variable, 1 if ShotSpotter is no longer present (post-treatment) and 0 if it is present (pre-treatment). The treatment is whether, at some point in time, ShotSpotter usage was cancelled. All cities that continued their employment of ShotSpotter were omitted from this regression.

Therefore, in our null hypothesis,

If H0: $\beta_2 = 0$, then I accept the null hypothesis.

If H1: $\beta_2 \neq 0$, then I reject the null hypothesis.

4. EMPIRICAL RESULTS

4.1 Regression #1

Table 4.1: ShotSpotter Effects on Violent Crime Rate

Variable	Coef.	Robust Std. Error	t	P > |t|	[95% Conf.	Interval]
ShotSpotter	-1.5060	0.3189	-4.72	0.000	-2.1313	-0.8808
Unemployment Rate	0.0006	0.0001	4.13	0.000	0.0003	0.0008
Poverty Rate	0.0511	0.0086	5.94	0.000	0.0342	0.0680
Median Household Income	0.0000	3.74e-06	2.72	0.007	2.83e-06	0.0000
Male Percentage	32.5505	7.4387	4.38	0.000	17.9664	47.1345
White Percentage	-4.0816	2.4547	-1.66	0.096	-8.8943	0.7311
Black Percentage	3.1640	2.8444	1.11	0.266	-2.4128	8.7408
American Indian & Alaska Native Percentage	45.2814	10.7008	4.23	0.000	24.3017	66.2610
Asian Percentage	-3.9866	2.0945	-1.90	0.057	-8.0929	0.1197
Hispanic Percentage	-13.4477	1.3226	-10.17	0.000	-16.0408	-10.8547
_cons	-9.2809	4.0583	-2.29	0.022	-17.2376	-1.3242

The results of the regression are presented in Table 4.1. According to the outcomes, ShotSpotter appears to be statistically significant at the 99% level, with a p-value below 0.01. The treatment effect is omitted due to the fact that the fixed effects account for any variation between the treatment and control group. Therefore, with the control and fixed effects, the difference between the control group and the treatment group is mitigated. The only control that is not significantly related to violent crime rates is the demographic measure of black percentage. Based on the ShotSpotter coefficient, given that the mean of violent crimes committed in all treatment cities is 8.56 people per 10,000 people every month, the decrease of 1.506 people is equivalent to a 17.59% decrease in violent crimes committed. Each city will be different, given that violent crimes vary from location to year. However, the overall mean gives a quick snapshot of the impact that ShotSpotter has on violent crimes based on the regression model.

