Policing for whom? Officer-involved shootings and police legitimacy in Chicago

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Abstract

This paper explores the effects of officer-involved shootings (OIS) on perceptions of police legitimacy and how those perceptions shape civilian action and behavior. I focus on Chicago, leveraging a rich dataset containing the universe of officer firearm discharge, and examine the effects of OIS on civilian reported crime. To identify the effects of OIS on civilian reported crime, I exploit the randomness of subjects' injury status from firearm discharges after adjusting for a broad set of officer, subject, and incident characteristics. I provide evidence that after accounting for these factors, whether or not a subject is injured is as good as random because police are trained to shoot to incapacitate the subject rather than to wound, disarm, or deter. Comparing districts with OIS where subjects are injured and districts with OIS where subjects are not injured, I find that reported crime falls by 2.8% following OIS resulting in injury. I find no differential effects for Black subjects, Black districts, White-Black officer-subject pairs, or fatally injured subjects. Instead I find even larger reductions when subjects are unarmed. I argue that these results are consistent with a model in which concerns about procedural justice are the primary determinants of citizens' perceptions of police legitimacy.

Keywords: Police, Trust, Legitimacy, Crime Reporting, Officer-involved Shooting

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1 Introduction

From the shootings of Michael Brown and Philando Castile to the recent deaths of George Floyd and Duante Wright, it is perhaps no surprise that U.S. trust in police is at an all-time low in Gallup's 27 years tracking the question (Ortiz (2020)). The images, videos, and descriptions of police shootings and use of force have sparked numerous protests, spawned the national movement Black Lives Matter, and elevated calls to defund the police.[1]

The public police violence tracking project Mapping Police Violence estimates that as of August 1, 2021 police in the U.S. have killed 564 people—over 2.5 deaths per day—while in 2020 there were 1,126 deaths ($\sim$3 deaths per day). These data indicate that Black Americans are disproportionately killed by police relative to their share of the population (28% of deaths compared to 13% of the population) (Mapping Police Violence (2021)). Pew Research found that Blacks are about half as likely as Whites to view police use of force or treatment of racial groups positively and were 30 percentage points less likely than Whites to believe that police do a good job protecting people from crime (DeSilver et al. (2020)).

On top of the staggering human costs of police violence, there are two additional costs that bear consideration, especially from an economic perspective: the equity and efficiency of public safety provision by the state. Police violence may cause inequities in the provision of public safety if civilians of color, and specifically Black civilians, are less likely to report crime to police or cooperate with investigations because of fears that police are not competent or that their involvement might make matters worse. Such changes in behavior may mean that police violence itself generates subsequent crime and instability in public safety (including differences across racially concentrated areas), elevating the priority of measures to reduce police use of force.[2] Lower clearance rates (the share of cases deemed closed) following police violence imply a less efficient police force and create incentives for policy makers to reallocate resources away from police and towards other public safety policies and services.

In this paper, I examine how officer-involved shootings (OIS) influence perceptions of police legitimacy and how those perceptions shape civilian action and behavior. I first show that negative sentiment in tweets about police spikes after OIS using two case studies–the shootings of Justine Damond (a 40 year old unarmed white woman) and Stephon Clark (a 22 year old unarmed Black man). Using all US tweets containing "cop", "cops", or "police" I classify the words in tweets as positive or negative. In the two weeks prior to these incidents, about 7% of words used in tweets about police are negative but this share spikes to

[1] According to data from Count Love, a public protest tracking initiative, 2020 saw over 8,000 protests for racial justice in the U.S. (Count Love (2021)).

[2] In 2021, the largest 50 cities in America directed 13.7% of their general expenditures towards law enforcement (Akinnibi et al. (2021)).

over 15% after news stories of Damond's shooting begin appearing and to 9% after Clark's shooting.

In order to say something about whether or not these perceptions influence actions, I then focus on Chicago, leveraging an incredibly rich dataset containing the universe of officer firearm discharges, and examine the effects of OIS on civilian reported crime. To identify the effects of OIS on civilian reported crime, I exploit the randomness of subjects' injury status from firearm discharges after adjusting for officer, subject, and incident characteristics (e.g. officer experience and weapon discharge history, race, age, gender; lighting and weather conditions; and subject weapon status, race, age, gender). I argue that after accounting for these factors, whether or not a subject is injured is as good as random because police are trained to shoot to incapacitate the subject rather than to wound, disarm, or deter. I then compare the rate of reported crime in police districts where there was an OIS with an injury to police districts where there was an OIS without an injury before and after the OIS. This identification strategy is appealing since OIS with and without subject injury have similar officer, subject, and incident characteristics and these characteristics struggle to predict subject injury.

Comparing districts with OIS where subjects are injured and districts with OIS where subjects are not injured, I find that reported crime falls by about 2.8% following OIS resulting in injury. These findings are consistent with the idea that OIS with and without subject injuries differ in two key dimensions. First, OIS with subject injuries may receive more media coverage than OIS without injuries. Second, OIS with subject injuries have the possibility of resulting in death whereas OIS without subject injury do not. In other words, OIS with subject injuries are more salient than OIS without subject injuries, which may explain the lack of change in crime reporting for districts with OIS where subjects are uninjured. When including TASER discharges I do not find any reduction in reported crime, further emphasizing the importance of salience.

Turning to which types of OIS might be driving this result, I find no differential effects for Black subjects, Black districts, or White-Black officer-subject pairs. I also do not find differential effects when subjects are fatally injured, though these estimates are much less precise than the others. Instead, I find large additional reductions in reported crime when subjects are unarmed. These results together suggest that it is the process rather than outcomes (i.e. procedural justice rather than distributive justice) that matters more for determining perceptions of police legitimacy and guiding citizen behavior. My findings support the idea that, irrespective of CPD policy, the shooting of an unarmed citizen is seen as procedurally unjust and damages not only perceptions of police legitimacy but also public engagement with law enforcement.

My work makes several contributions to understanding OIS and their consequences. First, I extend our knowledge about the determinants of police legitimacy beyond survey settings and examine manifestations of citizen behavior. Despite police legitimacy owning an extensive literature in criminology and sociology, it is mainly drawn from surveys and there has been relatively little well-identified empirical work done. A key challenge is the measurement of police legitimacy. Existing studies largely rely on surveys (see, for example, Kochel (2015a), Kochel (2015b), or White et al. (2018)) but these have two significant limitations: they are relatively infrequent, and responses do not map cleanly to civilian behaviors (e.g. Bobo and Thompson (2006) find that despite differences in attitudes towards police by Black and White respondents, their proposed actions were the same). My approach using Twitter data gives insight about perceptions while the reported crime data maps directly to civilian actions.

My work also expands on existing studies by moving beyond an event study framework, examining many OIS incidents, exploring which aspects of OIS might generate differential effects, and which types of crimes might be affected. Recent work examining the effects of OIS on crime reporting (Desmond et al. (2016), Ang et al. (2021)) and sentiment about police Oglesby-Neal et al. (2019) find lower crime reporting and more negative sentiments but use only a small number of high-profile cases that garnered media attention (furthermore there is debate about whether or not the crime reporting effect is genuine, see Zoorob (2020) and Desmond et al. (2020)).

Last, a common approach in studies examining the impacts of OIS and the "Ferguson effect" is to adjust for the rate of crime, as increases in crime could stretch police resources more thinly and explain lower clearance rates or increases in homicides. However, as the rate of crime is determined both by police behaviors (which this strand of research suggests are influenced by OIS) and police legitimacy through civilian reporting behavior, then the crime rate is actually an outcome and its inclusion introduces bias when estimating the effects of OIS on clearance rates and crime reporting. I leverage the acoustic gunshot detection system ShotSpotter to measure gun violence directly to examine how adjusting for underlying crime influences the effects of OIS on crime reporting.

The remainder of this paper is structured as follows. In Section 2, I detail how OIS can influence police legitimacy and reported crime. Section 3 describes the dataset and provides descriptive statistics. Section 4 presents the empirical strategy and required identifying assumption. Section 5 presents and discusses results. Section 6 concludes.

2 Framework

The theoretical effects of OIS with injuries on civilian crime reporting are unclear. Several channels are at work.

2.1 Police Legitimacy and Public Support of Police

One channel that OIS can influence reporting behaviour through is perceptions of police legitimacy. In order to operate efficiently, legal institutions need to draw on feelings of obligation and responsibility from members of the public to facilitate cooperation and compliance. Legitimacy is the belief by people that some authority deserves to be obeyed. When the public views institutions as legitimate, they will voluntarily comply with directives. Police legitimacy, therefore, is the belief by the public that they should defer to the police and assist with crime prevention.

Broadly speaking there are two main approaches to thinking about the determinants of police legitimacy. The outcomes based approach posits that police gain acceptance when they can credibly sanction rule breakers; effectively control crime; and fairly distribute services across the public. The procedural justice approach links legitimacy to the public's evaluations about the fairness of process that the police use to make their decisions and exercise their authority (Sunshine and Tyler (2003), Tyler and Huo (2002)). There is an extensive literature in criminology and sociology composed mainly of surveys examining the relative importance of these models describing how the public evaluates police legitimacy. This qualitative work finds that youth in high-crime areas have negative views of police often driven by repeated harassment and police misconduct and respondent narratives frequently centre around the fairness and justice of interactions rather than outcomes (Berg et al. (2016), Gau and Brunson (2010), Wolfe et al. (2016)). Personal interaction is not the only way to generate these perceptions of police legitimacy, the experience of others, often family members, matters as well and exhibits a similar focus on fairness and justice (Brunson (2007), Carr et al. (2007)).

Studies have also found that local conditions matter, with structurally disadvantaged neighborhoods being more likely to have lower perceptions of police legitimacy (Kirk and Papachristos (2011)). For example, McCarthy et al. (2020) find that complaints filed against CPD members disproportionately originate in racially segregated neighborhoods and that previous measures of legitimacy predict current complaint behaviour. Additionally, research has found that repeated exposure to media reports of police abuse is strongly positively related to perceptions of police misconduct (Kaminski and Jefferis (1998), Weitzer (2002), Weitzer and Tuch (2004)). That is, the media is mediating perceptions of police legitimacy.

How does police legitimacy interact with OIS and reporting behavior? Even when an OIS is deemed acceptable within the police department, the public may believe that the incident should have been addressed without the use of lethal force. This is an erosion of procedural justice which we expect to lower perceptions of police legitimacy. Kwak et al. (2019) use victimization survey to explore the relationship between procedural justice and crime reporting, finding that lower perceptions of procedural justice was associated with a lower probability of reporting crime by victims. In Anderson (1999)'s seminal ethnographic depiction of Philadelphia, he writes "Residents sometimes fail to call the police because they believe that the police are unlikely to come or, if they do come, may even harass the very people who called them." (p.321). Poor views of police legitimacy may mean that citizens do not call the police, worrying that officers may escalate a situation or engage in misconduct.

Circling back to the discussion about procedural justice, we might expect larger declines in reporting for OIS with unarmed subject as the disproportionate use of force should have a large negative impact on perceptions of police legitimacy. However, the distributive justice approach is often seen in popular media framing of OIS through a racial lens and means that we might expect to see larger effects when the victim is Black, when the shooting occurs in a majority Black district, or when the officer is White and subject is Black.

The elasticity of crime reporting to OIS might be different depending on the severity of the crime or the level of discretion that civilians have in reporting that crime. We might expect that more serious crimes like homicide or burglary require an immediate response and therefore have an inelastic response to OIS– those crimes were always going to be reported. However, civilians may believe that less serious crimes, like narcotics or liquor law violations, do not require alerting the police because of the lack of urgency or immediate threats to safety. While this is true in general, may be especially true in the aftermath of an OIS where citizens worry that alerting police could escalate a situation and result in another OIS. In this scenario, the expected elasticity of reporting to OIS should be high. Lastly, in the absence of legitimate police, violence becomes a problem solving tool used to mete out justice. As such, falling police legitimacy from an OIS could result in upward pressure on crime and in particular, violent crime.

2.2 Economic Model of Crime

Another channel is related to changes in the underlying crime rate. Becker (1968) introduced an economic theory of crime where individuals make decisions about committing a crime based on comparing the expected costs and benefits of doing so. Those costs are determined by and increasing in the probability of apprehension and the severity of the punishment. In this context, and OIS may increase the perceived cost of engaging in crime by making this cost more salient. Even if, traditionally, an optimizing agent would already take this cost into account, behaviour economics and cognitive psychology have identified biases and heuristics that influence decision making. In particular the availability heuristic might be at work here, where the ease to which an individual can recall an event influences the perceived probability that event occurs. If we consider that the severity of punishment includes death during apprehension, then an OIS should increase the cost of engaging in crime and create a disincentive to engage in criminal activity.

On the other hand, the notion of the Ferguson effect is based on the premise that police scale back proactive activities in the aftermath of an OIS because they are concerned about the perceptions of their actions under this additional scrutiny (Gaston et al. (2019)). The Ferguson effect is a proposed explanation for two phenomenon: 1) following OIS there is seen to be an increase in homicides and 2) following OIS there is a reduction in case clearance rates. In the context of the Becker model, a reduction in this police activity should lower the probability of apprehension and thus create an incentive to engage in criminal activity. And specifically, the Ferguson effect indicates that we should expect an increase for violent crime. However, there is an emerging consensus that this depolicing does not result in increased homicides.

Some have argued that the Becker model is a good description of behaviour for property and non-violent crimes but that it falls short in explaining violent crime behaviour because of the rationality assumption (see for example,). Under the assumption that violent crime is motivated more by proximity, opportunity, and emotions we might expect that a reduction in the probability of conviction would not alter the rate of violent crime and that instead we should see an increase instead in only non-violent crime.

Taken together this means that the direction of crime following an OIS is ambiguous and the direction of crime reporting following an OIS is likely negative. Even if there is a decline in crime reporting following an OIS, it could simply reflect a lower level of crime rather than a decline in perceived police legitimacy and crime reporting behaviour. In Section 5, I attempt to disentangle these two effects by using data about gun violence in Chicago measure by acoustic gunshot sensors (ShotSpotter).

2.3 Twitter and sentiment about police

Are perceptions of police changing after OIS? To answer this question I turn to Twitter data and analyze the sentiment and emotional content of police-related tweets and how that evolves before and after OIS. I use Twitter's Academic Research product track which allows full access to Twitter's archives through their API. I then searched for tweets that were tagged as being from the United States during 2017–2019 mentioning "cops", "cop", or "police" to build a corpus of tweets. I did not search for tweets specifically related to incidents of police brutality or officer-involved shootings/fatalities as I am interested in the sentiment of discourse about police overall in response to these incidents rather than discourse specifically about these incidents. I then remove stop words (commonly used function words such as "the" and "is") and separate tweets into individual words before applying the NRC Word-Emotion Association Lexicon (aka EmoLex) introduced by Mohammad and Turney (2013) which allows for binary sorting of words as positive and negative as well as their association with eight different emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust).[3]

In particular, I present two case studies of high profile police shootings in 2017 and 2018. Justine Damond was an unarmed 40 year old, White, Australian-American living in Minneapolis, Minnesota. Shortly after 11:30pm on July 15, 2018 she called 911 to report a possible assault taking place behind her house. Officers Mohamed Noor (33 year old, Black, Somali-American with 21 months of experience) and Matthew Harrity (25 year old, White, American with 1 year of experience) responded to the scene and determined the alley was empty and the scene was safe. According to testimony, the officers then heard a loud noise and Damond appeared immediately outside the police vehicle. Harrity drew is weapon but did not fire and Noor fired a shot through the vehicle's open window that fatally injured Damond (Park et al. (2017)).

