Armed with Technology:
The Effects on Fatal Shootings of Civilians by the Police

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July 14, 2016

Abstract

The police in the United States shot and killed 986 civilians in 2015. Deaths of civilians by the police in recent years have led to protests and disruptions in several large cities, such as New York, Chicago, and Baltimore. In this study, we investigate how the use of technology by the police affects use of lethal force on civilians. Drawing upon signal detection theory, we propose a simple, stylized model on a police officer's decision to shoot. This model posits how the use of technology for intelligence access (e.g., statistical analyses of crime data) and evidence gathering (e.g., wearable body cameras) affects use of deadly force on civilians by the police. Empirical investigations with a large-scale dataset on fatal shootings revealed both encouraging and surprising findings. We found that both the use of smartphones and the statistical analyses of crime data are associated with a decrease in deadly shootings. In contrast, the use of wearable body cameras is related to an increase in the deaths of civilians by the police, contrary to an intuitive expectation that the adoption of body cameras would prevent deadly shootings. Interestingly, we also found that the observed effect of technology use is more pronounced for African Americans or Hispanics than Whites or Asians and for armed suspects than unarmed ones. We contribute to the literature by demonstrating the far-reaching role of technology use in novel contexts, specifically in highly risky, violent environments.

Keywords: Fatal Shootings, Use of Force, Intelligence, Wearable Body Cameras, Police, Signal Detection Theory

1. Introduction

On October 20, 2014, police officers responded to reports of a break-in at a Southside Chicago neighborhood. In pursuit of the suspect, one of the responding officers shot and killed a 17-year-old African American male who was reportedly carrying a knife. The video camera in a nearby patrol vehicle recorded this incident, and the victim's family members requested to make the recording public in a lawsuit against the City of Chicago. The city had been refusing to do so, at the time that the mayor was running for a re-election. However, a judge ordered the city to release the video, which revealed that the officer shot at the victim 16 times. The release of the video erupted the African American community in Chicago, protesting over police brutality and demanding resignation of the Mayor of Chicago. The officer was charged for a first-degree murder, and the police commissioner was dismissed as well. The mayor also announced several reforms to his police department, including the expanded use of Tasers and wearable cameras (*The New York Times* 2016a).

The relationship between the police and the public in many U.S. cities is more acrimonious than ever before. According to *the Washington Post*, 986 civilians were shot and killed by on-duty police officers in 2015 in the U.S. (*The Washington Post* 2016a). Several high-profile use-of-force incidents by police officers have sparked fierce protests and community upheavals in several cities such as Chicago, Baltimore, St. Paul, Baton Rouge, and Ferguson. This led to intense scrutiny from the media and the public on police practices and policies on the use of force. At the same time, however, citing a recent rise in violent crime rates, some law enforcement officials including the Director of the Federal Bureau of Investigation (FBI) have raised a concern that a so-called "Ferguson effect" makes police officers reluctant to enforce laws aggressively (*CNN* 2015), undermining the effectiveness of policing. Some officials even attributed a recent rise in crime rates to the Ferguson effect (*The New York Time* 2016b). These remarks have renewed an ongoing debate on how to strike a balance between enforcing laws for public safety and protecting the rights and lives of citizens (Hahn and Jeffries 2003, Dantzker 2010).

Policymakers and law enforcement officials are considering the use of digital technologies as a means to resolve this dilemma by improving policing capabilities (Manning 2010, Pang and Pavlou 2016). For instance, data analytics has become an essential tool for the police to gain necessary intelligence for crime solving (Chan 2004, Skogan and Frydl 2004, Bachner 2013). It is also a pillar for predictive policing, an initiative in which the police predict and deter crimes before they take place (Pearsall 2010, Haberman and Ratcliffe 2012). Police officers in the field are increasingly equipped with a range of advanced technologies such as mobile devices, gunshot detection systems, and license plate readers (Ariel et al. 2015, *Government Technology* 2015, *The Baltimore Sun* 2016). Also, video cameras mounted on police vehicles (dash-cams) or worn by officers (wearable body-cams) are expected to improve the accountability and transparency of policing by providing evidence of encounters with citizens (U.K. Home Office 2007, Harris 2010, *Harvard Law Review* 2015). To the best of our knowledge, however, we do not have sufficient understanding of the effectiveness of these technologies, particularly in terms of the use of lethal force on civilians.