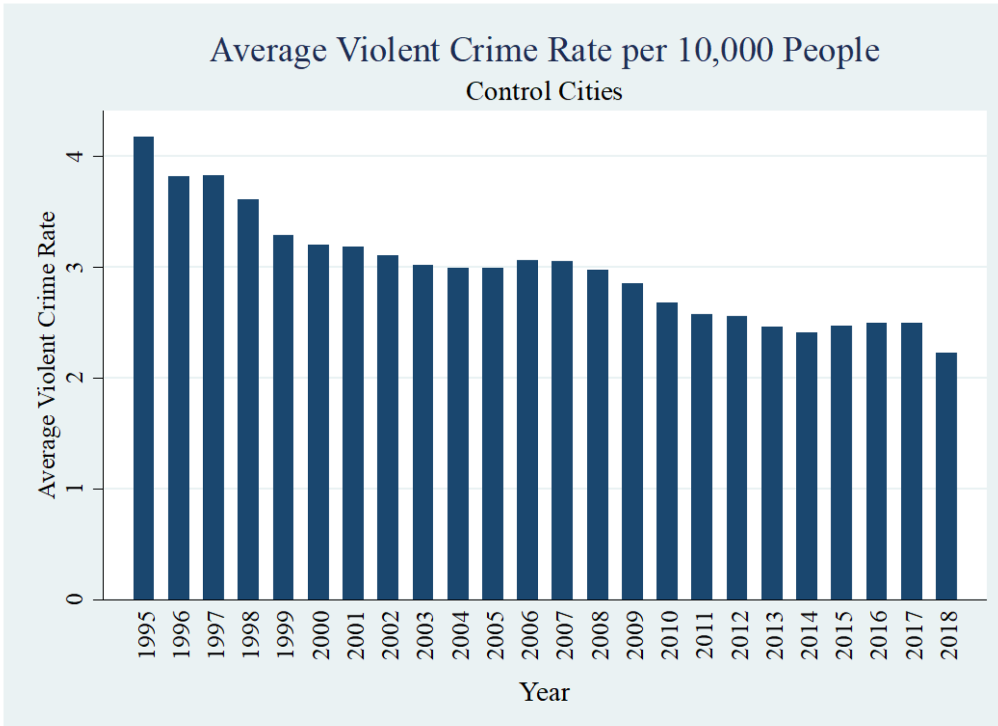

Figure 4.1: Control Group Graph for Violent Crime Rates Over Time (1995-2018)

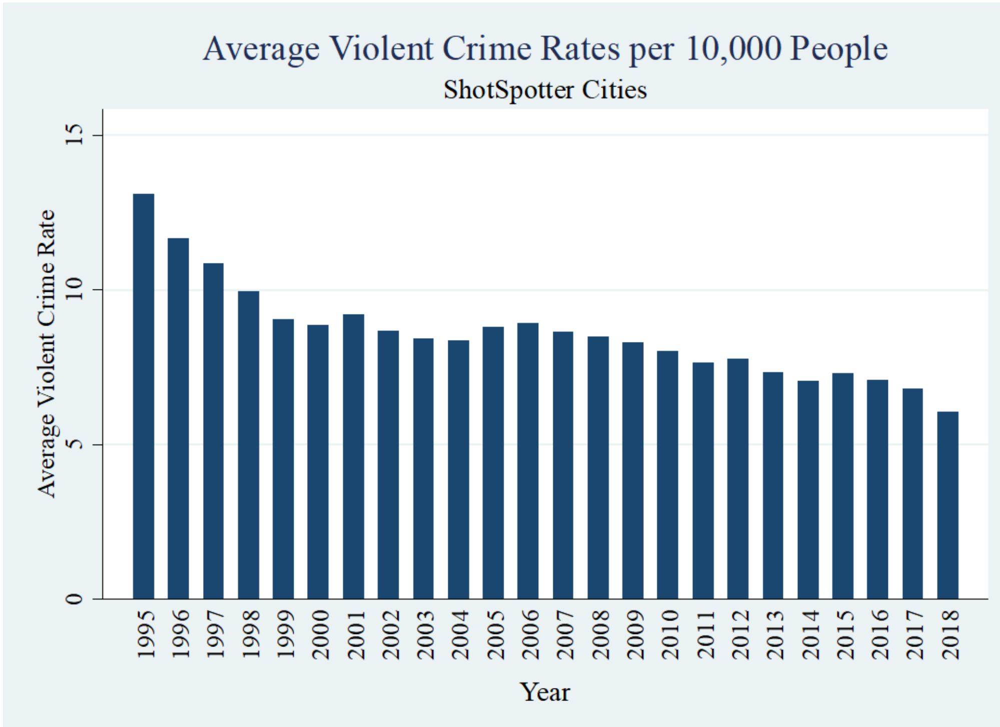

Figure 4.2: Treatment Graph for Violent Crime Rates Over Time (1995-2018)

In Figure 4.1 and Figure 4.2, the graphs show both the violent crime rates of control and treatment cities. Each graph has an overall decreasing trend which can be attributed to the crime drop from 1990's onward. The trends seem to mirror each other; however, treatment cities appear to have 3 times the number of violent crimes committed. There is a small increase in violent crimes in 2005 and 2015, where after a year or so, they both quickly resumed its continual decline. The difference in crime rates between the treatment and control cities are accounted for by using city and yearly fixed effects so that the variance won't impact the final results.