Stephon Clark was an unarmed 22 year old Black, American living in Sacramento, California. Shortly before 9:30pm pn March 18, 2018 he was shot by Sacremento police officers Terrence Mercadal (Black, American with 3 years of experience) and Jared Robinet (White, American with 4 years experience) who were responding to a call than someone was breaking nearby car windows. After being directed to the location of a suspect seen breaking a window with a tool bar by deputies in a helicopter, officers confronted a man who was later identified as Clark. Officers told him to show his hands and he fled to the back of the property before turning towards the officers with an object in his hands. Officers then fired on Clark, fatally injuring him.

Figures 1 and 2 show the average share of words per police-related tweet registering as positive, negative, and as each emotion for the entire month each of the shootings of Damond and Clark occurred in, respectively. In both figures overall sentiment for the month is more negative than positive and the most common emotions are fear and trust.

Figure 3 plots the average share of words in each police-related tweet that are positive or negative for a given day during the month of July 2017 and 4 does the same for March 2018. The horizontal axis plot the days since the Damond and Clark shootings, respectively. We can see that in the weeks before each shooting negative sentiment in police tweets was about 7% of words and that after each shooting negative sentiment in tweets about police spikes. For the Clark shooting negative sentiment is up to around 9% and for the Damond shooting it is up to nearly 15%.[4]

[3]The patterns are consistent when using other lexicons that assign words values from -5 to 5 instead of a binary classification.

[4]The large uptick right before the Clark shooting is a result of a Washington Post article about the continued deaths of Black Americans at the hands of police

3 Data

3.1 Reported Crime Incidents

Data on reported crime incidents covers the 2004–2019 period and comes from the city of Chicago's open data portal. These reports come from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting system and are censored at the block level. It is important to note that the data contained are preliminary and based on the incidents reported by third parties to the police department and may be unverified. That is, they represent the information as presented by those calling in requests for police service. The dataset contains the date, time, and location (censored at the block level) of the incident; the police beat and district the incident occurred in; the type of offense; and indicators for arrest and domestic violence.

The Chicago Police Department, reports its data to the FBI using the Uniform Crime Reporting Program. This system follows a hierarchy rule where if multiple offenses occur, only the most serious offense is recorded. The hierarchy is as follows: homicide, rape, robbery, aggravated assault, burglary, theft, motor vehicle theft, and lastly arson. The hierarchy rule already been applied to the reported crime data so that they conform with the UCR handling. This means that the data are an undercount though the FBI's examination of the effect of multiple reporting incidents indicates that they are a small share of overall incidents ($\sim$10%) and when UCR data is compared to its incident based successor, National Incident Based Reporting System (NIBRS), the undercounting appears to be relatively small ($\sim$2% increase in overall crimes if allowing up to 10 offenses per incident). I then use the Illinois Uniform Crime Reporting (IUCR) codes, to separate these crimes into Part I UCR offenses (which I refer to as "serious" crimes), Part I UCR violent offenses (which I refer to as "violent" crimes), and Part II UCR offenses (which I refer to as "less serious" crimes). Serious crimes are homicide, rape, robbery, aggravated assault, burglary, theft, motor vehicle theft, and arson. Violent crimes are homicide, rape, robbery, and aggravated assault. Less serious crimes include offenses such as vandalism, simple assault, weapons violations, disorderly conduct, drunkenness, narcotics and liquor laws, and disturbing the peace.

Table 1 presents descriptive statistics over my sample, with the first grouping of variables corresponding to crime reporting. On average, there are about 47 reported crimes per district-day. The majority of these are less serious crimes with about 28 reported each district-day (about 60% of all reported crimes). There are approximately 18 serious crimes reported per district-day and the majority of those are non-violent (about 84% of serious crimes).

Figure 5 plots the daily average reported crimes per district over the sample period. Two key features present themselves from this figure. First, reported crime has been on a downward trend over the sample period. Second, reported crime exhibits patterns of seasonality with local peaks during the summer. I address these in my empirical approach by including month, year, and district-year fixed effects. Figure 6 plots the distribution of reported crimes. Reported crimes are not particularly skewed, nor do they have an excess number of zeros. Still, in my analysis I transform the measures of reported crime using the natural log + 0.1 for ease of interpretation as semi-elasticities, though tables report the mean of the dependent variable in levels to help provide context. My main results are robust to estimating without the log transformation.

3.2 Officer Involved Shootings

Data detailing OIS covers 2004–2019 and comes from the Invisible Institute Citizens Police Data Project. This project used Freedom of Access to Information requests to obtain CPD records including tactical response reports. Tactical response reports (TRRs) are forms that Chicago Police officer must file when an officer discharges a firearm, impact munition, TASER, pepper spray or another chemical weapon or after qualifying use of force incidents.[5]

The TRRs include the location, date and time of the incident; officer information such as age, race, gender, appointment date, rank, duty status at the time of the incident, the type of firearm/weapon discharged; subject information such as age, race, gender, the charges against; weapon type (if any); and incident information such as the lighting and weather conditions, whether the OIS occurred inside or outside, whether or not subject is actively or passively resisting, used deadly force against an officer, and which party fired first.[6] I restrict my sample to include only OIS involving TASERs and firearms but use the entire pool of TRR incidents to create a variable that counts the total number of TRR incidents for a given officer. I explore OIS where TASERs are discharged because they are still weapons that can result in injury (∼42% of OIS involving TASERs result in injury in my sample) or death. If citizens being injured by police in OIS influences perceptions of police legitimacy and subsequent crime reporting behavior, it may not only be firearms that matter but TASERs as well.

Table 1 provides descriptive statistics. On average, these CPD members are 37 years old, White (52%), male (89%), officers (74%) in uniform (76%) with 10 years of experience and nine prior TRR incidents. These officers discharge TASERs 85% of the time and handguns in the remaining incidents (there are a handful of incidents where officers discharge a long gun but these are exceedingly uncommon). According to the Office of the Ispector General for the city of Chicago, in 2017 51% of officers were White, 23% Hispanic, and 21% were Black

[5]A TRR must be filed for any use of force incidents when: a subject is injured or alleges injury; a subject actively resists; a subject whose actions are "aggressively offensive" (with or without weapons) or who is threatening immediate use of of force that will likely result in injury; physically obstructing an officer; or an assault, threat of physical attacks, or physical attack against an officer even if the officer is not injured.

[6]An example TRR is provided in the Appendix.

while 77% were male and 23% were female. The average CPD officer was 42 years old with 14.7 years of experience. So, CPD officers who discharge their firearms or TASERs tend to be younger, more inexperienced, more male, less Black, and more Hispanic than the average CPD officer. Subjects are, on average, 30 years old, Black (77%), males (93%) who are unarmed (76%), and injured (55%). When armed, subjects most commonly have a hand gun (11% of all incidents). Over the course of an OIS, subjects are passively (3.41 actions) and actively (2.75 actions) resisting officer directives.

Subjects use deadly force in 17% of incidents, have assault charges in 63%, domestic charges in 14%, drug charges in 19% and weapons charges in 13%. OIS, on average, occur outside (75%) with clear weather (88%) and either under artificial light (55%) or daylight (31%). These data provide rich controls not only for our officer and subject characteristics but also allow me to deal with concerns about visibility and the danger of the incident which may be related to the injury status of the victim. Further discussion of the relationship between injury status and these covariates can be found in Section 4.

3.3 ShotSpotter

In order to test whether or not accounting for the underlying crime rate matters, I turn to ShotSpotter data obtained from the city of Chicago. ShotSpotter is an acoustic gunshot detection technology that makes use of sensors and microphone equipment to detect presence and locations gunshots. Approximately 15–20 sensors the size of toasters are deployed per square-mile and typically placed on street lights, rooftops, or on the sides of buildings. When a loud bang-like noise occurs, the sensors triangulate the location based on the time it takes for sound to reach the different sensors. These records are sent to ShotSpotter, where the company's analysts determine whether or not it is gunfire before reporting it to police within 1 minute (Yousef (2017)).

My sample begins on January 13, 2017 and continues to January 14, 2019. Beginning in 2017, four police districts (Englewood, Harrison, Austin and Deering) were outfitted with ShotSpotter technology with plans to expand to Ogden and Gresham districts by July. In October 2017, an expansion to six more districts was announced (Wentworth, Grand Crossing, South Chicago, Calumet, Chicago Lawn and Grand Central) for a total of 12 of the city's 25 districts (and approximately 130 square-miles of area) being covered by ShotSpotter. The first six districts were considered the tier of most violent in Chicago, while the next six were classified as the second most violent tier (Wasney (2017)).

The dataset contains the event date and time, the address (censored at the block level) and the latitude and longitude coordinates.

Table 1 provides descriptive statistics. The number of observations falls when compared to reported crime because of the limited time period and number of districts with ShotSpotter coverage. On average, there are about 1.68 incidents per district-day, and the bulk of those were incidents with multiple shots (0.99 incidents per district-day, or 59%). There are 6.52 rounds fired per day, which is about 3.9 rounds per incident.

3.4 Fatal Encounters

Because the CPD TRR data does not contain information about whether or not subjects are fatally injured, I use data from Fatal Encounters to match incidents and determine fatal incidents. Recent research has indicated that these data are quite accurate for fatal incidents (see for example Campbell et al. (2018)) even though their lack of representativeness of OIS overall is in part a motivation for this paper. These data contain the incident date, location (including longitude and latitude), and cause of death; subject name, age, and gender; as well as links to the news article(s) the information was drawn from. First, I assign the Fatal Encounters incidents in Chicago to the police districts they occured in. Next, I manually match each Fatal Encounters incident to OIS in the CPD TRR data based on the district the OIS occured in, the date of the incident, and subject race and age. Table 1 indicates that, overall, 2.5% of all OIS result in a fatal injury to the subject. These comprises 116 incidents, 101 of which are tied to firearm discharges (this is approximately 14% of all OIS with firearm discharges).

4 Strategy

4.1 Model Specification

4.2 Event Study

I first present an event-study specification to explore the dynamics of OIS with injured subjects.

The specification is:

$$Y_{dtmy} = \psi + \sum_{j=-14}^{14} \eta_j INJURY_{dt-jmy} + X'_{dtmy}\gamma + \omega_d + \varphi_m + \mu_y + \nu_{dy} + \epsilon_{dtmy}$$

where Y_{dtmy} is the reported crime rate in a given district d, on a given day tmy. $INJURY_{dt}$ is a dummy variable that assumes the value of one if the subject was injured by an OIS on a given day tmy. The leads and lags are defined similarly.

4.3 Injured and Not Injured

To examine the effects of OIS on community crime reporting, I restrict my sample to compare observations 14 days before and 14 days after of an OIS. I then compare crime reporting over a given window in districts where the OIS resulted in a subject injury to reporting over that same window in districts where the OIS did not result in a subject injury. This means that I am comparing crime reporting behavior in two groups of districts that both experienced an OIS on a given day. The only difference between these observations is that the OIS resulted in an injury in some districts and did not in others.

In my main specification I estimate:

$$Y_{dtmy} = \alpha + \beta INJURY_{dtmy} + X'_{dtmy}\lambda + \omega_d + \varphi_m + \mu_y + \nu_{dy} + \varepsilon_{dtmy}$$

where Y_{dtmy} is the reported crime rate in a given district d, on a given day tmy. X_{dtmy} is a vector of controls including officer, subject, and incident characteristics, ω_d, φ_m, μ_y, and ν_{dy} are district, month, year, district-year fixed effects. $INJURY_{dtmy}$ is a dummy that equals one for post-OIS days in districts with an injury and zero for pre-OIS and post-OIS days for districts without an injury. The coefficient of interest is β and provides an estimate of the before and after change in crime reporting in districts that experienced an OIS resulting in an injury compared to district that experienced an OIS that did not result in an injury. As officers operate out of a specific district I cluster the standard errors at the district level to allow errors to be correlated within districts.

I choose the 14 day time horizon because a) ff media coverage is mediating this effect (as is suggested in the literature (e.g. Weitzer (2002), Weitzer and Tuch (2004))) then these effects may be short-lived, especially as these are much smaller in scale than OIS used in other studies; b) it can take several days for the media to obtain details on an OIS from witnesses, police, and officials and then begin reporting; c) there is on average an OIS involving firearms in Chicago overall every 8 days in my sample. I later explore the stability of the results to this choice.

4.4 Identification Assumption

The identifying assumption required is that the injury status of a subject from a given OIS (D_{dtmy}) is exogenous, conditional on observables (X_{dtmy}). More formally in a potential outcomes framework, this assumption is given as:

$$\boldsymbol{E}[Y_{dt}|X_{dt}, D_{dt} = 1] - \boldsymbol{E}[Y_{dt}|X_{dt}, D_{dt} = 0] = \boldsymbol{E}[Y_{1dt} - Y_{0dt}|X_{dt}]$$

where Y_{dt} is the reported crime, Y_{1dt} is reported crime for a district with an injury-resulting OIS, and Y_{0dt} is reported crime for a district without an injury-resulting OIS.

The intuition of this identification assumption is provided by FBI Special Agent John Huber, "We don't shoot to kill; we shoot to stop." (Lane (2016)). Members of the public often want to know why police officers fire so many times, or why they do not attempt to shoot to disarm, wound, or injure rather the subjects they are pursuing. The answer provided by law enforcement is that in the context where discharging a firearm is an option, officers place themselves, other officers, and other members of the public at risk if they are unable to incapacitate the subject presenting an immediate threat to life or serious injury. If, for example, an officer attempts to shoot a gun out of a subject's hand and misses, not only do they risk harming someone else, the threat posed by the subject is still present. Because officers' first priority in this context is incapacitating the subject, they are trained to target the center mass and central nervous system, which is also likely to result in death. CPD directives prohibit firing warning shots, at subjects who pose only a threat to themselves, fleeing suspects, as well as into buildings, windows, or openings where the subject is not visible. To bring this back to the identification assumption, when an officer discharges their firearm, the intent is always to hit and incapacitate the subject by aiming for their center of mass.[7] Failing to do so is not strategic behavior meant to deter, disarm, or displace, it is the result of officers being unable to hit the subject.

The 1985 US Supreme Court ruling in *Tennessee v. Garner* lead to restrictions in the application of deadly force by police officers. They were no longer able to apply deadly force simply to prevent a subject from escaping, instead the use of deadly force required that the subject pose an immediate danger of death or serious injury to the officer or others. This was followed by the 1989 Supreme Court ruling in *Graham vs. Connor* that now required courts to take the context of a shooting into account, including understand that the decisions of officers happen in a split-second, in order to determine whether or not a shooting is justified. These two rulings backstop the CPD (and all other law enforcement agencies) directives and guidelines on use of deadly force. The CPD's directive indicates that officers may only use force only as a last resort to protect against "an imminent threat to life or to prevent great bodily harm to the member or another person" (CPD (2017)).