Police officers have every reason to avoid killing civilians, whether or not they are criminal. Whenever an officer-involved death occurs, a police department or an external law enforcement agency (e.g. a state police or a prosecutor's office) has to spend considerable costs and manpower to investigate the incident. The police officers themselves have to undergo an intense internal-affairs investigation and close scrutiny from the media. Whether or not the shooting is deemed justified, the municipality could face a lawsuit from the family of the deceased, which could take several years to conclude in the courts or have to pay a substantial compensation to settle. After the shooting-death incident mentioned above, the City of Chicago agreed to pay the victim's family $5 million in a settlement (*The New York Times* 2016a). The City of Cleveland also recently settled with the family of a 12-year-old shooting victim for $6 million (*The Washington Post* 2016b). Besides, a civilian death by the police deteriorates the relationship of the police with the public, thus damaging the effectiveness of law enforcement (Thurman and Reisig 1996, Skolnick and Barley 1998). Against this backdrop, we investigate how police technology use for intelligence analyses and access (e.g., smartphones) and evidence gathering (e.g. wearable body cameras) affects the use of lethal force and deaths of civilians (Table 1).

Table 1. Police Technology Use

Intelligence Analyses	Records	Computerized records of criminal incidents - Narrative descriptions of offenses - State statutes or municipal offense codes - Victim characteristics - Suspect characteristics - Offense location - Offense date and time
	Statistical Analyses	If a police department conducts research or statistical analyses using computerized records
Intelligence Access	Access	Information that patrol officers have direct access from the field - Motor vehicle records - Driver license records - Criminal history - Outstanding warrants - Protection orders - History at address
	Smartphone	If police officers in the department use smartphones
Evidence Gathering	Camera mounted on patrol vehicles (dash cams) Wearable body cameras (body cams)	

To theorize the role of technology use, we draw upon signal detection theory (Green and Swets 1988, Wicknes 2002, MacMillan 2002, Correll et al. 2002, 2014) to propose a simple, stylized model for a police officer's decision to pull the trigger. We model that when deploying deadly force, the officer takes two factors into consideration – (i) a risk that a suspect poses an imminent, life-threatening danger to bystanders and/or the officer herself and (ii) a perceived risk that she would be held accountable for the death. Based on this model, we derive how technology use influences fatal shootings by police officers. First, technology use for intelligence analyses and access help reduce the ambiguity in the degree of violence of the suspect perceived by an officer. Second, the use of evidence gathering technologies, such as wearable body cameras, is likely to help the officer justify her shooting, making her less reluctant to deploy fatal force.

We test these predictions with a novel dataset that integrates multiple data sources. The unit of analysis in this study is a local police department in the U.S. We collected the records of civilian deaths by police shootings in 2015 from *the Washington Post*. In addition to these data, we acquired additional police homicide records in 2013-2014 from killedbypolice.net and the FBI. We also obtained information on police technology use from the Law Enforcement Management and Administration Survey (LEMAS) published by the U.S. Department of Justice. We built a large-scale dataset of 2,652 local police departments across the U.S. The dependent variable is the number of civilians shot and killed by officers in 2015. As our identification strategy, we adopted a spatial-autoregressive model to account for unobserved local heterogeneity (Arraiz et al. 2010, Drukker et al. 2013). We controlled for a variety of indicators for crime rates, police operations, and demographic and socioeconomic conditions.

Our empirical analysis produced several interesting findings. First, we found that in police departments that conduct statistical analyses of digitized crime data, there are 2.15% fewer fatal shootings, substantiating our theoretical prediction that criminal intelligence can prevent police officers from using lethal force. Similarly, the use of smartphones by officers for intelligence access is related to 2.72% fewer deadly shootings. We obtained similar results from the alternative data from killedbypolice.net and the FBI. Surprisingly, we found that the use of wearable video cameras is associated with a 3.64% increase in shooting-deaths of civilians by the police. We explain that video recordings collected during a violent encounter with a civilian can be used in favor of a police officer as evidence that justifies the shooting. Aware of this evidence, the officer may become less reluctant to engage in the use of deadly force. We conducted more in-depth analyses with incident circumstances (e.g. whether a subject was armed) and demographics of victims (e.g. race, age), and we obtained more intriguing findings. Notably, the above-mentioned effect of technology use on fatal shootings is more pronounced for (a) African American or Hispanic victims than Whites or Asians and (b) for armed suspects than unarmed civilians.

We contribute to the Information Systems (IS) literature by showing the significant impacts of technology use in highly uncertain and violent encounters. To the best of our knowledge, this study is the first to theorize how technology use shapes human behaviors in a risky, life-or-death setting. To do so, we adopted a new interdisciplinary approach that integrates theories from multiple disciplines – IS, criminology, and psychology. We also contribute to the literature by uncovering the nuanced effects of technology use that vary by race, gender, and age. By doing so, this study extends the literature on the societal impacts of IS (e.g. Chan and Ghose 2016, Greenwood and Wattal 2016, Jha et al. 2016, Venkatesh et al. 2016) and uniquely contribute by venturing out from the comfort zone in the business sector and tacking one of the most contentious societal challenges in the U.S and other countries.