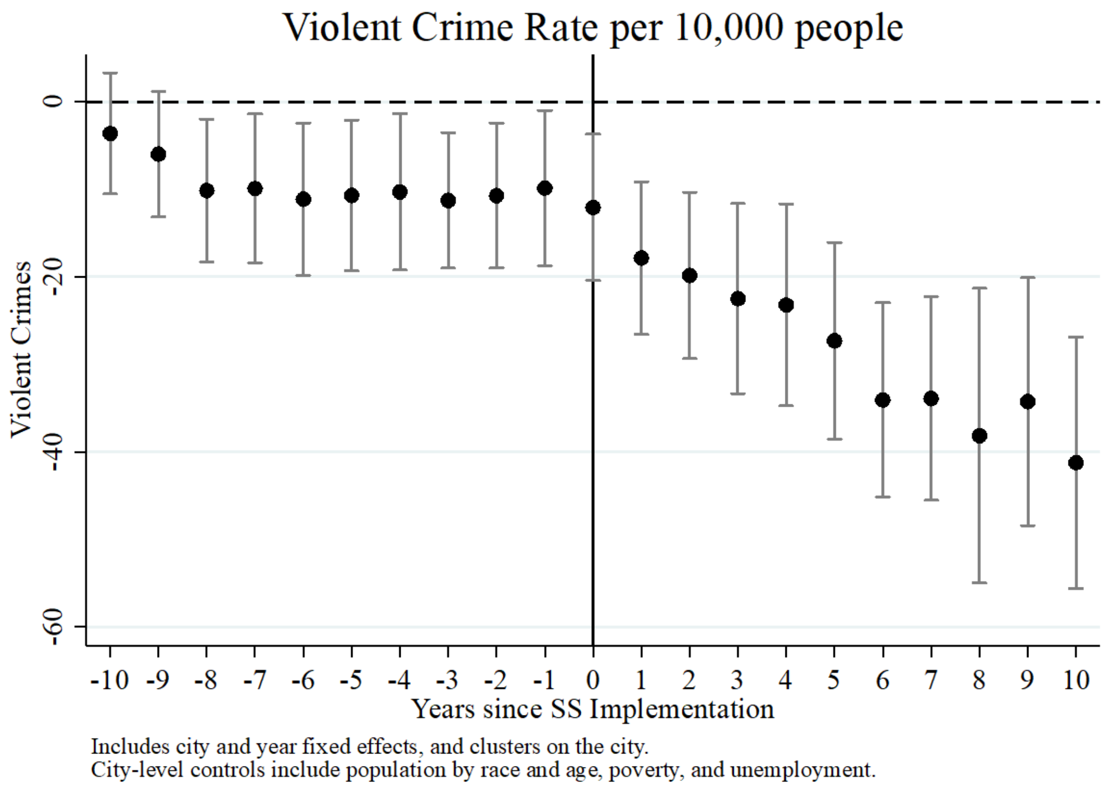

Figure 4.3: Coefficient Plot of Treatment Cities

Figure 4.3 depicts a coefficient plot of the cities that at some point installed ShotSpotter. I normalized time with "0" being the time when ShotSpotter was installed. Everything to the right of zero is the post-treatment, whereas all values to the left of "0" is the pre-treatment period. It appears to have a decreasing trend which may indicate that the technology has a negative effect on violent crime rates. Throughout the time prior to installation of ShotSpotter, the violent crime rate was already decreasing around 10 violent crimes per 10,000 people every month, which complies with the findings of the continual crime drop present in the United States. However, there is a noticeable greater decline in violent crime rates after the employment of ShotSpotter. Though the larger decline may not fully be attributed to the technology, as often there are supporting policies, resources and technologies that are invested by police departments to fight violent crime, ShotSpotter appears to have a visible impact in its reduction.

When separating violent crime rates into individual categories (assault with a gun, aggravated assault, robbery, rape, murder), which can be found in the appendix (Figure A.1-A.5), all categories of violent crime appear to decrease at varying rates. Assault with a gun (reference Figure A.1) has the smallest rate of decline and maintains a small steady negative rate of less that -1 per year. The aggravated assault rate (reference Figure A.2) quickly declines, and the effect slows down 5 years post-implementation. Robbery rates (reference Figure A.3), along with rape rates (reference Figure A.4), appear to maintain a negative trend both pre- and post-treatment, making it difficult to see if ShotSpotter had an impact in this area. Finally, murder rates (reference Figure A.5) look to be increasing pre-ShotSpotter and post-ShotSpotter there is a clear decline in the rate of murders committed.