4.5 Predicting Injury Status

Table 2 presents the unconditional balance for covariates split by subject injury status. Though the identification strategy is about conditioning on these observables, it is interesting to first examine how they breakdown between injured and uninjured subjects. First, we can see that CPD members involved in OIS where subjects are injured are more often male, less experienced, more likely to be an officer, more likely to be injured, more likely to discharge a hand gun (and consequently less likely to discharge a TASER). Appendix Table A1 provides the same breakdown restricting to only OIS where officers discharge a firearm and indicates that only an officer's injury status and likelihood of discharging

[7] Technically speaking, TASER discharges are meant to target the "lower-center of mass" which provides better incapacitation and a directive to this effect was issued by the TASER company in 2009 (TASER (2009)).

a hand gun (in this case the alternative weapon is a long gun) are statistically different. This suggests that much of what is captured here is the difference between officers who discharge firearms and who discharge TASERs. The main results I present are for firearms only, though when pooling the two, I control for discharged weapon type.

Next, we can see that subjects who are injured are less likely to: be Black and more likely to be White or Hispanic; be armed; have a drug, weapon, or assault charge, have a hand gun. When examining only firearm discharges, differences disappear between subject race, and weapons and assault charges but remain for the others (these OIS that result in injury have subjects who are more likely to have a domestic charge).

Lastly, OIS that result in subject injury have: fewer counts of active resistance; more counts of passive resistance; subjects more likely to use deadly force; officers who fire first; artificial lighting conditions and happen indoors. For OIS with firearm discharges differences disappear for counts of active resistance and whether or not the officer fired first but remain for the others (these OIS that result in injury are also more likely to happen in daylight).

Overall, even unconditionally there is some balance between OIS with injured and uninjured subjects, especially among OIS with firearm discharges. Regardless, I control for all of these covariates in my analysis.

Next, to provide suggestive evidence in support of this identification assumption, I estimate a linear probability model where the dependent variable is whether or not a subject is injured in a given OIS. I include the full suite of officer, subject, and incident characteristics. The purpose of this exercise is to examine how predictive of injury status these covariates are after accounting for the full set. If it is difficult to predict injury status, we should expect to see few statistically significant results and coefficients that are very close to 0. In fact, this is precisely what I find. Figure 7 presents the coefficients and standard errors from this exercise for officer level characteristics, while Figures 8 and 9 do the same for subject and incident characteristics, respectively. Solid circles indicate that the estimate is statistically significant at the 5% level while hollow circles indicate the the estimate is not statistically significant at the 5% level. The type of weapon used by a subject, the weather and lighting conditions, whether an OIS is indoors, officer experience, TRR history, and age are all are not predictive of subject injury status. Only a few of these characteristics are statistically significant–female, Black, or Hispanic officers are all less likely to injure an subject, conditional on discharging their weapon, as are officers not in uniform; incidents involving a weapons charge are less likely to result in an injury while those with an assault charge are more likely to result in an injury. Interestingly, incidents where neither party fired first are more likely to result in an injury. However, even those characteristics that are statistically significant are clustered around zero, indicating that no one characteristic explains subject injury status well after accounting for the others.

Overall, even unconditionally there is some balance between OIS with injured and uninjured subjects, especially among OIS with firearm discharges, and many of these covariates do not appear to be good predictors of subject injury status. Regardless, I control for all of these covariates in my analysis.

5 Results

In this section I first present event study results, then the comparisons of crime reporting in districts with OIS resulting in injury, and finally results related to mechanisms and effect heterogenity.

5.1 Event Study and Dynamics

Figure 10 plots ln(Reported Crime + 0.1) in districts with OIS where officer discharged firearms resulting in injury at daily intervals for the 14 days before and after the OIS. The full suite of officer, subject, and incident controls as well as year, month, district, and district-year fixed effects are included. What emerges is a clear shift downwards in point estimates on reported crime after an OIS and confidence intervals that exclude zero for many of these daily level estimates. Even though this is not a difference-in-differences research design, divergent pre-trends may still call into question whether or not a subject's injury status as good as randomly assigned, conditional on these controls. That the figure does not indicate pre-trend issues provides some reassurance that the use of districts with OIS that do not result in subject injury as the control group is appropriate. Appendix Figure 11 provides the analogous chart for OIS with subject injuries and where the subject was unarmed and reaches similar conclusions.

5.2 Injury v.s. Non-Injury OIS

Table 3 presents my main results from Equation (4.3). The dependent variable is ln(Reported Crime + 0.1). Only district-day observations up to 14 days before and after an OIS are included. The pattern that reveals itself is that OIS with an injured subject reduce reported crime more than OIS with uninjured subjects in the days following the attacks. Column 1 includes officer controls and I find that OIS with subject injured reduce reported crime in the 14 days following by about 3.7%. Columns 2 and 3 add subject and incident controls, respectively, and have nearly identical point estimates as column 1. Column 4 brings in month fixed-effects and column 5 adds district-year fixed effects, both of which shrink the estimated effect size (down to 3.1% and 2.8% respectively). All columns include district and year fixed effects. Column 5, with its district specific annual trends in crime is my preferred specification.

Appendix Table A2 presents the analogous results including TASER incidents. When TASER events are included, the estimated effect is not statistically significant and is much smaller in magnitude with quite tight confidence intervals. When taken with the results above, this suggests that while reported crime does not respond to OIS where officers discharge TASERs, it does respond to incidents where officers discharge firearms. This may mean that TASER incidents are not as salient to the public and therefore less likely to alter reporting behavior, or this may reflect a lack of deterrence effects on crime by TASERS.

In Appendix Table A3, I explore the sensitivity of my findings to alternative choices of pre- and post-OIS periods. The baseline for equation 4.3 is 14 days before and 14 days after the OIS. Column 1 repeats the baseline estimate from column 5 of Table 3. Columns 2 and 3 reduce the post OIS period to 13 and 12 days, respectively. Columns 4 and 5 reduce the pre period to 13 and 12 days respectively. The estimated effects are all identical and statistically significant at the 1% level (except column 4 which is at the 5% level). These findings suggest that moving the pre- and post-OIS interval backward and forward from the date of the OIS has no effect on the main conclusions of this paper.

Following the discussion in Section 2, I test whether or not these reductions in reported crime following OIS with injured subjects are limited to serious, violent, or less serious crimes. Table 4 provides provides estimates of column 5 in Table 3 but switches the dependent variables from a measure of all reported crimes to these subsets. Column 1 simply repeats the estimates for all reported crimes. The dependent variable in column 2 is more serious crime–only reported Part I Index Crimes (homicide, rape, robbery, aggravated assault, burglary, motor vehicle theft, arson). In column 3 the dependent variable is violent crime (homicide, rape, robbery, and aggravated assault). Lastly, column 4 has a dependent variable measuring reported less serious offenses (things like narcotics, weapons, and liquor violations or simple assault). These dependent variables have all been log transformed (log (x+ 0.1)) to aid with interpretation and to address zeros that occur in these smaller subsets for all reported crime. When splitting reported crime up this way, the point estimates are all negative and roughly the same magnitude as column 1 (all reported crime), staying around 2.2%–3.3% reductions in reported crime. However, only column 4 measuring the effects of OIS with injured subjects on reported less serious crime is statistically significant at conventional levels. As noted in Table 1, about 60% of reported crime is less serious, making inference on serious and violent crime less precise. As such, I cannot rule out equivalence between the estimated effects on the different types of crime.

5.3 Channels and Heterogeneity

Because changes in both reporting behavior and criminal behavior are consistent with the data, I turn to ShotSpotter in an attempt to disentangle them.

Table 5 repeats the analysis in Table 3 but instead uses the natural log of the count of ShotSpotter incidents as the dependent variable. The results suggests that it is unclear that there is a difference in detected ShotSpotter incidents in districts with an OIS where officers discharge firearms and injure someone compared to districts without such an injury. The point estimate is negative and, given that ShotSpotter data exists for only 13 districts, the standard errors are quite large and therefore these estimates are quite imprecise.

Appendix Table A4 provides estimates of Equation (4.3) while incorporating ShotSpotter data. In column 1, I re-estimate the results presented in Table 3 but restrict the sample to only the districts with ShotSpotter technology over the entire sample period. I do this to check that any results obtained when controlling for ShotSpotter events are not simply a result of these districts having different behavior than the other districts. In fact, the estimated effect for these districts is directly in line with that from Table 3. In column 2, I repeat this exercise but now restrict the sample to only the period where I have ShotSpotter data (2017-2019). Lastly, in column 3 I control for the number of ShotSpotter events on a given district-day.

The results from columns 2 and 3 highlight several important points. First, turning to the last row of column 3, ShotSpotter incidents are positively correlated with reported crime. This is reassuring in that crime and reported crime move together and in the same direction. Second, and perhaps most notably, the previous findings of negative and statistically significant point estimates disappear. Looking at the size of the sample for these columns, this might be unsurprising–the standard errors on the coefficient of interest are ten times larger than those in previous estimates. Lastly, even after controlling for the number of ShotSpotter events, the point estimate and standard errors of the coefficient of interest are unchanged. So, while this sample is very small and we cannot rule out relatively large positive or negative effects of OIS on reported crime, these results do provide suggestive evidence that accounting for some measure of underlying crime does not dramatically alter the estimates of crime reporting behavior.

Table 6 examines whether or not there are differential effects of these OIS. Column 1 repeats the results from column 5 of Table 3, my preferred specification. Row 1 presents the baseline interaction and coefficient of interest from Equation (4.3). Column 2 adds a triple interaction term, looking for differential effects for OIS resulting in an injury when a subject is unarmed compared to when a subject is armed. I find that reported crime falls by an additional 4.8% following an OIS in districts where a subject is injured and unarmed than in districts with an OIS where a subject is injured but unarmed.

Column 3 introduces an interaction for whether or not the subject was fatally injured by the OIS. Interestingly, there does not appear to be additional reduction in reporting when the subject is killed. If the decline in reporting rate is driven by deterrence-induced reductions in crime a la the Becker model, then we should expect to see further reductions in reported crime when the subject is fatally injured than when simply injured as that represents a much larger shock to the perceived costs of engaging in crime. This is especially true because the fatal encounters data is drawn from media sources, meaning that salience should be high for these OIS. The results from column 3 provide some suggestive evidence in favor of the crime reporting behavior channel rather than the reduction in underlying crime channel.

Column 4 adds a similar interaction term to explore differing effects when the subject is Black. While reported crime still falls after an OIS with an injury compared to an OIS without, there does not appear to be different effects in reported crime when the subject is Black compared to when the subject is not Black. Column 5 repeats the exercise for OIS in majority Black districts and again I do not find differential effects in reported crime following an OIS resulting in an injury. Column 6 examines whether or not OIS resulting in injury might reduce reported crime more when the officer and subject do not share a race. Specifically, it looks at White officers and Black subjects and the results do not indicate differential effects on reported crime. I find that there are no differential impacts on reported crime after an OIS when the officer is White and the subject is Black.

The results from columns 4–6 are somewhat surprising given evidence in this literature that white officers are much more likely to use force against Black subjects and in minority neighborhoods (see for example Ba et al. (2021), Hoekstra and Sloan (2020)) and that the discussion in popular media often centres the contrasting race of the subject and officer in coverage. Combining these results with those from column 2 suggests that procedural justice matters more in determining police legitimacy rather than distributive justice and that police firing on unarmed subjects is perceived as procedurally unjust, regardless of the CPD's internal policy.

Appendix Tables A14, A15, A16 repeat this analysis for each of the different types of crime. Overall, the same pattern of no apparent effects along racial dimensions but negative effects for unarmed subjects appears. For serious crime, these race-based coefficients are all very small, though somewhat imprecisely estimated. The exception is for OIS with fatally injured subjects which indicates an increase in reported crime, statistically significant at the 5% level. This coefficient is also positive for less serious crimes though is not statistically significant and is less precisely estimated. However, for less serious crime the estimated effect for OIS with unarmed subjects who are injured is statistically significant at the 5% level, quite large (an additional 6.5% reduction in reported less serious crimes), and we can rule out equivalence with that of serious crimes. This is consistent with the notion that we might expect to see larger reductions in reported crime among crimes where witnesses or bystanders have more discretion in reporting.

6 Conclusion

In this paper I estimate the impacts of OIS on crime reporting in Chicago by exploiting the natural randomness in subject injury status. I find that OIS that result in an injury reduce reported crime by about 2.8% in comparison to OIS that do not result in injury. Furthermore, I do not find differential effects on crime reporting when the subject is Black, when the officer-subject pair is White-Black, nor when the OIS occurs in a majority Black district. However, I do find that when a subject is unarmed the decline in reported crime is even larger (an additional 4.8% reduction). The lack of differential effects along racial dimensions suggests that citizens' perceptions of police legitimacy are not driven by notions of distributive justice and when paired with the results about unarmed subjects indicate that it is likely notions of procedural justice that more strongly influence perceptions of police legitimacy.

These findings are in line with those of the qualitative literature in sociology and criminology, that a procedural justice model is how citizens evaluate police legitimacy. I also provide mild suggestive evidence that accounting for a measure of crime does not dramatically shift the estimated effect but when paired with the a lack of differential effects on reporting after OIS with a fatally injured subject suggest that these changes in reported crime are unlikely to simply reflect lower underlying criminal activity.

Overall, these findings are relevant for understanding the consequences of OIS on the efficiency and effectiveness of public safety provision more broadly and police services more specifically. Most notably, these reductions in citizen assistance may now be partly responsible for the reductions in police clearance rates which have previously been characterized as resulting from lower proactive policing activities. For example, if police departments sought to combat lower clearance rates by maintaining levels of proactive policing, my results suggest that clearance rates may still suffer.

This area is still in need of further research. My results are unable to say anything about the other channels through which reductions in police legitimacy may impact public safety provision and policing such as non-cooperation with police during ongoing investigations (e.g. refusal to pick suspects out of a lineup, provide testimony, or give witness statements) or reliance on a code of the street to deliver justice. In order to address these channels more detailed data of police investigations or criminal activity is needed. Additionally, more work is needed to examine the direct and indirect effects of OIS and police legitimacy on other aspects of the criminal justice system and police efficiency.

References

Akinnibi, F., Holder, S. and Cannon, C.: 2021, Cities Say They Want to Defund the Police. Their Budgets Say Otherwise.
URL: *https://www.bloomberg.com/graphics/2021-city-budget-police-funding/*

Anderson, E.: 1999, *Code of the Street: Decency, Violence, and the Moral Life of the Inner City*, WW Norton & Company.

Ang, D., Bencsik, P., Bruhn, J. and Derenoncourt, E.: 2021, Police violence reduces civilian cooperation and engagement with law enforcement, *HKS Working Paper No. RWP21-022* .