This study offers crucial implications for policymakers and practitioners in law enforcement. In response to nationwide attention on the police use of lethal force, a number of police departments are considering increased use of wearable body cameras, hoping that this approach will ultimately reduce deaths of civilians by the police (Ariel et al. 2015). We provide empirical evidence that demonstrates otherwise; the use of body cameras by officers is associated with more deaths of civilians. Our research informs policymakers in law enforcement that the use of technology for intelligence analyses and access can be more effective in preventing civilian deaths, particularly for African Americans and Hispanics.

2. Prior Work

In the IS literature, there is a dearth of research on crimes and violence. Among the few studies, Chan et al. (2016) found that the introduction of broadband Internet to a locality was associated with an increase in hate crimes. Greenwood and Wattal (2016) found that the entry of a ride-sharing service led to a decrease in alcohol-involved vehicular homicides. Based on the IT productivity literature, Garicano and Heaton (2010) expected to find positive effects of IT use on police performance measured by crime occurrence and clearance rates, but they only found insignificant effects. Hekim et al. (2013) also did not find a significant impact of IT use on crime clearance rates. A few prior studies in the criminology and public administration literatures have examined how technology use influences police practices, policies, and outcomes. For example, Nunn (2001) found that more computer use in police departments was associated with an increase in operational expenditures and a decrease in the size of the police force. In a qualitative case study, Chan (2001) found that IT use was associated with improved transparency in interactions with citizens and increased use of data by police officers. To the best of our knowledge, our study is the first to investigate the impact of technology use on fatal shootings by the police.

The criminology literature has been interested in analyzing police officers' decisions to shoot. Prior studies extensively drew upon signal detection theory from psychology to model this decision (e.g. Correll et al. 2002, 2006, 2007a, Kenworth et al. 2011, Ma and Correll 2011, Akinola and Mendes 2012, Sandler et al. 2012, Sim et al. 2013, Ma et al. 2013). These studies conducted experiments with videogames that simulated a confrontation with a criminal suspect (e.g. Correll et al. 2002). In a 2-by-2 manipulation, a suspect was shown to be either Black or White and either armed with a gun or unarmed. Student participants were asked to press a button to shoot if the target appeared to be armed. The results demonstrated substantial racial bias by the participants in shooting decisions. Specifically, they shot unarmed Black targets more frequently than unarmed Whites (false alarms) and missed to shoot armed White targets more frequently than armed Blacks (misses) (Correll et al. 2002). Subsequent studies produced substantiating but more nuanced findings (e.g. Correll et al. 2006, 2007b, Ma and Correll 2011, Kenworthy et al. 2011, Sadler et al. 2012, Ma et al. 2013). For instance, Correll et al. (2007a) and Sim et al. (2013) showed that actual police officers demonstrated racial bias in shooting decisions to a lesser extent than untrained civilian participants.

The criminology literature has also examined which factor influences police use-of-force incidents using archival datasets (e.g. Jacobs and O'Brien 1998, Alpert and MacDonald 2001, Smith 2003, 2004, McElvain and Kposowa 2008). For instance, Jacobs and O'Brien (1998) showed that killings by police officers in large U.S. cities are affected by crime rates (murder), divorce rates, and the racial make-up of population. McElvain and Kposowa (2008) found that the characteristics of police force such as gender, age, and educational attainment are significantly related to the deaths of criminals by the police. Our study differs from prior literature in that ours is the first to investigate the impact of technology use by the police on civilian deaths. In addition, prior studies use police homicide data from the FBI, which is considered to be incomplete, as we explain below. In contrast, this study uses a more comprehensive civilian-death dataset from independent sources (the Washington Post and killedbypolice.net).

In sum, our theoretical model draws upon and integrates research streams from three distinct disciplines – the impact of technology on law enforcement, the behavioral model of police use of force, and the antecedents of crimes and violence.

3. Theoretical Model

On April 23, 2015, the Long Beach, California, Police Department responded to a report of trespassers in a vacant apartment. During an encounter with suspects, one officer fatally shot and killed a 19-year-old Hispanic male. According to the officer's account, while turning toward him, the suspect was bending his knees and extending his arm to grab what appeared to be a gun. In fear of his life, the officer fired at the suspect three times. A subsequent investigation, however, found no weapon on the suspect (*Long Beach Press-Telegram* 2015).