4.2 Regression #2

Table 4.2: ShotSpotter Removal Effects on Violent Crime Rate

Variable	Coef.	Robust Std. Error	t	P > |t|	[95% Conf. Interval]	
ShotSpotter	0.3438	0.5407	0.64	0.553	-1.0461	1.7337
Unemployment Rate	-0.0545	0.0232	-2.35	0.066	-0.1141	0.0051
Poverty Rate	11.7428	6.9266	1.70	0.151	-6.0627	29.5483
Median Household Income	0.0002	0.0001	1.25	0.267	-0.0002	0.0005
Male Percentage	1765.791	660.7875	2.67	0.044	67.1826	3464.399
White Percentage	479.0332	559.7334	0.86	0.431	-959.8074	1917.874
Black Percentage	341.0155	564.1334	0.60	0.572	-1109.136	1791.167
American Indian & Alaska Native Percentage	3539.276	2282.542	1.55	0.182	-2328.186	9406.738
Asian Percentage	829.2663	587.6749	1.41	0.217	-681.4001	2339.933
Hispanic Percentage	-567.4969	194.3611	-2.92	0.033	-1067.118	-67.8758
_cons	-1264.83	647.1176	-1.95	0.108	-2928.299	398.6385

The results in Table 4.2 describe the regression pertaining to the cities that ended their contract with ShotSpotter. The pre- and post-treatment are defined by when ShotSpotter was active and when it was cancelled. The coefficient for ShotSpotter is positive indicating a potentially increase in violent crimes after its removal; however, it is not statistically significant (p-value > 0.1). The upward trend is seen in the coefficient plot below on Figure 4.4. Interestingly, many of the controls are also not statistically significant except unemployment rate, male percentage, and Hispanic percentage. It is important to note that the treatment group for this regression is very small since there are only 6 cities available for analysis (reference Table A.2). Furthermore, half of the treatment cities only used ShotSpotter for 1 year, making its impact very difficult to study. The city with the longest time that ShotSpotter was implemented was Beloit, WI (3.5 years) and stopped in 2012. The other cities have only recently removed ShotSpotter, with Canton stopping in 2014, Brockton stopping in 2015, Detroit and Charlotte stopping in 2016, and San Antonio stopping in 2017. Since the data only goes till 2018, it is difficult to see the post-treatment effect as clearly.