Ba, B. A., Knox, D., Mummolo, J. and Rivera, R.: 2021, The role of officer race and gender in police-civilian interactions in Chicago, *Science* **371**(6530), 696–702.

Becker, G. S.: 1968, Crime and Punishment: An Economic Approach, *Journal of Political Economy* **76**(2), 169–217.

Berg, M. T., Stewart, E. A., Intravia, J., Warren, P. Y. and Simons, R. L.: 2016, Cynical streets: Neighborhood social processes and perceptions of criminal injustice, *Criminology* **54**(3), 520–547.

Bobo, L. D. and Thompson, V.: 2006, Unfair by design: The war on drugs, race, and the legitimacy of the criminal justice system, *Social Research: An International Quarterly* **73**(2), 445–472.

Brunson, R. K.: 2007, "Police don't like black people": African-American young men's accumulated police experiences, *Criminology & Public Policy* **6**(1), 71–101.

Campbell, B. A., Nix, J. and Maguire, E. R.: 2018, Is the number of citizens fatally shot by police increasing in the post-Ferguson era?, *Crime & Delinquency* **64**(3), 398–420.

Carr, P. J., Napolitano, L. and Keating, J.: 2007, We never call the cops and here is why: A qualitative examination of legal cynicism in three Philadelphia neighborhoods, *Criminology* **45**(2), 445–480.

Count Love: 2021, Count Love.
URL: *https://countlove.org/*

CPD: 2017, General Order G03-02 Use of Force, *Technical report*, Chicago Police Department.

DeSilver, D., Lipka, M. and Fahmy, D.: 2020, 10 things we know about race and policing in the US, *Pew Research, June* **3**, 2020.

Desmond, M., Papachristos, A. V. and Kirk, D. S.: 2016, Police violence and citizen crime reporting in the black community, *American Sociological Review* **81**(5), 857–876.

Desmond, M., Papachristos, A. V. and Kirk, D. S.: 2020, Evidence of the effect of police violence on citizen crime reporting, *American Sociological Review* **85**(1), 184–190.

Gaston, S., Cunningham, J. P. and Gillezeau, R.: 2019, A Ferguson effect, the drug epidemic, both, or neither? Explaining the 2015 and 2016 US homicide rises by race and ethnicity, *Homicide Studies* **23**(3), 285–313.

Gau, J. M. and Brunson, R. K.: 2010, Procedural justice and order maintenance policing: A study of inner-city young men's perceptions of police legitimacy, *Justice Quarterly* **27**(2), 255–279.

Hoekstra, M. and Sloan, C.: 2020, Does race matter for police use of force? Evidence from 911 calls, *NBER Working Paper No. 26774* .

Kaminski, R. J. and Jefferis, E. S.: 1998, The effect of a violent televised arrest on public perceptions of the police, *Policing: An International Journal of Police Strategies & Management* **21**(4), 683–706.

Kirk, D. S. and Papachristos, A. V.: 2011, Cultural mechanisms and the persistence of neighborhood violence, *American Journal of Sociology* **116**(4), 1190–1233.

Kochel, T.: 2015a, Assessing the initial impact of the Michael Brown shooting and police and public responses to it on St Louis county residents' views about police, *Carbondale:Southern Illinois University Carbondale* .

Kochel, T.: 2015b, Ferguson's long term impact on public views about police, *Carbondale: Southern Illinois University Carbondale* .

Kwak, H., Dierenfeldt, R. and McNeeley, S.: 2019, The code of the street and cooperation with the police: Do codes of violence, procedural injustice, and police ineffectiveness discourage reporting violent victimization to the police?, *Journal of Criminal Justice* **60**, 25–34.

Lane, E.: 2016, Why do police shoot so many times? FBI, experts answer on officer-involved shootings.
URL: *https://www.nola.com/news/crime_police/article_ae82835c-0212-5e50-a175-85601a1ed8bb.html*

Mapping Police Violence: 2021, Mapping Volice Violence.
URL: *https://mappingpoliceviolence.org/*

McCarthy, B., Hagan, J. and Herda, D.: 2020, Neighborhood climates of legal cynicism and complaints about abuse of police power, *Criminology* **58**(3), 510–536.

Mohammad, S. M. and Turney, P. D.: 2013, Crowdsourcing a word–emotion association lexicon, *Computational Intelligence* **29**(3), 436–465.

Oglesby-Neal, A., Tiry, E. and Kim, K.: 2019, Public perceptions of police on social media, *Urban Institute* pp. 1–12.

Ortiz, A.: 2020, Confidence in police is at record low, gallup survey finds, *Sec. US The New York Times. August* **12**.

Park, M., Grinberg, E. and Yan, H.: 2017, Minneapolis woman killed by police: What we know.
URL: *https://www.cnn.com/2017/07/18/us/minneapolis-woman-shooting-what-we-know/index.html*

Sunshine, J. and Tyler, T. R.: 2003, The Role of Procedural Justice and Legitimacy in Shaping Public Support for Policing, *Law & Society Review* **37**(3), 513–548.

TASER: 2009, Training bulletin 15.0 medical research update and revised warnings.
URL: *https://media.cdn.lexipol.com/pdfs/TASER_Media_Bulletin.pdf*

Tyler, T. R. and Huo, Y. J.: 2002, *Trust in the law: Encouraging public cooperation with the police and courts*, Russell Sage Foundation.

Wasney, M.: 2017, The Shots Heard Round the City. Are Chicago's new shot detection and predictive policing technologies worth it?
URL: *https://southsideweekly.com/shots-heard-round-city-shotspotter-chicago-police/*

Weitzer, R.: 2002, Incidents of Police Misconduct and Public Opinion, journal = Journal of Criminal Justice, **30**(5), 397–408.

Weitzer, R. and Tuch, S. A.: 2004, Race and Perceptions of Police Misconduct, *Social Problems* **51**(3), 305–325.

White, C., Weisburd, D. and Wire, S.: 2018, Examining the impact of the Freddie Gray unrest on perceptions of the police, *Criminology & Public Policy* **17**(4), 829–858.

Wolfe, S. E., Nix, J., Kaminski, R. and Rojek, J.: 2016, Is the effect of procedural justice on police legitimacy invariant? Testing the generality of procedural justice and competing antecedents of legitimacy, *Journal of Quantitative Criminology* **32**(2), 253–282.

Yousef, O.: 2017, Gunshots Or Fireworks? How Chicago Cops Know.
URL: *http://interactive.wbez.org/everyotherhour/shotspotter/*

Zoorob, M.: 2020, Do police brutality stories reduce 911 calls? Reassessing an important criminological finding, *American Sociological Review* **85**(1), 176–183.

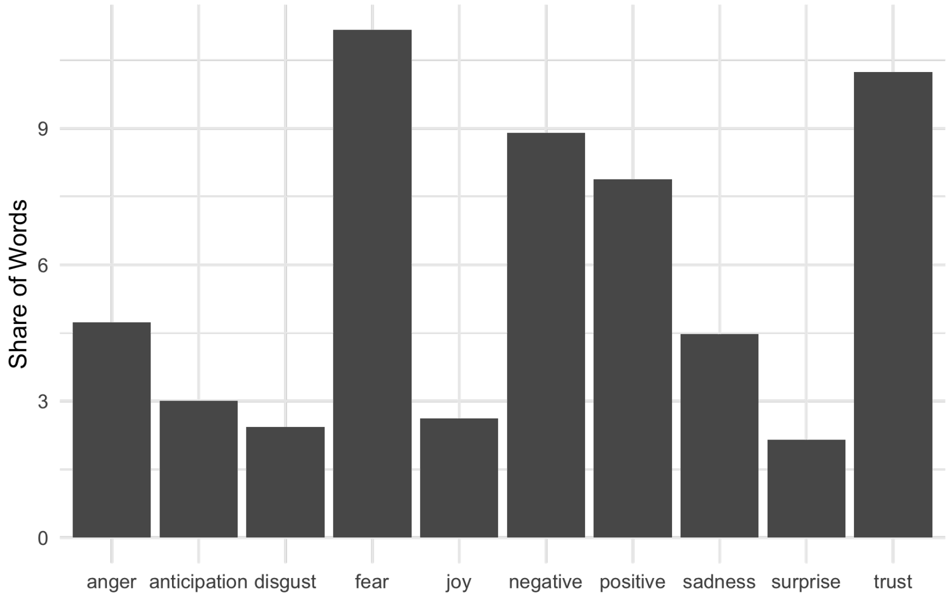

Figure 1: Share of words per tweet classified as positive, negative, or each emotion. Time period is July 1—31 2017. Tweets selected to include “cops”, “cop”, or “police” and are rstricted to the United States.

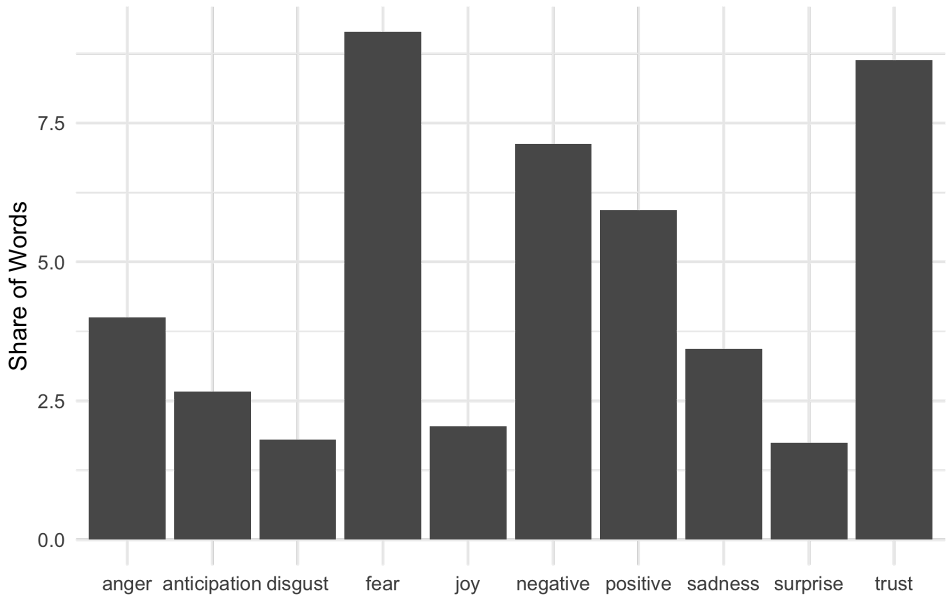

Figure 2: Share of words per tweet classified as positive, negative, or each emotion. Time period is March 1—31 2018. Tweets selected to include “cops”, “cop”, or “police” and are rstricted to the United States.

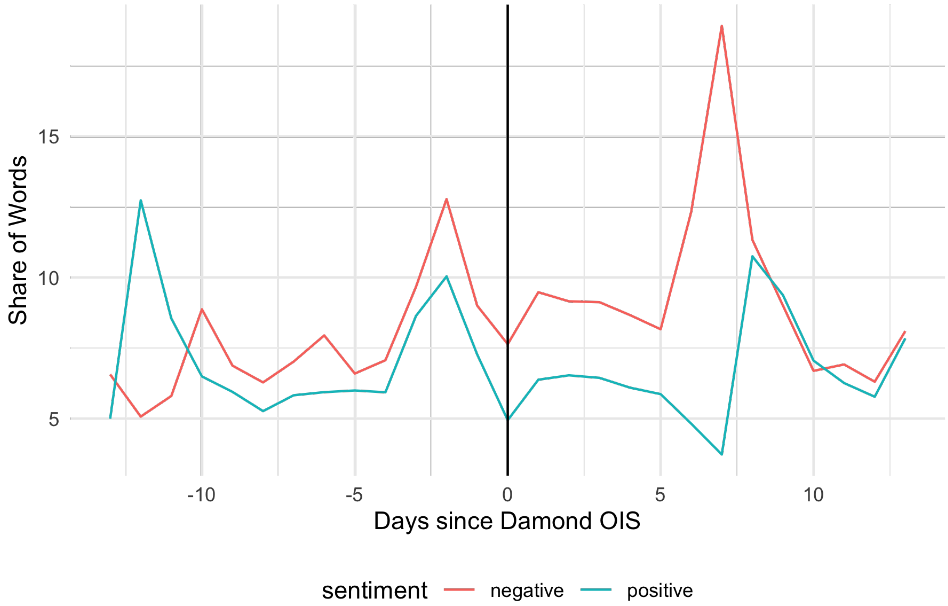

Figure 3: Share of words per tweet classified as positive or negative. Time period is July 1—31 2017. Tweets selected to include “cops”, “cop”, or “police” and are rstricted to the United States.

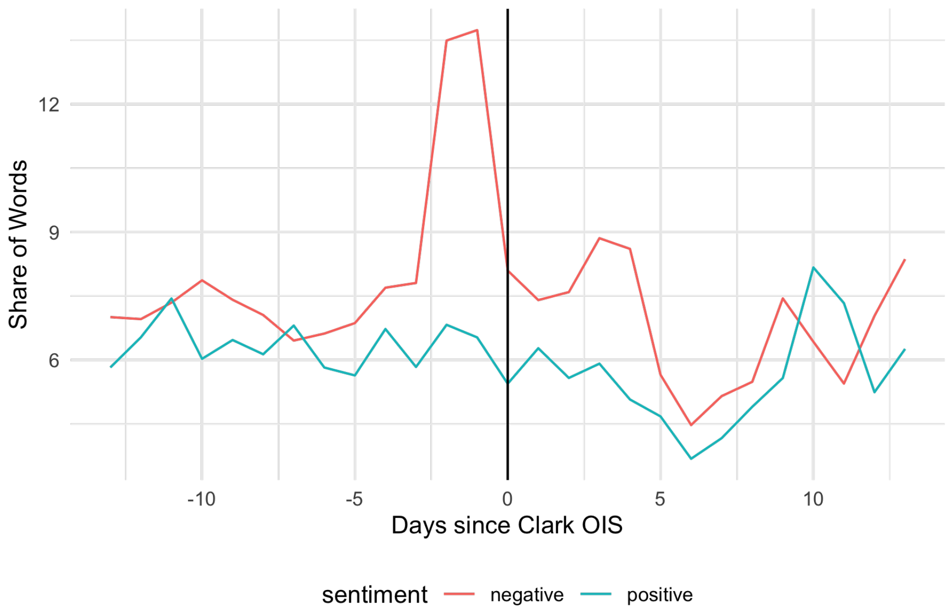

Figure 4: Share of words per tweet classified as positive or negative. Time period is March 1—31 2018. Tweets selected to include “cops”, “cop”, or “police” and are rstricted to the United States.