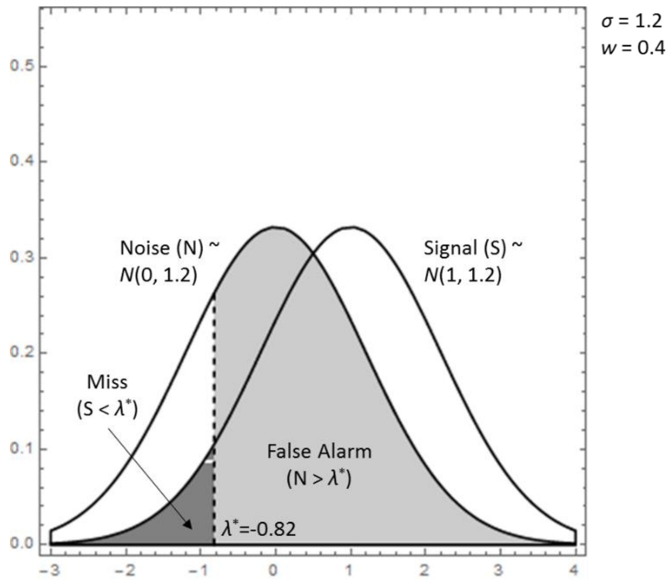
In order to model such a confrontation between a police officer and a potentially violent suspect in a highly uncertain, life-threatening circumstance, we introduce a simple, stylized model that depicts the officer's decision to deploy a lethal weapon. According to signal detection theory, the officer's decision can be modelled as a yes-or-no decision under uncertainty (Correll et al. 2002, 2006, 2007a). Such decisions include diagnosing a tumor by a doctor, predicting an earthquake by a seismologist, calling whether a ball is a strike by a baseball umpire, or deciding whether a person is guilty or not by a juror (MacMillan 2002).

3.1. The Model

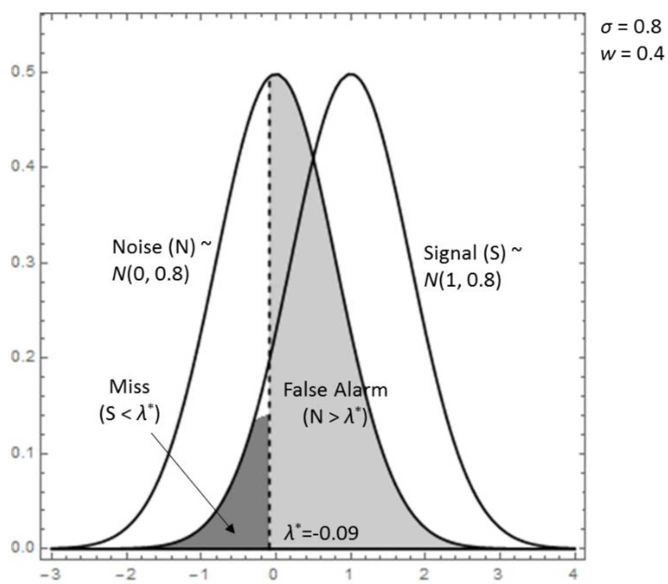
Facing with a potentially violent suspect, a police officer must detect whether or not he is armed with lethal weapon that could pose life-threatening danger to others and decide whether to overpower him with deadly force. In such an uncertain and risky situation, she should make this decision within a split second. If the suspect is indeed armed and she fails to neutralize him, she herself or other bystanders could be in grave danger. A risk to the officer, however, is that he could be unarmed, and mistakenly killing an unarmed suspect could result in punishment or criminal liability against the officer. This is a major, life-or-death, decision that needs to be made under extremely stressful conditions.

Figure 1. Shooting Decision by Signal Detection Theory

(a) Higher Uncertainty



(b) Lower Uncertainty



Signal detection theory explains that when confronted with the suspect, the officer receives an ambiguous sign on threats and has to discern whether it is a noise (e.g. the absence of threat) and a correct signal (the presence of threat). For instance, in the example of Long Beach shooting introduced above, the officer had to determine whether the suspect was trying to grab a gun (signal) or something else that is non-threatening (noise), and it turned out that the officer made an incorrect decision that the suspect was armed. Following signal detection theory, both perceived noise (*N*) and perceived signal (*S*) are assumed to be stochastic; specifically, in line with the theory, we assume that *N* and *S* follow a normal distribution.

$$N \sim \mathrm{N}(0, \sigma) \text{ and } S \sim \mathrm{N}(1, \sigma) \quad (1)$$

In this distribution, the variance (σ) represents the uncertainty the officer faces in distinguishing noise and signal. As shown in Figures 1-(a) and 1-(b), when σ is lower, it becomes easier for the officer to determine whether the suspect is life-threatening or not. Signal detection theory puts forth that as shown in Figure 1, the officer decides to pull a trigger when the cue she perceives is stronger than a certain criterion λ. It results in one of the four outcomes as in Table 2.