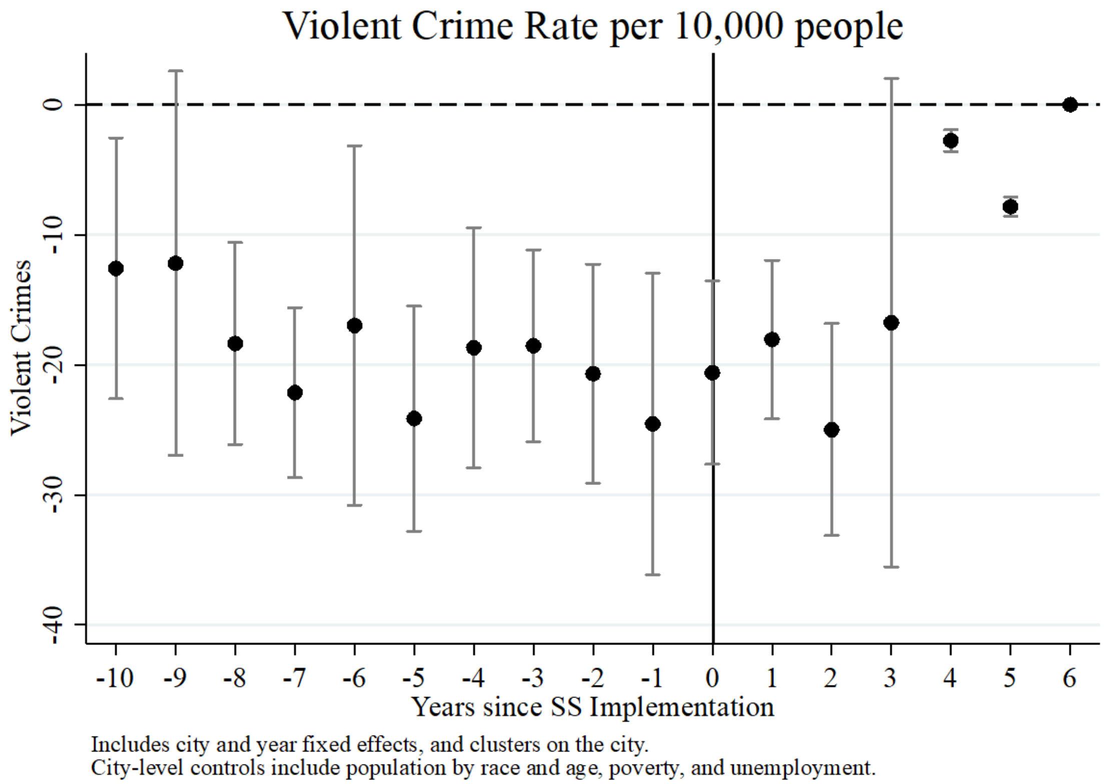

Figure 4.4: Coefficient Plot Pre and Post Treatment for Removal

5. CONCLUSION

This study sought to find the relationship between ShotSpotter technology and the rates of crimes committed within cities across the United States. The results of this analysis indicated that the effects of implementing ShotSpotter on violent crime rates were consistent with Shukla, et. all (2013) which found that equilibrium density of crime burden declines when there is an increase in the level of technology used in fighting crime. Though a difference-in-difference regression, I found a significant negative correlation, at the 99% coefficient level, between ShotSpotter and violent crime rates. In the regression, city and year fixed effects were included, along with controls for unemployment rate, poverty percentage, median household income, gender demographics, and race demographics. Though, as stated in Byrne and Marx (2011), there is a challenge of necessary complementary factors being present in measuring the impact of soft technology, the findings of this analysis captured a clear negative correlation between ShotSpotter and violent crime. This result may suggest that the police departments were able to effectively utilize the technology to better fight crime.

On the other hand, with the second regression showing the impact of removing ShotSpotter, the results suggest that the technology is positively correlated with violent crime rates, though it is not statistically significant. There is potential for further research to be done on the impact of discontinuing the use of ShotSpotter as violent crime data becomes more available, along with the discontinuing a more cities employing ShotSpotter with budget constraints following the 2020 Covid-19 pandemic. Additionally, given that the cost is high, it would be beneficial in the future to create a cost-benefit analysis to compare and observe the technology's effectiveness based on its price to other forms of violent crime mitigation.

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APPENDIX

Table A.1: List of Cities That Have ShotSpotter

City	State	ORI	Start Month	Start Year
Birmingham	AL	AL00102	12	2007
Montgomery	AL	AL00301	5	2009
Glendale	AZ	AZ00713	12	2002
Oakland	CA	CA00109	1	2008
San Pablo	CA	CA00711	4	2011
Richmond	CA	CA00710	4	2009
Fresno	CA	CA01005	7	2015
Salinas	CA	CA02708	12	2016
Sacramento County	CA	CA03404	7	2015
San Diego	CA	CA03711	11	2016
San Francisco	CA	CA03801	1	2013
Stockton	CA	CA03905	7	2013
East Palo Alto	CA	CA04127	1	2013
Redwood City	CA	CA04113	3	2000
San Mateo County	CA	CA04116	11	2006
Denver	CO	CODPD00	1	2015
Hartford	CT	CT00064	5	2012
New Haven	CT	CT00093	9	2009
Wilmington	DE	DE00206	6	2014
Washington	DC	DCMPD00	1	2006
Jacksonville	FL	FL01602	6	2017
Miami Gardens	FL	FL01397	12	2012
Miami-Dade County	FL	FL01300	4	2017
Riviera Beach	FL	FL05007	4	2010
Savannah	GA	GA02503	11	2014
Chicago	IL	ILCPD00	2	2017
Peoria	IL	IL07207	11	2013
East Chicago	IN	IN04503	7	2014
South Bend	IN	IN07102	2	2014
Louisville	KY	KY05680	6	2017
Baton Rouge	LA	LA01702	12	2007
Pittsfield	MA	MA00222	4	2017
New Bedford	MA	MA00311	7	2011
Springfield	MA	MA00718	5	2008