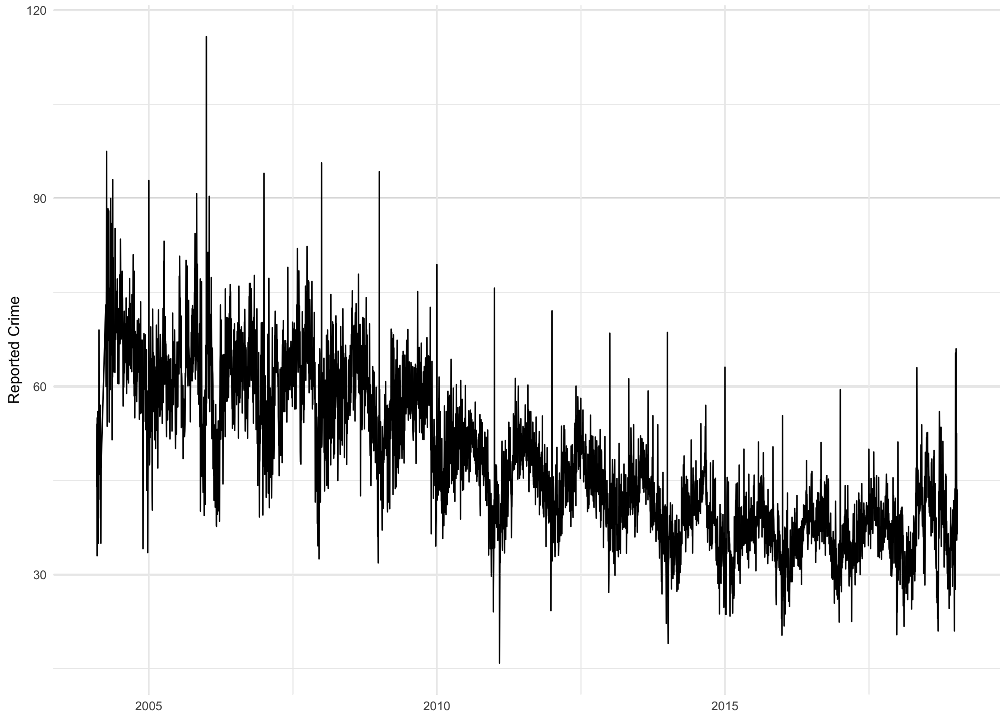

Figure 5: This figure plots the daily average reported crimes per district over the sample period (2004–2019).

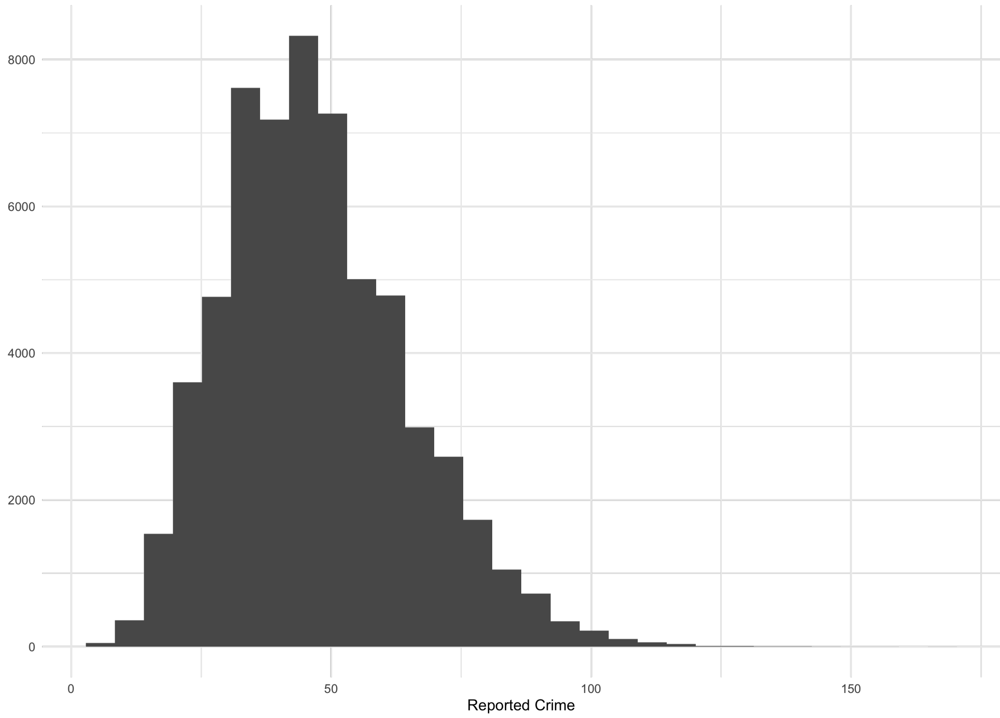

Figure 6: This figure plots a histogram of reported crimes over the sample period (2004–2019).

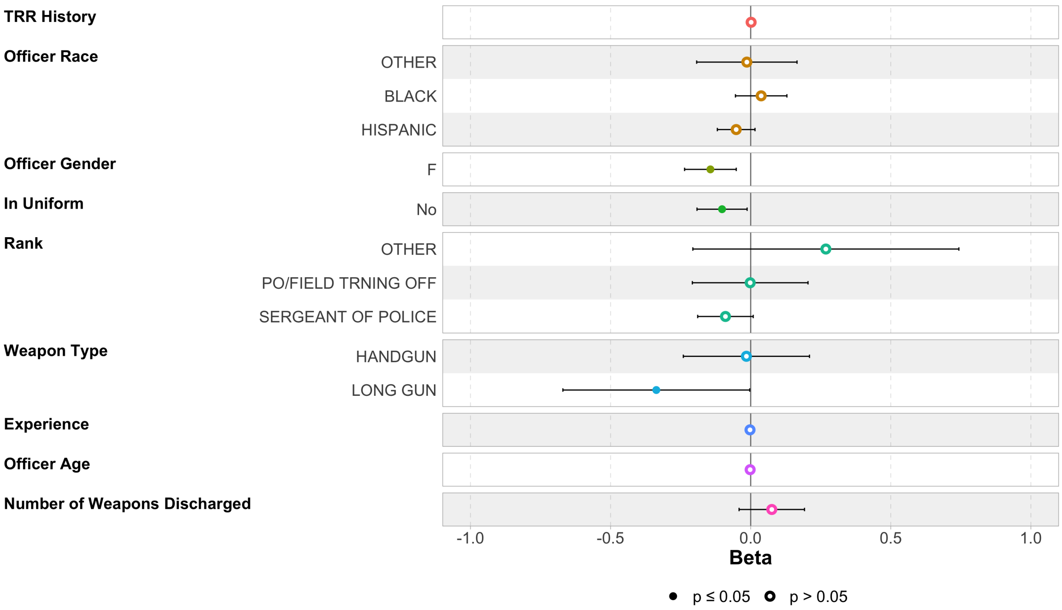

Figure 7: This figure plots estimated coefficients from regressing subject injury on all officer, subject, and incident characteristics. Only coefficients from officer variables are presented in this figure. Full circles are statistically significant at the 5% level, hollow circles are not statistically significant at the 5% level.

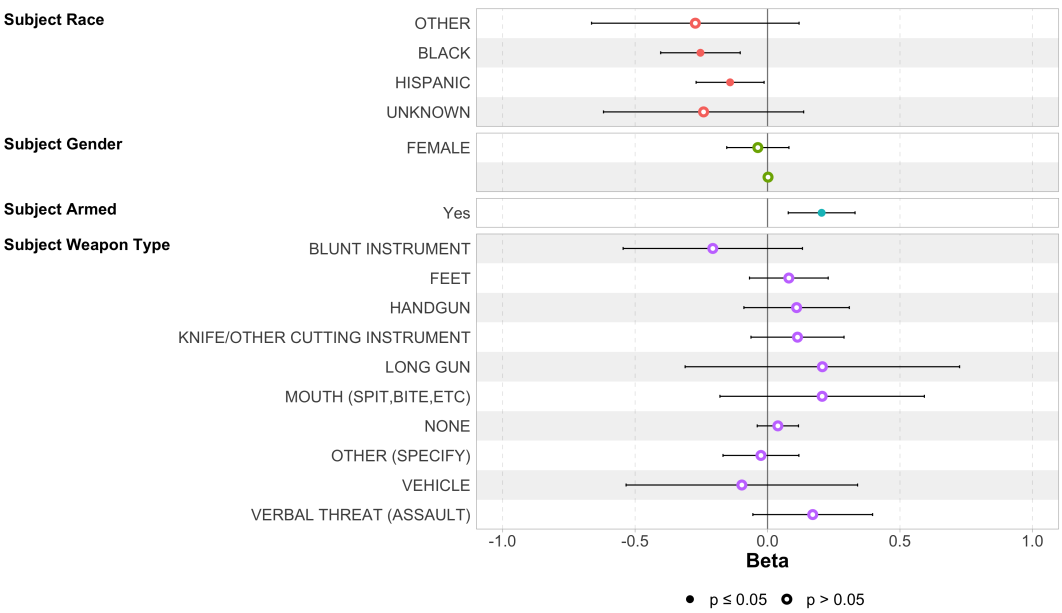

Figure 8: This figure plots estimated coefficients from regressing subject injury on all officer, subject, and incident characteristics. Only coefficients from subject variables are presented in this figure. Full circles are statistically significant at the 5% level, hollow circles are not statistically significant at the 5% level.

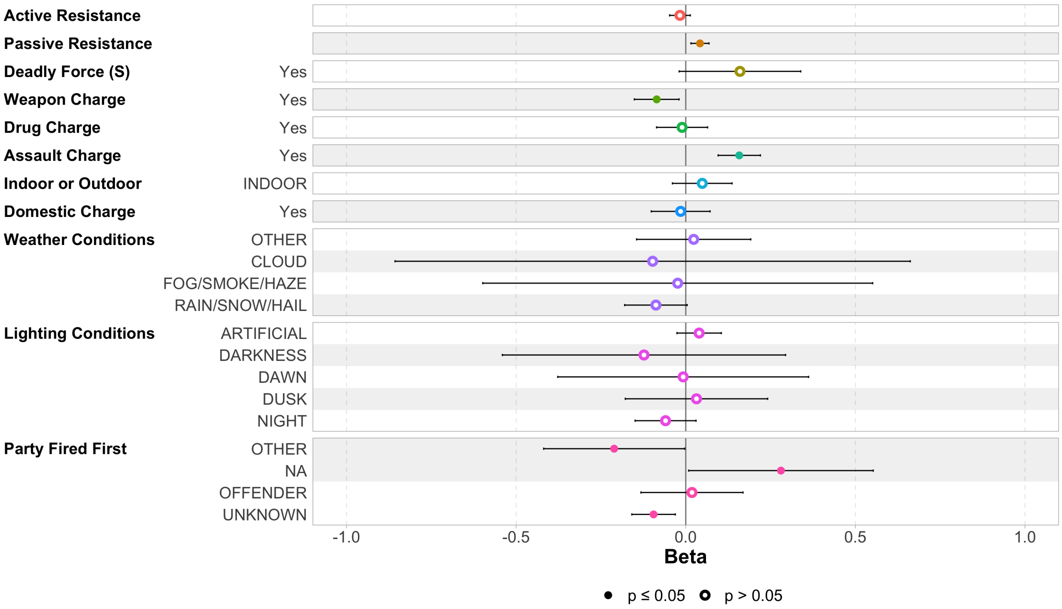

Figure 9: This figure plots estimated coefficients from regressing subject injury on all officer, subject, and incident characteristics. Only coefficients from incident variables are presented in this figure. Full circles are statistically significant at the 5% level, hollow circles are not statistically significant at the 5% level.

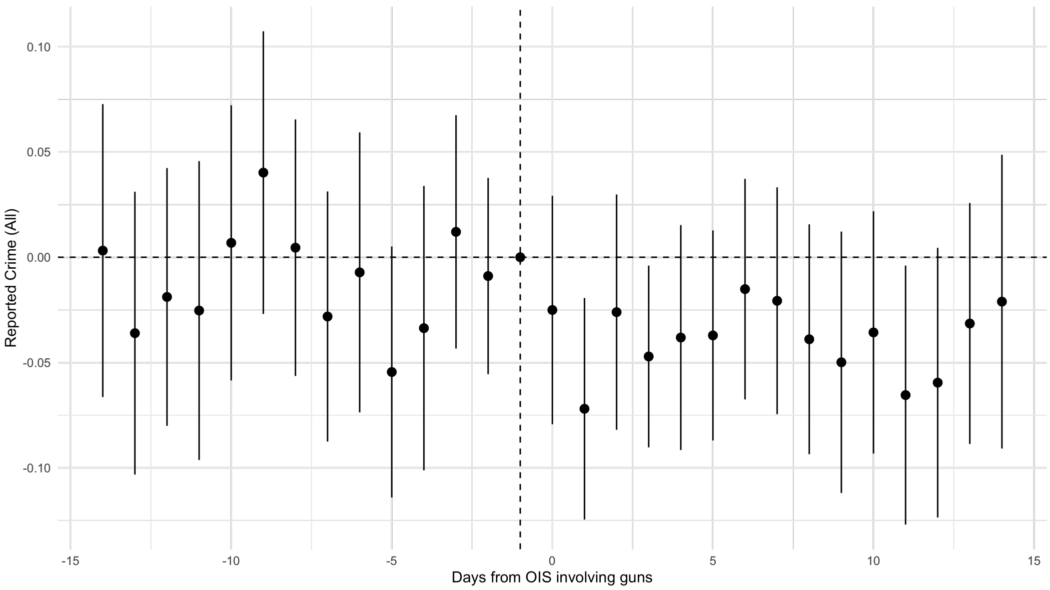

Figure 10: This figure plots ln(Reported Crime + 0.1) in districts with OIS where officer discharged firearms resulting in injury at daily intervals for the 14 days before and after the OIS. The full suite of officer, subject, and incident controls as well as year, month, district, and district-year fixed effects are included.

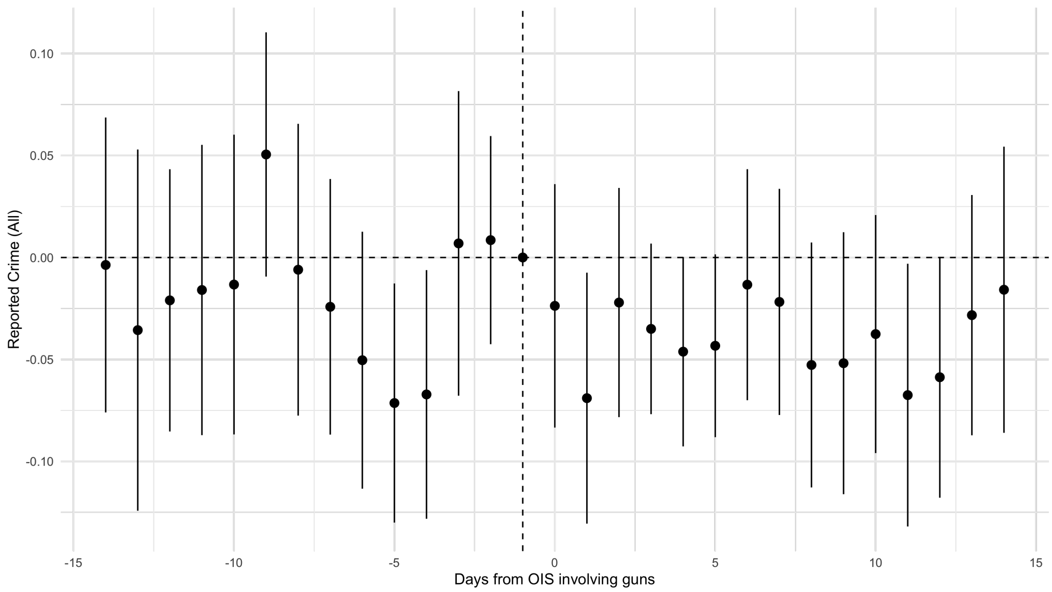

Figure 11: This figure plots ln(Reported Crime + 0.1) in districts with OIS where officer discharged firearms resulting in injury against an unarmed subject at daily intervals for the 14 days before and after the OIS. The full suite of officer, subject, and incident controls as well as year, month, district, and district-year fixed effects are included.