Table 2. The Four Possible Outcomes of a Shooting Decision

	Not Shooting	Shooting
Noise (Non-Threatening)	Correct Reject $P(N < \lambda)$	False Alarm $P(N > \lambda)$
Signal (Threatening)	Miss $P(S < \lambda)$	Correct Hit $P(S > \lambda)$

In deciding to pull the trigger, the officer takes into consideration a tradeoff between (i) immediate dangers to lives of bystanders and herself and (ii) risks of becoming liable for her use of lethal force. Thus, the officer's interest in this situation is to minimize both a miss, which could lead to deaths of the innocent and herself, and a false alarm, which could result in a death of the unarmed suspect that the officer could be held responsible for. The dilemma to the officer is that too low a criterion λ carries a high possibility of a miss, while too high a λ carries a high likelihood of a false alarm. We assume that the officer chooses the optimal λ that minimizes the following risk function.

$$\min_{\lambda} R = P(\text{Miss}) + w\, P(\text{False Alarm}) = P(S < \lambda) + w\, P(N > \lambda) \quad (2)$$

In other words, the officer minimizes the weighted sum of the odds of a miss and a false alarm. We can reasonably assume $0 < w < 1$, since it is more important for the officer to protect the lives of the innocent.

The first order condition is given by

$$\frac{\partial R}{\partial \lambda} = \frac{1}{\sqrt{2\pi}\sigma}\left(e^{-\frac{1-\lambda}{2\sigma^2}} - we^{-\frac{\lambda}{2\sigma^2}}\right). \quad (3)$$

Solving $\frac{\partial R}{\partial \lambda} = 0$ produces

$$\lambda^* = \frac{1}{2} + \sigma^2 \log w. \quad (4)$$

The second-order condition confirms that λ^* minimizes R.

$$\frac{\partial^2 R}{\partial \lambda^2}_{\lambda=\lambda^*} = \frac{\sqrt{w}}{\sqrt{2\pi}\sigma^3} e^{-\frac{1+4\sigma^2(\log w)^2}{8\sigma^2}} > 0 \quad (5)$$

3.2. The Impact of Technology Use for Intelligence Analyses and Access

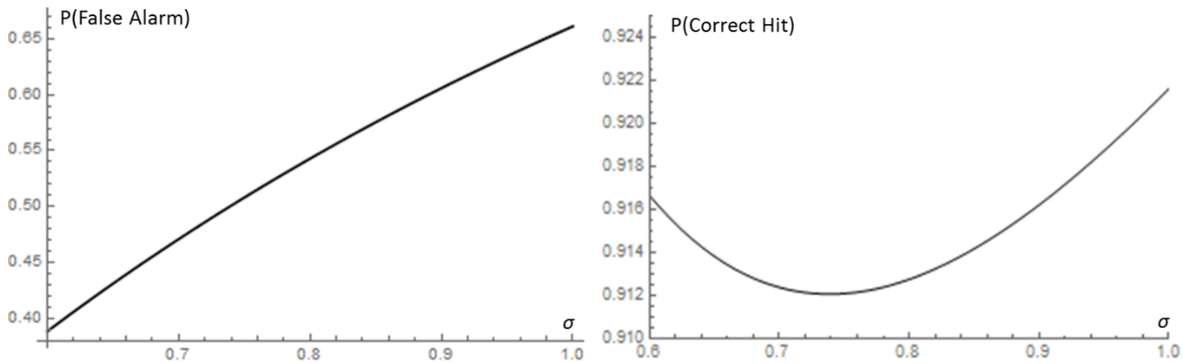
We posit that the use of technology for intelligence analyses and access reduces perceived ambiguity (σ), and we examine how a decrease in σ affects the officer's decision to shoot.

Lemma 1. (The Effect of Uncertainty on the Shooting Criterion) $\frac{\partial \lambda^*}{\partial \sigma} = 2\sigma \log w < 0$ since $0 < w < 1$.

Lemma 1 indicates that the more uncertain the cues (σ) are, the lower criterion (λ^*) the officer uses to shoot. Figures 1-(a) and 1-(b) illustrate this effect. When the signal and the noise are more uncertain, there is a greater risk of a miss (failing to shoot an armed and dangerous suspect), causing the officer to shoot more liberally with a lower λ^*. On the other hand, when the officer becomes more certain in discerning between perceived signal and noise, she uses a higher criterion and deploys force more conservatively.