Table A.1: Continued

Somerville	MA	MA00939	2	2016
Everett	MA	MA00917	8	2014
Cambridge	MA	MA00911	6	2017
Boston	MA	MA01301	10	2007
Worcester	MA	MA01460	3	2014
Minneapolis	MN	MN02711	4	2007
Kansas City	MO	MOKPD00	9	2012
Jennings	MO	MO09541	6	2017
St. Louis	MO	MOSPD00	1	2013
Omaha	NE	NB02802	1	2013
Las Vegas	NV	NV00201	11	2017
Atlantic City	NJ	NJ00102	5	2013
Camden	NJ	NJ00408	5	2013
East Orange	NJ	NJ00706	12	2006
Newark	NJ	NJNPD00	11	2008
Trenton	NJ	NJ01111	10	2009
Rochester	NY	NY02701	7	2006
Hempstead	NY	NY02906	2	2013
Long Beach	NY	NY02902	12	2015
New York City	NY	NY03030	3	2015
Syracuse	NY	NY03301	9	2017
Newburgh	NY	NY03502	8	2017
Yonkers	NY	NY05908	12	2009
Rocky Mount	NC	NC03301	7	2011
Wilmington	NC	NC06502	1	2013
Goldsboro	NC	NC09601	7	2016
Cincinnati	OH	OHCIP00	8	2017
Youngstown	OH	OH05009	3	2010
Pittsburgh	PA	PAPPD00	9	2013
Milwaukee	WI	WIMPD00	1	2013

Table A.2: List of Cities That Discontinued ShotSpotter

City	State	ORI	Start Month	Start Year	End Month	End Year
Brockton	MA	MA01203	1	2013	9	2015
Detroit	MI	MI82349	2	2015	2	2016
Charlotte	NC	NC06001	9	2012	2	2016
Canton	OH	OH07604	5	2013	9	2014
San Antonio	TX	TXSPD00	4	2016	8	2017
Beloit	WI	WI05401	4	2009	11	2012