Table 1: Descriptive Statistics

	Mean	Median	P5	P95	N
Reported Crime					
Reported Crime	47.19	45.00	22.00	80.00	60,365
Reported Less Serious Crime (Part II Index)	28.67	27.00	11.00	52.00	60,365
Reported More Serious Crime (Part I Index)	18.52	18.00	7.00	33.00	60,365
Reported Violent Crime (Part I Index)	3.01	3.00	0.00	7.00	60,365
ShotSpotter Incidents					
Multiple Shot ShotSpotter Incidents	0.99	0.00	0.00	5.00	5,274
ShotSpotter Incidents	1.68	0.00	0.00	7.35	5,274
ShotSpotter Rounds	6.52	0.00	0.00	32.00	5,274
Single Shot ShotSpotter Incidents	0.51	0.00	0.00	3.00	5,274
Officer Characteristics					
Age	37.79	37.00	27.00	52.00	4,654
Black	0.18	0.00	0.00	1.00	4,654
Experience (Yrs)	10.34	9.56	1.34	23.09	4,654
Hispanic	0.26	0.00	0.00	1.00	4,654
In Uniform	0.76	1.00	0.00	1.00	4,654
Male	0.89	1.00	0.00	1.00	4,654
Number of weapons discharged	1.06	1.00	1.00	2.00	4,654
Officer fired Handgun	0.15	0.00	0.00	1.00	4,654
Officer fired Long gun	0.00	0.00	0.00	0.00	4,654
Officer fired TASER	0.85	1.00	0.00	1.00	4,654
Prior Incidents	9.36	6.00	0.00	29.00	4,654
Rank: Officer	0.74	1.00	0.00	1.00	4,654
White	0.52	1.00	0.00	1.00	4,654
Subject Characteristics					
Age	30.15	27.00	19.00	50.00	4,654
Armed	0.24	0.00	0.00	1.00	4,654
Black	0.77	1.00	0.00	1.00	4,654
Hispanic	0.14	0.00	0.00	1.00	4,654
Injured	0.45	0.00	0.00	1.00	4,654
Male	0.93	1.00	0.00	1.00	4,654
Weapon: Fists	0.13	0.00	0.00	1.00	4,654
Weapon: Handgun	0.11	0.00	0.00	1.00	4,654
Weapon: Knife	0.00	0.00	0.00	0.00	4,654
Weapon: Long Gun	0.00	0.00	0.00	0.00	4,654
Weapon: None	0.54	1.00	0.00	1.00	4,654
White	0.07	0.00	0.00	1.00	4,654
Subject Fatally Injured	0.02	0.00	0.00	0.00	4,655
Incident Characteristics					
Active resistance	2.75	3.00	1.00	5.00	4,654
Artificial light	0.55	1.00	0.00	1.00	4,654
Assault charge	0.63	1.00	0.00	1.00	4,654
Clear weather	0.88	1.00	0.00	1.00	4,654
Cloudy weather	0.00	0.00	0.00	0.00	4,654
Darkness	0.01	0.00	0.00	0.00	4,654
Dawn	0.00	0.00	0.00	0.00	4,654
Daylight	0.31	0.00	0.00	1.00	4,654
Deadly force (S)	0.17	0.00	0.00	1.00	4,654
Domestic charge	0.14	0.00	0.00	1.00	4,654
Drug charge	0.19	0.00	0.00	1.00	4,654
Fog/Haze/Smoke weather	0.00	0.00	0.00	0.00	4,654
Indoor	0.25	0.00	0.00	1.00	4,654
Officer fired first	0.70	1.00	0.00	1.00	4,654
Passive resistance	3.41	3.00	1.00	6.00	4,654
Rain/Snow/Hail weather	0.08	0.00	0.00	1.00	4,654
Weapon charge	0.13	0.00	0.00	1.00	4,654

Note: Time period is 2004–2019 (ShotSpotter 2017–2019). Including TASER events there are 60,365 district-day observations. ShotSpotter data's reduced time period means there are only 5, 724 district-day observations. Including TASER events there are 4,654 officer-involved shootings in the sample. "Prior Incidents" is a variable that equals the count of previous tactical response report incidents for a given officer at the time of the shooting. "Passive resistance" are counts of passive resistance in an incident (e.g. failure to comply with a verbal command). " Active resistance" are counts of active resistance in an incident (e.g. physically resisting arrest). "Deadly force (S)" is a binary variable that takes 1 if a subject used deadly force against an officer.

Table 2: Unconditional Covariate Balance by Subject Injury Status

	Subject Uninjured			Subject Injured			
Variable	N	Mean	SD	N	Mean	SD	Test
Officer Characteristics							
Officer Black	2568	0.172	0.378	2086	0.181	0.385	F=0.655
Officer White	2568	0.519	0.5	2086	0.529	0.499	F=0.441
Officer Hispanic	2568	0.273	0.446	2086	0.253	0.435	F=2.336
Officer Male	2568	0.878	0.328	2086	0.905	0.294	F=8.489***
Officer Age	2568	37.913	7.676	2086	37.647	7.573	F=1.399
Experience (Yrs)	2568	10.532	6.794	2086	10.103	6.779	F=4.594**
Prior Incidents	2568	9.27	9.576	2086	9.471	10.789	F=0.452
In Uniform	2568	0.755	0.43	2086	0.774	0.418	F=2.245
Rank: Officer	2568	0.725	0.447	2086	0.76	0.427	F=7.611***
Officer Injured	2568	0.084	0.277	2086	0.131	0.338	F=27.923***
Officer Fired Handgun	2568	0.111	0.315	2086	0.187	0.39	F=53.56***
Officer Fired TASER	2568	0.882	0.322	2086	0.81	0.393	F=48.156***
Number of weapons discharged	2568	1.055	0.245	2086	1.066	0.277	F=2.121
Subject Characteristics							
Subject Black	2568	0.797	0.402	2086	0.746	0.435	F=17.311***
Subject White	2568	0.055	0.227	2086	0.082	0.275	F=14.402***
Subject Hispanic	2568	0.127	0.333	2086	0.153	0.36	F=6.541**
Subject Male	2568	0.934	0.249	2086	0.936	0.244	F=0.113
Subject Age	2568	29.948	10.263	2086	30.388	10.298	F=2.114
Subject Armed	2568	0.191	0.393	2086	0.297	0.457	F=72.266***
Domestic charge	2568	0.134	0.341	2086	0.146	0.353	F=1.349
Drug charge	2568	0.204	0.403	2086	0.17	0.376	F=8.63***
Assault charge	2568	0.592	0.492	2086	0.685	0.465	F=42.586***
Weapon charge	2568	0.122	0.327	2086	0.146	0.353	F=5.697**
Weapon: None	2568	0.584	0.493	2086	0.484	0.5	F=46.787***
Weapon: Fists	2568	0.129	0.336	2086	0.128	0.334	F=0.032
Weapon: Handgun	2568	0.083	0.275	2086	0.135	0.342	F=33.836***
Weapon: Long Gun	2568	0.002	0.044	2086	0.004	0.066	F=2.151
Incident Characteristics							
Active resistance	2568	2.815	1.362	2086	2.675	1.497	F=11.122***
Passive resistance	2568	3.377	1.291	2086	3.445	1.3	F=3.169*
Deadly force (S)	2568	0.132	0.339	2086	0.219	0.414	F=62.344***
Officer fired first	2568	0.682	0.466	2086	0.714	0.452	F=5.596**
Daylight	2568	0.318	0.466	2086	0.296	0.457	F=2.701
Artificial light	2568	0.527	0.499	2086	0.572	0.495	F=9.276***
Darkness	2568	0.005	0.074	2086	0.006	0.076	F=0.019
Dawn	2568	0.005	0.068	2086	0.005	0.069	F=0.004
Clear weather	2568	0.873	0.333	2086	0.879	0.327	F=0.294
Cloudy weather	2568	0.002	0.044	2086	0.002	0.049	F=0.109
Fog/Haze/Smoke weather	2568	0.003	0.056	2086	0.003	0.058	F=0.021
Rain/Snow/Hail weather	2568	0.085	0.279	2086	0.074	0.262	F=1.916
Indoor	2568	0.234	0.423	2086	0.261	0.439	F=4.443**

Note: Time period is 2004–2019. "Prior Incidents" is a variable that equals the count of previous tactical response report incidents for a given officer at the time of the shooting. "Passive resistance" are counts of passive resistance in an incident (e.g. failure to comply with a verbal command). " Active resistance" are counts of active resistance in an incident (e.g. physically resisting arrest). "Deadly force (S)" is a binary variable that takes 1 if a subject used deadly force against an officer. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Effect of OIS involving firearms on crime reporting

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.023^{*}	0.018	0.018	0.011	0.014
	(0.013)	(0.013)	(0.012)	(0.011)	(0.011)
OIS	0.030^{***}	0.029^{***}	0.027^{***}	0.023^{***}	0.020^{**}
	(0.010)	(0.009)	(0.008)	(0.006)	(0.007)
Subject Injured x OIS	-0.037^{**}	-0.036^{**}	-0.037^{**}	-0.031^{***}	-0.028^{***}
	(0.015)	(0.015)	(0.014)	(0.010)	(0.010)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 4: Effect of OIS involving firearms on types of reported crime

	All	Serious	Violent	Less Serious
	(1)	(2)	(3)	(4)
Subject Injured	0.014	-0.000	0.017	0.023
	(0.011)	(0.014)	(0.039)	(0.014)
OIS	0.020^{**}	0.013	0.046	0.024^{**}
	(0.007)	(0.011)	(0.034)	(0.011)
Subject Injured x OIS	-0.028^{***}	-0.022	-0.031	-0.033^{***}
	(0.010)	(0.017)	(0.047)	(0.011)
Observations	10,276	10,276	10,276	10,276
Clusters	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193

Note: Dependent variable in column 1 is ln(Reported Crime + 0.1), in column 2 is ln(Reported Serious Crime + 0.1), in column 3 is ln(Reported Violent Crime + 0.1), and in column 4 is ln(Reported Less Serious Crime + 0.1). Serious crimes are UCR Part I index crimes. Violent crimes are a subset of UCR Part I index crimes: homicide, rape, robbery, and aggravated assault. Less serious crimes are UCR Part II index crimes. All columns include district and year fixed effects. All columns include officer, subject, and incident contols as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 5: Effect of OIS involving firearms on ShotSpotter incidents

	ln(ShotSpotter + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.615	0.026	-7.658***	0.352	0.995
	(1.036)	(0.197)	(0.180)	(3,305.982)	(9,399.729)
OIS	0.272	0.268	0.268	0.311	0.311
	(0.165)	(0.167)	(0.167)	(0.186)	(0.190)
Subject Injured x OIS	-0.064	-0.123	-0.123	-0.222	-0.222
	(0.196)	(0.186)	(0.187)	(0.216)	(0.220)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	413	413	413	413	413
Clusters	13	13	13	13	13
Mean (dep. var)	1.684	1.684	1.684	1.684	1.684

Note: Dependent variable is ln(ShotSpotter + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 6: Heterogeneous effect of OIS involving firearms on reported crime

	ln(Reported Crime + 0.1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subject Injured x OIS	-0.028***	-0.021*	-0.025**	-0.047*	-0.038**	-0.034*
	(0.010)	(0.011)	(0.010)	(0.023)	(0.018)	(0.018)
Subject Injured x OIS x Subject Unarmed		-0.048**				
		(0.020)				
Subject Injured x OIS x Subject Dead			0.060			
			(0.058)			
Subject Injured x OIS x Black Subject				0.027		
				(0.025)		
Subject Injured x OIS x Black District					0.017	
					(0.021)	
Subject Injured x OIS x Different Races						0.014
						(0.022)
Observations	10,276	10,276	10,277	10,276	10,276	10,276
Clusters	22	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include officer, subject, and incident contols as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

7 Appendix

TACTICAL RESPONSE REPORT / Chicago Police Department

INCIDENT

DATE OF INCIDENT	TIME	ADDRESS OF OCCURRENCE	LOCATION CODE	BEAT/OCCUR.	VIDEO RECORDED INCIDENT ☐ BWC ☐ IN-CAR VIDEO ☐ OTHER VIDEO

BUSINESS NAME ☐ DNA	EXACT AREA WITHIN LOCATION (E.G., BASEMENT, STAIRWAY ,BEDROOM)	ASSIGNMENT TYPE ☐ ON-VIEW ☐ OTHER ☐ SUPERVISOR DIRECTED ☐ CALL FOR SERVICE

EVENT NO.	RD NO.	IUCR CODE	IR NO.	CB NO.	INVOLVED A PURSUIT? ☐ NO ☐ FOOT ☐ VEHICLE ☐ OTHER

LIGHTING ☐ DUSK ☐ DAYLIGHT ☐ DAWN ☐ DARKNESS ☐ ARTIFICIAL	WEATHER ☐ RAIN ☐ CLEAR ☐ SNOW/ICE ☐ CLOUDY ☐ FOG	PATROL TYPE? ☐ BICYCLE ☐ SQUADROL ☐ OTHER: ☐ POLICE CAR ☐ MOTORCYCLE/PAPV ☐ VAN/BUS ☐ FOOT	MEMBER WAS? ☐ ALONE ☐ WITH PARTNER	ASSIST UNITS ON SCENE? ☐ YES ☐ NO	INCIDENT ☐ INDOOR ☐ OUTDOOR

INVOLVED MEMBER

RANK	LAST NAME	FIRST NAME	EMPLOYEE NO.	WATCH	SEX ☐ M ☐ F	RACE	AGE	HT.	WT.

DATE OF APPT.	UNIT & BEAT OF ASSIGN.	DUTY STATUS ☐ ON ☐ OFF	IN UNIFORM? ☐ YES ☐ NO	TYPE OF MEMBER INJURY ☐ None / None Apparent ☐ Minor Swelling ☐ Minor Contusion/Laceration ☐ Complaint of Substantial Pain ☐ Significant Contusion ☐ Laceration Requiring Sutures ☐ Broken/Fractured Bone(s) ☐ Heart Attack/Stroke/Aneurysm ☐ Gun Shot ☐ Fatal ☐ Other (Explain)

SUBJECT INFORMATION

☐ DNA

LAST NAME	FIRST NAME	M.I.	SEX ☐ M ☐ F	RACE	D.O.B.	HT.	WT.