Figure 2. The Impact of Uncertainty on the Likelihood of Shooting

(a) False Alarm (b) Correct Hit



Lemma 2. (The Effect of Uncertainty on the Likelihood of Shooting)

(a) (False Alarm) $\frac{\partial}{\partial \sigma} P(N > \lambda^*) = \frac{1-2\sigma^2 \log w}{2\sqrt{2\pi}\sigma^2} e^{-\frac{(1+2\sigma^2 \log w)^2}{8\sigma^2}} > 0.$

(b) (Correct Hit) $\frac{\partial}{\partial \sigma} P(S > \lambda^*) = -\frac{1+2\sigma^2 \log w}{2\sqrt{2\pi}\sigma^2} e^{-\frac{(1-2\sigma^2 \log w)^2}{8\sigma^2}} > 0$ if and only if $\sigma > \frac{1}{\sqrt{-2\log w}}$ or $\lambda^* < 0$.

Lemma 2-(a) shows that a lower uncertainty (σ) monotonically leads to a less likelihood of shooting due to a false alarm (Figure 2-a). On the other hand, Lemma 2-(b) shows that a decrease in σ is associated with fewer correct hits only when σ is high, as illustrated in Figure 2-(b). When uncertainty (σ) is sufficiently low, on the other hand, the officer can easily distinguish between the absence (noise) and the presence (signal) of threats, and thus, a decrease in σ leads to more correct hits.

We theorize that the use of technology for intelligence analyses and access reduces the ambiguity (σ) that a police officer faces when confronted with a violent suspect. For instance, with intelligence access technologies, such as smartphones or in-vehicle laptops, the officer is able to obtain actionable intelligence about the potential offender, such as criminal history, behavioral characteristics, types of weapons, or his *modus operandi*, real-time and on the fly. Intelligence access technologies can also help the officer better determine whether the suspect poses a life-threatening danger to her or others. Moreover, statistical analyses of digitized crime data provide police officers with a range of credible intelligence, such as crime prediction, behavioral patterns of organized criminals, or movement of weapons and drugs. Such technologies provide intelligence at a granular level, such as neighborhoods or blocks, enabling the police to conduct more targeted policing (Pearsall 2010, Haberman and Ratcliffe 2012). Accordingly, if intelligence suggests that the suspect is unlikely to be dangerous, the officer would refrain from deploying lethal force against him. With intelligence that the suspect is likely to be armed and dangerous, the officer can coordinate with fellow officers to overwhelm him with backup support and prevent him from resisting violently. This leads us to propose:

Proposition 1. *(The Impact of Technology Use for Intelligence Analyses and Access)*
(i) The use of intelligence analyses and access technology is associated with a reduction in the shooting-deaths of unarmed targets (Lemma 2-a).
(ii) If technology use for intelligence analyses and access reduces the uncertainty (σ) moderately, it would lead to a decrease in the shooting-deaths of armed targets (Lemma 2-b).
(iii) But if technology use for intelligence analyses and access further reduces σ substantially, it would lead to an increase in the fatal shootings to armed targets (Lemma 2-b).

A rationale for Proposition 1-(iii) is that when σ is sufficiently low, police officers would be able to easily distinguish threatening targets from non-threatening civilians. In the following sections, we will empirically examine to what extent technology use for intelligence affects deaths of civilians.

3.3. The Impact of Evidence Gathering Technology

Here, we put forth that the use of technology for evidence gathering decreases the weight (w) in the risk function (Eq. 2). We explain why this would be the case below.

Lemma 3. (The Impact of Weight on the Shooting Criterion) $\frac{\partial \lambda^*}{\partial w} = \frac{\sigma^2}{w} > 0$

Lemma 4. (The Impact of Weight on the Likelihood of Shooting)

(a) (Correct Hit) $\frac{\partial}{\partial w} P(S > \lambda^*) = -\frac{\sigma}{w\sqrt{2\pi}} e^{-\frac{\left(1-2\sigma^2 \log w\right)^2}{8\sigma^2}} < 0$

(b) (False Alarm) $\frac{\partial}{\partial w} P(N > \lambda^*) = -\frac{\sigma}{w\sqrt{2\pi}} e^{-\frac{\left(1+2\sigma^2 \log w\right)^2}{8\sigma^2}} < 0$

Lemma 3 suggests that when a police officer weighs the risk of a false alarm more importantly (i.e. w is high), she uses a higher criterion (λ^*), pulling the trigger more conservatively. According to Lemma 4, this higher λ^* always leads to lower chances of shooting both threatening and non-threatening suspects (correct hits and false alarms, respectively).