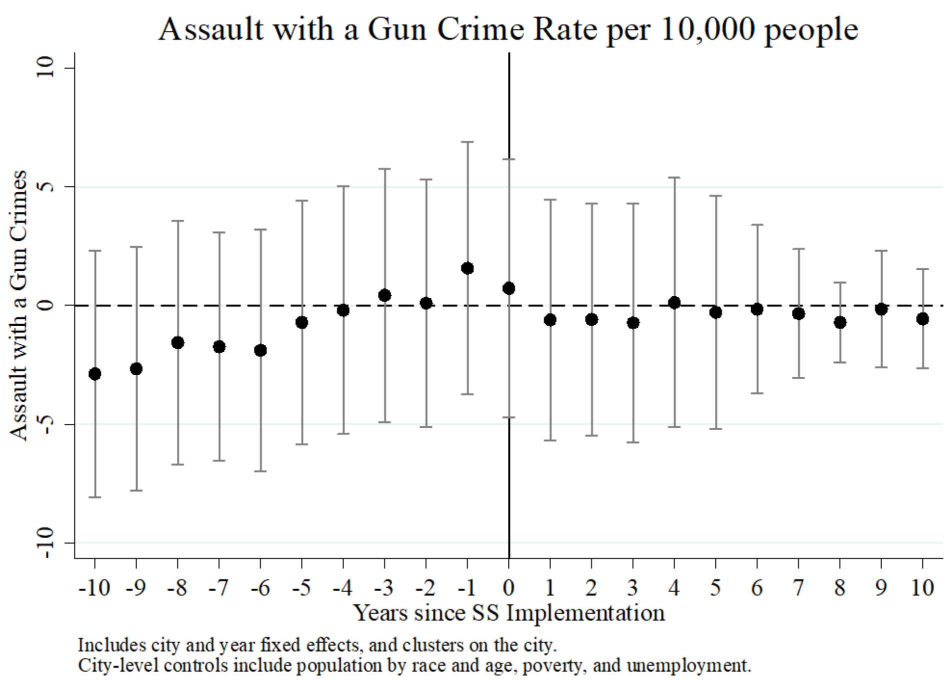

Figure A.1: Assault with a Gun Crime Rate per 10,000 people

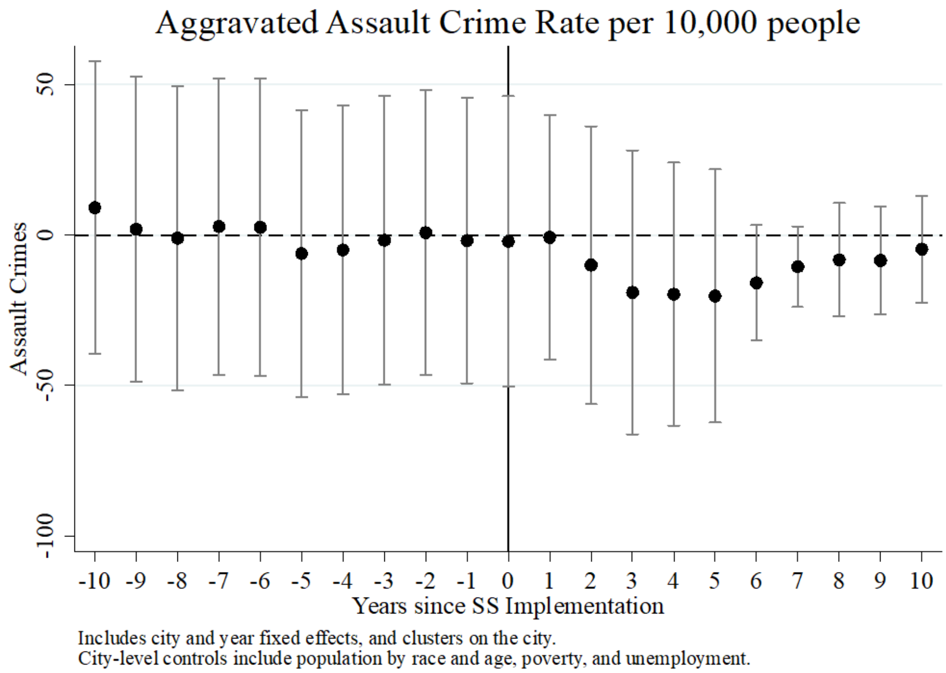

Figure A.2: Aggravated Assault Crime Rate per 10,000 people

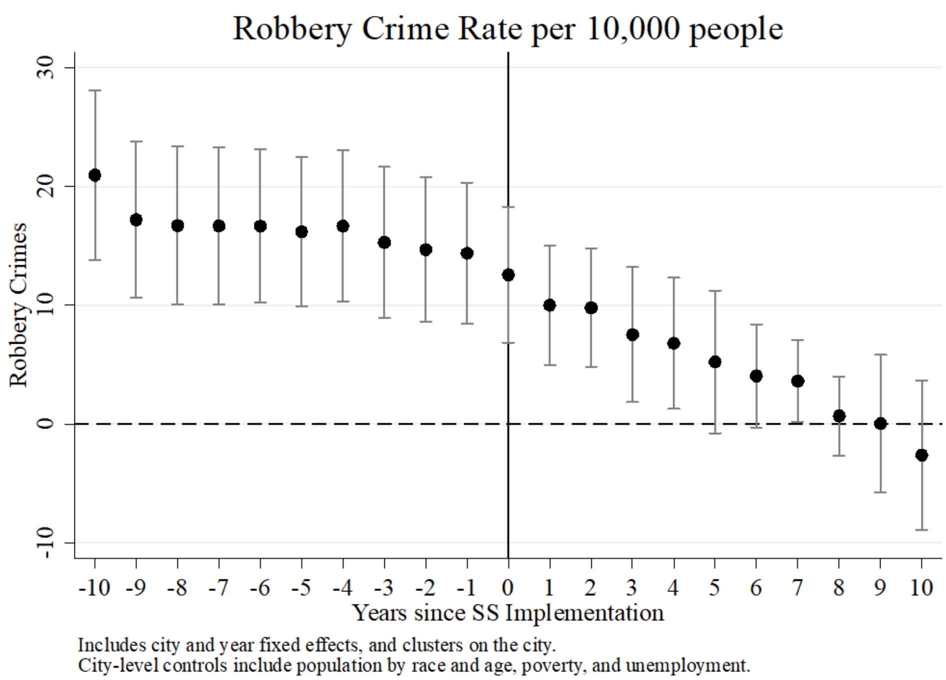