ADDRESS	TELEPHONE NO.	CONDITION ☐ Apparently Normal ☐ Injured by Member ☐ Injured Not by the Member's Force ☐ Alleges Injury by Member ☐ Under Influence of Alcohol ☐ Under Influence of Drugs ☐ Mental Illness / Emotional Disorder ☐ Disability ☐ OTHER (Specify)

MEDICAL TREATMENT? ☐ Refused Medical Aid ☐ Offered/EMS Requested ☐ Performed by Member ☐ Performed by CFD EMS ☐ Taken to Hospital (Specify) ☐ OTHER (Specify)	SUBJECT INJURY BY MEMBER'S USE OF FORCE? ☐ None/None Apparent ☐ Subject Alleged Injury ☐ Non-Fatal - Minor Injury ☐ Non-Fatal - Major Injury ☐ UNK ☐ Fatal

SUBJECT'S ACTIONS (Check all that apply)

☐ DNA ☐ UNK

☐ DID NOT FOLLOW VERBAL DIRECTION
☐ UNABLE TO UNDERSTAND VERBAL DIRECTION
☐ VERBAL THREATS
☐ STIFFENED (DEAD WEIGHT)
☐ PULLED AWAY
☐ FLED
☐ IMMINENT THREAT OF BATTERY - NO WEAPON
☐ PHYSICAL ATTACK WITHOUT WEAPON. (SPECIFY)
☐ HAND/ARM/ELBOW STRIKE
☐ KNEE/LEG STRIKE
☐ MOUTH/TEETH/SPIT
☐ PUSH/SHOVE/PULL
☐ GRAB/HOLD/RESTRAIN
☐ WRESTLE/GRAPPLE
☐ OTHER (DESCRIBE)
☐ THROWN OBJECT (DESCRIBE)
☐ IMMINENT THREAT OF BATTERY WITH WEAPON
☐ ATTEMPT TO OBTAIN MEMBER'S WEAPON
☐ PHYSICAL ATTACK WITH WEAPON
☐ USED FORCE LIKELY TO CAUSE DEATH OR GREAT BODILY HARM
☐ OTHER (DESCRIBE)

WAS SUBJECT ARMED WITH WEAPON? ☐ NO ☐ YES, DESCRIBE BELOW:
☐ BLUNT OBJECT (DESCRIBE) ☐ KNIFE/CUTTING INSTRUMENT ☐ SHOTGUN
☐ SEMI-AUTO PISTOL ☐ EXPLOSIVE DEVICE
☐ CHEMICAL WEAPON ☐ TASER/STUN GUN ☐ VEHICLE ☐ REVOLVER ☐ RIFLE ☐ OTHER (DESCRIBE)

☐ WEAPON/OBJECT PERCEIVED AS:

WEAPON USE:
☐ DNA ☐ Used - Attempt to Attack Member ☐ Obtained Member's Weapon
☐ Possessed ☐ Used - Attacked Member ☐ Member at Gunpoint
☐ Displayed, Not Used ☐ Member Shot/Shot At

DID THE SUBJECT COMMIT AN ASSAULT OR BATTERY AGAINST THE INVOLVED MEMBER PERFORMING A POLICE FUNCTION? ☐ NO ☐ YES	SUBJECT ACTIVITY Drug-Related? ☐ YES ☐ NO	Gang-Related? ☐ YES ☐ NO

TYPE OF ACTIVITY
☐ Ambush - No Warning ☐ Traffic Stop ☐ Disturbance - Domestic ☐ Investigatory Stop ☐ Man with a Gun ☐ Disturbance - Mental Health ☐ Disturbance - Riot/Mob Action/Civil Disorder ☐ Disturbance - Other ☐ Other - Describe in Narrative ☐ Processing/Transporting/Guarding Arrestee ☐ Pursuing/Arresting Subject

MEMBER 'S RESPONSE (Check all that apply)

☐ DNA ☐ UNK

REASON FOR RESPONSE? ☐ Defense of Self ☐ Defense of Department Member ☐ Defense of Member of Public ☐ Overcome Resistance or Aggression ☐ Stop Self-Inflicted Harm ☐ Fleeing Subject ☐ Subject Armed with Weapon ☐ Unintentional

FORCE MITIGATION EFFORTS

☐ MEMBER PRESENCE ☐ ZONE OF SAFETY ☐ MOVEMENT TO AVOID ATTACK ☐ TACTICAL POSITIONING ☐ NONE
☐ VERBAL DIRECTION/ CONTROL TECHNIQUES ☐ SPECIALIZED UNITS ☐ ADDITIONAL UNIT MEMBERS ☐ OTHER

CONTROL TACTICS

☐ ESCORT HOLDS ☐ WRISTLOCK ☐ ARMBAR ☐ CONTROL INSTRUMENT ☐ PRESSURE SENSITIVE AREAS ☐ EMERGENCY HANDCUFFING ☐ HANDCUFFS/PHYSICAL RESTRAINTS ☐ OTHER

RESPONSE WITHOUT WEAPONS

☐ OPEN HAND STRIKE ☐ TAKE DOWN ☐ ELBOW STRIKE ☐ CLOSED HAND STRIKE/ PUNCH ☐ KNEE STRIKE ☐ KICKS ☐ OTHER

RESPONSE WITH WEAPONS

☐ OC/CHEMICAL WEAPON ☐ OC/CHEMICAL WEAPON W/ AUTHORIZATION* ☐ LRAD W/ AUTHORIZATION* ☐ TASER ☐ CANINE ☐ BATON/EXPANDABLE BATON ☐ LESS LETHAL SHOTGUN (DESCRIBE BELOW) ☐ OTHER IMPACT MUNITIONS (DESCRIBE BELOW) ☐ REVOLVER ☐ SEMI-AUTO PISTOL ☐ RIFLE ☐ SHOTGUN ☐ OTHER

*AUTHORIZED BY (NAME)	RANK	STAR NO.	UNIT NO.

WAS ANY REPORTABLE FORCE USED AGAINST THE SUBJECT WHILE HANDCUFFED OR OTHERWISE IN PHYSICAL RESTRAINTS?
☐ NO ☐ YES IF YES, DESCRIBE SUBJECT'S ACTIONS AND MEMBER'S RESPONSE IN THE NARRATIVE SECTION.

WEAPON DISCHARGE

☐ DNA

WEAPON TYPE: ☐ CHEMICAL WEAPON ☐ TASER ☐ SEMI-AUTO PISTOL ☐ REVOLVER ☐ RIFLE ☐ SHOTGUN ☐ OTHER	NO. OF DISCHARGES OF THE WEAPON.	WEAPON SERIAL NO.	WEAPON CERT. NO.

DID THIS WEAPON CONTRIBUTE TO A SUBJECT INJURY? ☐ YES ☐ NO	DID THE DISCHARGE RESULT IN A SELF-INFLICTED INJURY? ☐ NO ☐ YES-SUBJECT ☐ YES-MEMBER	WAS SUBJECT VEHICLE USE AS A WEAPON? ☐ NO ☐ YES - AGAINST MEMBER ☐ YES - AGAINST OTHER PERSON

WAS DISCHARGE ONLY TO DESTROY/DETER AN ANIMAL? ☐ YES ☐ NO	WAS THIS AN UNINTENTIONAL DISCHARGE DURING A NON-CRIMINAL INCIDENT? ☐ YES ☐ NO	PERSON/OBJECT(S) STRUCK BY THE DISCHARGE OF MEMBER'S WEAPON (CHECK ALL THAT APPLY): ☐ SUBJECT ☐ OTHER PERSON ☐ DEPARTMENT MEMBER ☐ ANIMAL ☐ VEHICLE ☐ NONE ☐ UNKNOWN ☐ OTHER OBJECT

TASER DISCHARGE ONLY	TASER CARTRIDGE ID NO.(S)	PROPERTY INVENTORY NO.	CARTRIDGES DISCHARGED ☐ 1 ☐ 2 ☐ DNA ☐ OTHER	ADDITIONAL ENERGY CYCLES ☐ TRIGGER ☐ DNA ☐ 1 ☐ 2 ☐ OTHER ☐ ARC ☐ DNA ☐ 1 ☐ 2 ☐ OTHER	CONTACT STUN ☐ 1 ☐ 2 ☐ DNA ☐ OTHER	SPARK DISPLAY ☐ 1 ☐ 2 ☐ DNA ☐ OTHER

FIREARM DISCHARGE ONLY	WHO FIRED FIRST SHOT? ☐ MEMBER ☐ OTHER (Specify) ☐ OFFENDER	TOTAL NO. OF SHOTS MEMBER FIRED	WAS FIREARM RELOADED DURING INCIDENT? ☐ YES ☐ NO	MAKE/ MANUFACTURER	MODEL	DID MEMBER FIRE AT A VEHICLE? ☐ NO ☐ YES

NOTIFICATIONS AND NARRATIVE

NOTIFICATIONS (ALL INCIDENTS): ☐ IMMEDIATE SUPERVISOR ☐ DISTRICT OF OCCURRENCE

NOTIFICATIONS (WEAPONS DISCHARGE AND DEADLY FORCE): ☐ OEMC ☐ CPIC

NARRATIVE (IF APPLICABLE, DESCRIBE WITH SPECIFICITY, (1) THE USE OF FORCE INCIDENT, (2) THE SUBJECT'S ACTIONS, AND (3) THE DEPARTMENT MEMBER'S RESPONSE, INCLUDING FORCE MITIGATION EFFORTS AND SPECIFIC TYPES AND AMOUNT OF FORCE USED. THE INVOLVED MEMBER **WILL NOT COMPLETE THE NARRATIVE SECTION** FOR ANY FIREARM DISCHARGE INCIDENTS (WITH OR WITHOUT INJURY) OR IN ANY USE OF FORCE INCIDENTS RESULTING IN DEATH.)

REPORTING MEMBER (Print Name)	STAR/EMPLOYEE NO.	SIGNATURE

REVIEWING SUPERVISOR

TYPE OF SUBJECT INJURY
☐ None / None Apparent
☐ Minor Swelling
☐ Minor Contusion
☐ Minor Laceration/Abrasion
☐ Complaint of Substantial Pain
☐ Significant Contusion
☐ Laceration Requiring Sutures
☐ Broken/Fractured Bone(s)
☐ Gun Shot
☐ Fatal
☐ Other (Explain)

HOW WAS INJURY SUSTAINED?
☐ Intentional Act by Member
☐ Unintentional Act by Member
☐ Intentional Act by Self
☐ Unintentional Act by Self
☐ Intentional Act by Other
☐ Unintentional Act by Other

WITNESSES ☐ **UNK**

LAST NAME	FIRST NAME	M.I.	SEX ☐ M ☐ F	RACE	DATE OF BIRTH

ADDRESS	TELEPHONE NO.	WITNESS INTERVIEW ☐ INTERVIEWED ☐ REFUSED ☐ NOT AVAILABLE ☐ OTHER (Specify) ______

WITNESS STATEMENT

☐ ADDITIONAL WITNESSES

REVIEWING SUPERVISOR: COMMENTS

SUPERVISOR ON-SCENE RESPONSE ☐ NO ☐ YES

EVIDENCE TECHNICIAN? ☐ NOTIFIED ☐ RESPONDED ☐ DNA

ATTACHMENTS: ☐ **CASE REPORT** ☐ **ARREST REPORT** ☐ **SUPPLEMENTARY REPORT** ☐ **INVENTORY** ☐ **IOD REPORT** ☐ **TASER DOWNLOAD** ☐ **OTHER**

REVIEWING SUPERVISOR:

☐ **I HAVE COMPLIED WITH THE DUTIES OUTLINED IN G03-02-02.**

☐ **LOG NUMBER OBTAINED FROM THE CIVILIAN OFFICE OF POLICE ACCOUNTABILITY (COPA).**

LOG NO. OBTAINED. ______

☐ **I HAVE REVIEWED THIS TACTICAL RESPONSE REPORT AND AFFIRM THAT THE REPORT IS LEGIBLE AND COMPLETE.**

REVIEWING SUPERVISOR NAME (Print)	STAR NO.	SIGNATURE	DATE/TIME COMPLETED

DISTRIBUTION OF TRR: IF A PAPER TRR WAS COMPLETED DUE TO AN UNAVAILABILITY OF THE AUTOMATED TACTICAL RESPONSE REPORT APPLICATION:

1. **THE ORIGINAL TRR WILL BE FORWARDED TO DIRECTOR, RECORDS DIVISION - TO BE INCLUDED WITH THE CORRESPONDING CASE FILE.**
2. **A COPY OF THE PAPER TRR AND THE ATTACHMENTS WILL BE FORWARDED TO:**
   - **A. THE INVESTIGATING SUPERVISOR RESPONSIBLE FOR THE INVESTIGATION,**
   - **B. CIVILIAN OFFICE OF POLICE ACCOUNTABILITY (COPA), AND**
   - **C. DIRECTOR, INFORMATION SERVICES DIVISION, TO ENSURE DATA ENTRY AND ATTACHMENT SCANNING INTO THE AUTOMATED TACTICAL RESPONSE REPORT (A-TRR) APPLICATION.**

TRR ______ OF ______ TRR(S)

Table A1: Unconditional Covariate Balance by Subject Injury Status, OIS with firearms only

	Subject Uninjured			Subject Injured			
Variable	N	Mean	SD	N	Mean	SD	Test
Officer Characteristics							
Officer Black	302	0.228	0.421	397	0.249	0.433	F=0.409
Officer White	302	0.444	0.498	397	0.501	0.501	F=2.278
Officer Hispanic	302	0.278	0.449	397	0.237	0.426	F=1.546
Officer Male	302	0.927	0.26	397	0.95	0.219	F=1.532
Officer Age	302	37.169	7.555	397	36.693	6.957	F=0.746
Experience (Yrs)	302	9.841	6.264	397	9.637	5.818	F=0.197
Prior Incidents	302	7.45	8.703	397	8.073	9.521	F=0.79
In Uniform	302	0.401	0.491	397	0.499	0.501	F=6.695***
Rank: Officer	302	0.897	0.304	397	0.884	0.32	F=0.305
Officer Injured	302	0.126	0.332	397	0.212	0.409	F=8.842***
Officer Fired Handgun	302	0.947	0.224	397	0.982	0.132	F=6.781***
Officer Fired TASER	302	0	0	397	0	0	
Number of weapons discharged	302	1.01	0.129	397	1.02	0.141	F=0.974
Subject Characteristics							
Subject Black	302	0.752	0.433	397	0.786	0.411	F=1.138
Subject White	302	0.026	0.161	397	0.05	0.219	F=2.547
Subject Hispanic	302	0.182	0.387	397	0.149	0.356	F=1.409
Subject Male	302	0.974	0.161	397	0.987	0.112	F=1.814
Subject Age	302	27.162	10.126	397	27.889	9.763	F=0.921
Subject Armed	302	0.685	0.465	397	0.884	0.32	F=44.619***
Domestic charge	302	0.026	0.161	397	0.06	0.239	F=4.546**
Drug charge	302	0.225	0.418	397	0.141	0.349	F=8.391***
Assault charge	302	0.679	0.468	397	0.69	0.463	F=0.103
Weapon charge	302	0.358	0.48	397	0.353	0.478	F=0.018
Weapon: None	302	0.298	0.458	397	0.123	0.329	F=34.335***
Weapon: Fists	302	0.046	0.211	397	0.045	0.208	F=0.004
Weapon: Handgun	302	0.397	0.49	397	0.526	0.5	F=11.632***
Weapon: Long Gun	302	0.013	0.115	397	0.023	0.149	F=0.833
Incident Characteristics							
Active resistance	302	1.023	0.973	397	1.073	0.9	F=0.491
Passive resistance	302	2.368	1.345	397	2.728	0.98	F=16.791***
Deadly force (S)	302	0.94	0.237	397	0.992	0.087	F=16.27***
Officer fired first	302	0.788	0.409	397	0.768	0.422	F=0.388
Daylight	302	0.391	0.489	397	0.272	0.446	F=11.189***
Artificial light	302	0.467	0.5	397	0.627	0.484	F=18.29***
Darkness	302	0.003	0.058	397	0	0	F=1.315
Dawn	302	0.007	0.081	397	0.013	0.112	F=0.616
Clear weather	302	0.887	0.317	397	0.899	0.301	F=0.253
Cloudy weather	302	0.003	0.058	397	0	0	F=1.315
Fog/Haze/Smoke weather	302	0	0	397	0.003	0.05	F=0.76
Rain/Snow/Hail weather	302	0.066	0.249	397	0.068	0.252	F=0.009
Indoor	302	0.139	0.347	397	0.128	0.335	F=0.167