Lemma 4 suggests that the use of evidence gathering technologies, such as video cameras mounted on patrol vehicles (dash-cams) or worn by officers (body-cams), increases fatal shootings by the police. With video cameras, the officer would believe that the video recordings are likely to help justify her use of force (Harris 2010), reducing the perceived risk of false alarms (w). For instance, in *Scott v. Harris* (550 US 372), the U.S. Supreme Court ruled in an 8-1 decision that the use of deadly force by Sheriff's Deputy Harris in Georgia was justified, and the Justices used the video recording from the defendant's patrol vehicle as key evidence in their decisions (The U.S. Supreme Court 2007), creating a national precedent for use of force litigations with video recordings. Kahan et al. (2009) conducted an experiment with this case and found that 74% of the participants who watched the same video agreed that the deputy appropriately used force to the subject who posed danger to the public. Ariel et al. (2015) found in a randomized field experiment that the use of wearable body cameras is associated with a 92% reduction in the number of use-of-force complaints per officer from citizens. Jennings et al. (2015) also obtained a similar finding and also found that the majority of the officers who worn body cameras perceived the cameras to be helpful in evidence collection and recollection of events. Consequently, in her risk calculation, the officer will put more emphasis on preventing misses (i.e. a lower λ^*), which according to Lemma 4, lead to more use of deadly force against the criminal target.

Proposition 2. *The use of evidence gathering technology is associated with an increase in shooting-deaths of civilian targets.*

In sum, our stylized model based on signal detection theory provides the following propositions. First, the use of technology for intelligence analyses and access can reduce fatal shootings by police officers if it moderately reduces ambiguity (σ) that the officer faces in violent encounters. Second, with a substantial decrease in σ, intelligence technology use can lead to an increase in fatal shootings. Third, the model predicts that the use of evidence gathering technologies is associated with an increase in the use of deadly force. We will empirically test these predictions in the sections to follow.

4. Research Methodology

4.1. Data and Measures

We conducted empirical analyses with a dataset that combines information from a variety of public sources. The unit of analysis is local police departments in the U.S. (cities, townships or counties).

The dependent variable is the number of civilians shot and killed by on-duty police officers in 2015. This data is collected from the Washington Post police-involved shooting database, which compiles the entire civilian shooting-death records in 2015 from news reports, social media, online sources, and other public records. The Washington Post obtained additional information from its own follow-up investigations and by filing Freedom of Information Act requests to law enforcement agencies. This dataset provides detailed, comprehensive information of shooting incidents such as a victim's gender, race, age, and mental status and types of weapon that the victim used, all of which we use in our analyses below. The dataset does not include records of civilian deaths by off-duty police officers and non-shooting deaths (e.g. civilian deaths by vehicle accidents involved with patrol cars). We excluded incidents by federal and state law enforcement officials (e.g. the FBI, the Drug Enforcement Agency, or a state highway patrol) and specialized police agencies (e.g. park, transit, or school police). Carefully reading each shooting-death report, we identified to which department the police officer who killed a civilian belongs.[1]

[1] For instance, suppose that a police officer in City A chased a suspect who fled to a nearby jurisdiction (City B) and ended up killing him in City B. We coded that the suspected is killed by the officer from City A, not City B. In a case that a suspect is killed by officers from multiple agencies, we conducted an extensive search to find out which officer killed the suspect, and if it is unclear, we excluded the case.

For additional analyses with homicides by the police in 2013 and 2014, we collected data from the two sources – (i) a Web site called killedbypolice.net and (ii) the Uniform Crime Reports (UCR) database[2] maintained by the FBI. Like the Washington Post, killedbypolice.net uses news and Internet sources to build a compilation of civilian deaths by police officers. Nonetheless, we deem the data from killedbypolice.net to be less reliable, because the site is completely anonymous and does not disclose about who operates the site and builds the database, from which source it collects information, and which methodology it uses. The UCR Supplementary Homicide Reports from the FBI includes the number of "felons" killed by police officers (Smith 2004, McElvain and Kposowa 2008). However, this data source is considered to be incomplete, because it only includes the deaths of those who the police determined to be "felons"; in other words, it only reports incidents of police-caused homicides the department itself deemed justified (*Five Thirty Eight* 2014). Indeed, the UCR reports that the number of civilians killed by police in 2011-2013 is as many as 450 per year; on the other hand, the Washington Post reports that 986 citizens were killed by police in 2015 (*The Washington Post* 2016a). Consequently, we consider the Washington Post database to be more comprehensive, reliable, and objective than the two other sources.

We obtained police IT data and other information on police operations from the Law Enforcement Management and Administrative Statistics (LEMAS) collected by the Bureau of Justice Statistics (the BJS) under the U.S. Department of Justice (DOJ). In 2013, the BJS conducted a survey with a random sample of 2,800 state and local law enforcement agencies. This dataset includes information on police personnel, operations, equipment, policies, and technology use.