Figure A.3: Robbery Crime Rate per 10,000 people

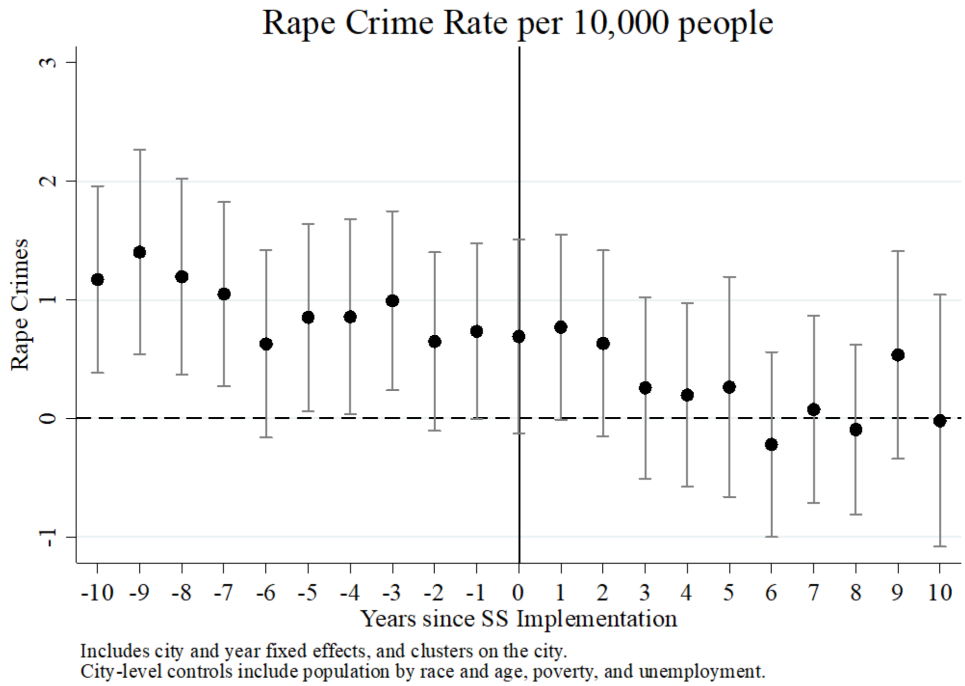

Figure A.4: Rape Crime Rate per 10,000 people

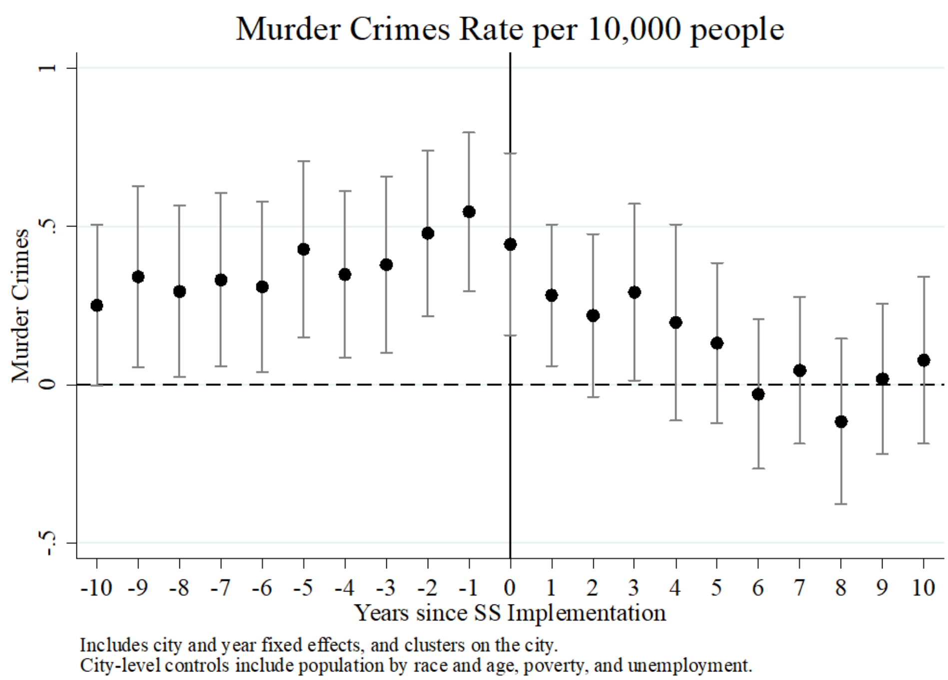

Figure A.5: Murder Crime Rate per 10,000 people