Note: Time period is 2004–2019. “Prior Incidents” is a variable that equals the count of previous tactical response report incidents for a given officer at the time of the shooting. “Passive resistance” are counts of passive resistance in an incident (e.g. failure to comply with a verbal command). “ Active resistance” are counts of active resistance in an incident (e.g. physically resisting arrest). “Deadly force (S)” is a binary variable that takes 1 if a subject used deadly force against an officer. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A2: Effect of OIS involving firearms and TASERs on crime reporting

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.006	0.007	0.008	-0.003	-0.000
	(0.007)	(0.007)	(0.007)	(0.005)	(0.004)
OIS	0.018***	0.019***	0.019***	0.009**	0.007**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Subject Injured x OIS	-0.004	-0.005	-0.006	-0.003	-0.004
	(0.008)	(0.008)	(0.007)	(0.006)	(0.004)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	60,365	60,365	60,365	60,365	60,365
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A3: Testing sensitivity of estimates to pre and post periods

	ln(Reported Crime + 0.1)				
	Pre: 14 Post: 14	Pre: 13 Post: 14	Pre: 12 Post: 14	Pre: 14 Post: 13	Pre: 14 Post: 12
	(1)	(2)	(3)	(4)	(5)
Subject Injured x OIS	-0.028***	-0.028***	-0.028***	-0.028**	-0.028***
	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)
Observations	10,276	9,959	9,630	9,902	9,959
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include officer, subject, and incident controls as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4: Effet of OIS involving firearms on crime reporting accounting for ShotSpotter incidents

	ln(Reported Crime)		
	(1)	(2)	(3)
Subject Injured	0.013	0.059	0.002
	(0.012)	(3,192.608)	(3,831.695)
OIS	0.024**	0.013	0.010
	(0.009)	(0.032)	(0.033)
Subject Injured x OIS	-0.031***	0.001	0.002
	(0.010)	(0.091)	(0.089)
ShotSpotter Incidents			0.013**
			(0.004)
Observations	8,344	413	413
Clusters	13	13	13
Mean (dep. var)	51.648	51.648	51.648

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5: Heterogeneous effect of OIS involving firearms and TASERs on reported crime

	ln(Reported Crime + 0.1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subject Injured x OIS	-0.004	-0.007	-0.008	-0.007	-0.012**	-0.003
	(0.004)	(0.011)	(0.006)	(0.004)	(0.005)	(0.004)
Subject Injured x OIS x Subject Unarmed		0.005				
		(0.013)				
Subject Injured x OIS x Black Subject			0.005			
			(0.008)			
Subject Injured x OIS x Black District				0.008		
				(0.008)		
Subject Injured x OIS x Different Races					0.013**	
					(0.006)	
Subject Injured x OIS x Subject Dead						0.007
						(0.057)
Observations	60,365	60,365	60,365	60,365	60,365	60,366
Clusters	22	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(ReportedCrime). All columns include officer, subject, and incident controls as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6: Effect of OIS involving firearms and armed subjects on reported crime

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.023*	0.018	0.006	-0.002	0.001
	(0.013)	(0.013)	(0.015)	(0.012)	(0.012)
OIS	0.030***	0.029***	0.029**	0.020***	0.021***
	(0.010)	(0.009)	(0.010)	(0.006)	(0.007)
Subject Injured x OIS	-0.037**	-0.036**	-0.032**	-0.021*	-0.021*
	(0.015)	(0.015)	(0.015)	(0.012)	(0.011)
Subject Unarmed		-0.036**	-0.056**	-0.047***	-0.013
		(0.017)	(0.026)	(0.012)	(0.014)
Subject Injured x Subject Unarmed			0.073*	0.070***	0.072***
			(0.038)	(0.019)	(0.023)
OIS × Subject Unarmed			-0.009	0.009	-0.003
			(0.018)	(0.013)	(0.012)
Subject Injured x OIS x Subject Unarmed			-0.032	-0.057**	-0.048**
			(0.028)	(0.022)	(0.020)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A7: Effect of OIS involving firearms and Black subjects on reported crime

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.023*	0.018	0.048	0.008	0.014
	(0.013)	(0.013)	(0.030)	(0.017)	(0.020)
OIS	0.030***	0.029***	0.046***	0.034***	0.038***
	(0.010)	(0.009)	(0.014)	(0.009)	(0.010)
Subject Injured x OIS	-0.037**	-0.036**	-0.067**	-0.049**	-0.047*
	(0.015)	(0.015)	(0.024)	(0.021)	(0.023)
Subject Unarmed		-0.036**	-0.041**	-0.030***	-0.000
		(0.017)	(0.018)	(0.009)	(0.009)
Subject Injured x Black Subject			-0.041	0.003	-0.002
			(0.033)	(0.017)	(0.025)
Subject Injured x OIS x Black Subject			0.043	0.025	0.027
			(0.030)	(0.023)	(0.025)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A8: Effect of OIS involving firearms in majority Black districts on reported crime

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.043*	0.038*	0.039*	0.013	0.028*
	(0.021)	(0.020)	(0.020)	(0.017)	(0.016)
OIS	0.049***	0.047***	0.042**	0.026*	0.030**
	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)
Subject Injured x OIS	-0.064**	-0.062**	-0.058**	-0.039*	-0.038**
	(0.024)	(0.023)	(0.022)	(0.020)	(0.018)
OIS × Black District	-0.031	-0.029	-0.024	-0.005	-0.016
	(0.020)	(0.018)	(0.018)	(0.015)	(0.015)
Subject Injured x Black District	-0.034	-0.033	-0.034	-0.004	-0.021
	(0.025)	(0.021)	(0.021)	(0.016)	(0.019)
Subject Injured x OIS x Black District	0.046	0.042	0.035	0.012	0.017
	(0.028)	(0.027)	(0.026)	(0.021)	(0.021)
Black District				-0.009	
				(32,857.696)	
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A9: Effect of OIS involving firearms and White-Black officer-subjects on reported crime

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.023*	0.016	0.011	0.004	0.011
	(0.013)	(0.013)	(0.024)	(0.016)	(0.012)
OIS	0.030***	0.029***	0.030**	0.030***	0.025**
	(0.010)	(0.009)	(0.012)	(0.009)	(0.010)
Subject Injured x OIS	-0.037**	-0.035**	-0.044**	-0.039**	-0.034*
	(0.015)	(0.015)	(0.020)	(0.017)	(0.018)
Subject Injured × diff_raceYes			0.009	0.012	0.002
			(0.035)	(0.017)	(0.017)
Subject Injured x OIS x Different Races			0.016	0.011	0.014
			(0.028)	(0.019)	(0.022)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A10: Effect of OIS involving firearms and fatally injured subjects on reported crime

	ln(Reported Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.023*	0.018	0.013	0.009	0.013
	(0.013)	(0.013)	(0.013)	(0.011)	(0.012)
OIS	0.030***	0.029***	0.027***	0.024***	0.020**
	(0.010)	(0.009)	(0.008)	(0.006)	(0.007)
Subject Injured x OIS	-0.037**	-0.037**	-0.034**	-0.028**	-0.025**
	(0.015)	(0.015)	(0.016)	(0.012)	(0.010)
Subject Dead			-0.020	0.037	-0.002
			(0.033)	(0.053)	(0.069)
Subject Injured x Subject Dead			0.065	-0.022	0.019
			(0.044)	(0.056)	(0.071)
OIS × Subject Dead			-0.015	-0.106**	-0.087
			(0.049)	(0.050)	(0.056)
Subject Injured x OIS x Subject Dead			-0.020	0.080	0.060
			(0.057)	(0.055)	(0.058)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,277	10,277	10,277	10,277	10,277
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A11: Effect of OIS involving firearms on reported serious crime

	ln(Reported Serious Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.024	0.018	0.017	0.007	0.002
	(0.018)	(0.020)	(0.019)	(0.017)	(0.014)
OIS	0.029*	0.027*	0.024*	0.013	0.013
	(0.014)	(0.014)	(0.012)	(0.011)	(0.011)
Subject Injured x OIS	-0.041*	-0.041*	-0.042*	-0.029	-0.022
	(0.022)	(0.023)	(0.023)	(0.018)	(0.017)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A12: Effect of OIS involving firearms on reported violent crime

	ln(Reported Violent Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	-0.011	-0.013	-0.018	-0.029	0.017
	(0.031)	(0.032)	(0.036)	(0.032)	(0.040)
OIS	0.065**	0.060*	0.052	0.038	0.046
	(0.030)	(0.031)	(0.031)	(0.030)	(0.034)
Subject Injured x OIS	-0.043	-0.042	-0.038	-0.018	-0.029
	(0.045)	(0.047)	(0.048)	(0.042)	(0.048)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A13: Effect of OIS involving firearms on reported less serious crime

	ln(Reported Less Serious Crime + 0.1)				
	(1)	(2)	(3)	(4)	(5)
Subject Injured	0.023	0.021	0.020	0.013	0.026*
	(0.014)	(0.013)	(0.012)	(0.010)	(0.015)
OIS	0.032**	0.033***	0.030**	0.030***	0.025**
	(0.012)	(0.011)	(0.011)	(0.008)	(0.011)
Subject Injured x OIS	-0.036**	-0.036**	-0.035**	-0.034***	-0.034***
	(0.016)	(0.016)	(0.014)	(0.010)	(0.011)
Officer Controls	✓	✓	✓	✓	✓
Subject Controls		✓	✓	✓	✓
Incident Controls			✓	✓	✓
Month FEs				✓	✓
District × Year FEs					✓
Observations	10,276	10,276	10,276	10,276	10,276
Clusters	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Crime + 0.1). All columns include district and year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A14: Heterogeneous effects of OIS involving firearms on reported serious crime

	ln(Reported Serious Crime + 0.1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subject Injured x OIS	-0.022	-0.021	-0.020	-0.025	-0.027	-0.020
	(0.017)	(0.015)	(0.018)	(0.031)	(0.027)	(0.025)
Subject Injured x OIS x Subject Unarmed		-0.007				
		(0.032)				
Subject Injured x OIS x Subject Dead			0.095**			
			(0.045)			
Subject Injured x OIS x Black Subject				0.004		
				(0.037)		
Subject Injured x OIS x Black District					0.008	
					(0.033)	
Subject Injured x OIS x Different Races						-0.000
						(0.034)
Observations	10,276	10,276	10,277	10,276	10,276	10,276
Clusters	22	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Serious Crime + 0.1). Serious crimes are UCR Part I Index crimes. All columns include officer, subject, and incident controls as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A15: Heterogeneous effects of OIS involving firearms on reported violent crime

	ln(Reported Violent Crime + 0.1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subject Injured x OIS	-0.029	-0.034	-0.012	-0.065	-0.058	-0.123*
	(0.048)	(0.052)	(0.047)	(0.079)	(0.062)	(0.071)
Subject Injured x OIS x Subject Unarmed		-0.025				
		(0.086)				
Subject Injured x OIS x Subject Dead			-1.310***			
			(0.200)			
Subject Injured x OIS x Black Subject				0.052		
				(0.094)		
Subject Injured x OIS x Black District					0.048	
					(0.082)	
Subject Injured x OIS x Different Races						0.189*
						(0.105)
Observations	10,276	10,276	10,277	10,276	10,276	10,276
Clusters	22	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Violent Crime + 0.1). Violent crimes are the following UCR Part I index crimes–homicide, rape, aggravated assault, and robbery. All columns include officer, subject, and incident controls as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A16: Heterogeneous effects of OIS involving firearms on reported less serious crime

	ln(Reported Less Serious Crime + 0.1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Subject Injured x OIS	-0.034***	-0.024*	-0.032**	-0.063*	-0.049**	-0.046**
	(0.011)	(0.012)	(0.012)	(0.032)	(0.021)	(0.022)
Subject Injured x OIS x Subject Unarmed		-0.065**				
		(0.027)				
Subject Injured x OIS x Subject Dead			0.069			
			(0.074)			
Subject Injured x OIS x Black Subject				0.041		
				(0.038)		
Subject Injured x OIS x Black District					0.026	
					(0.025)	
Subject Injured x OIS x Different Races						0.026
						(0.032)
Observations	10,276	10,276	10,277	10,276	10,276	10,276
Clusters	22	22	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193	47.193	47.193

Note: Dependent variable is ln(Reported Less Serious Crime + 0.1). Less serious crimes are UCR Part II index crimes. All columns include officer, subject, and incident controls as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A17: Effect of OIS involving firearms and TASERs on types of reported crime

	All (1)	Serious (2)	Violent (3)	Less Serious (4)
Subject Injured	-0.000	-0.001	0.010	-0.001
	(0.004)	(0.007)	(0.016)	(0.004)
OIS	0.007**	0.005	0.025**	0.007*
	(0.003)	(0.004)	(0.010)	(0.004)
Subject Injured x OIS	-0.004	-0.004	-0.018	-0.002
	(0.004)	(0.007)	(0.019)	(0.005)
Observations	60,365	60,365	60,365	60,365
Clusters	22	22	22	22
Mean (dep. var)	47.193	47.193	47.193	47.193

Note: Dependent variable in column 1 is ln(Reported Crime + 0.1), in column 2 is ln(Reported Serious Crime + 0.1), in column 3 is ln(Reported Violent Crime + 0.1), and in column 4 is ln(Reported Less Serious Crime + 0.1). Serious crimes are UCR Part I index crimes. Violent crimes are a subset of UCR Part I index crimes: homicide, rape, robbery, and aggravated assault. Less serious crimes are UCR Part II index crimes. All columns include district and year fixed effects. All columns include officer, subject, and incident controls as well as district, year, month, and district-year fixed effects. Standard errors clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$