Combing the data from the Washington Post and the LEMAS, we built a cross-sectional dataset of 2,657 local police departments. Table 3 describes the profiles of police departments in the sample. Our sample covers both large and small cities and both urban and rural areas across the U.S. According to *t*-tests, the departments in the sample are not significantly different from others with respect to population

[2] At the time of our data collection in March 2016, the UCR database for 2015 was not available.

or crime rates. They are also nationally representative in terms of median income, racial make-up, and other demographics.

Table 3. Profiles of Police Departments

Population	Number of Departments
> 1,000,000	40
500,000 – 1,000,000	76
200,000 – 500,000	173
100,000 – 200,000	259
50,000 – 100,000	396
20,000 – 50,000	527
10,000 – 20,000	380
< 10,000	806
Urban/Rural	**Number of Departments**
Urban [1)]	1,611
Rural	1,046
Share of White Population	**Number of Departments**
> 90%	841
70% - 90%	1,104
50% - 70%	462
< 50%	250
Median Household Income	**Number of Departments**
> $70,000	372
$50,000 - $70,000	740
$30,000 - $50,000	1,349
< $30,000	196

[1)] Located in Metropolitan Statistical Areas with population over 200,000

Tables 4A describes the main variables. Technology use for intelligence analyses and access are measured as follows: *Records* is the number of categories in computerized data that a police department maintains (e.g. offense descriptions, suspect and victim characteristics, and offense locations). *Statistical Analyses* is a dummy variable that is equal to one if the police department conducted research or statistical analyses using computerized records of criminal incidents in 2013. *Access* is the number of data categories that patrol officers in the field have direct electronic access to (e.g. criminal histories, driver license records, and outstanding warrants). *Smartphone* is a dummy variable that is equal to one if officers use smartphones for data collection and access. For the use of evidence gathering technology, we used two variables – *Dash Camera* and *Body Camera* – which are equal to one if the police department uses video cameras installed on patrol vehicles and worn by officers, respectively. Table 5 provides the descriptive statistics.

Table 4A. Variable Definitions and Data Sources (Main Variables)

Variable	Definition	Data Sources
Dependent Variable		
Civilian Killed	Number of civilians shot and killed by police department in 2015	The Washington Post
Independent Variables – Police IT Use		
Records	# of computerized crime data records categories	Law Enforcement Management and Administration Survey (LEMAS) from the BJS
Statistical Analyses	1 if department conducts research or statistical analysis with computerized crime data	
Access	# of crime data categories accessible by patrol officers	
Smartphone	1 if officers are equipped with smartphones	
Dash Camera	1 if patrol vehicles are equipped with video cameras	
Body Camera	1 if patrol officers are equipped with video cameras	
Control Variables – Crime Occurrence and Clearance		
Crime Occurrence	Log (# of crimes known to police in 2013-2014)	Uniform Crime Reports (UCR) from the FBI
Crime Clearance	Share of crimes cleared to crimes known in 2013-2014	
Officer Assaults	Log(# of officers killed and assaulted in the line of duty in 2013-2014)	
Control Variables – Basic Locality Information		
Population	Log (population)	UCR
Miles	Log (square-miles covered by department)	
MSA Core City	1 = core city of metropolitan area; 0 = otherwise	
Control Variables – Police Operation		
Operational Budget	Log (operational budget ($) per capita)	LEMAS
Education Requirements	Educational requirements for new officers (1 = no requirement, 4 = high school or higher)	
White Officer	Share of White officers to total officers with arrest powers	
Female Officer	Share of female officers	
Weapon	# of types of sidearm (e.g. 10mm) allowed in duty	
Special Units	# of special units dedicated to certain crimes	
Community Policing	# of community policing training hours	

Table 4B. Variable Definitions (Demographic and Socio-Economic Conditions)

Variable	Definition
Data Sources - American Community Survey from the U.S. Census Bureau	
Control Variables – Demographic Information	
Male	Share of male population
White	Share of White-only population
Young	Share of young (15-24) population
High School	Share of population with a high school degree or higher
Control Variables – Economic Conditions	
Income	Median household income ($ thousand)
Inequality	Gini coefficient for income inequality
Vacant Homes	Number of vacant homes per capita
Control Variables – Social Conditions	
Moved	Share of population who moved within one year
Female Household Head	Share of female household heads (a single mother or a single grandmother)
Two Parent Household	Share of households with two parents

4.2. Identification Strategy

We took several approaches to address potential endogeneity concerns. First, our estimation controls for state and MSA (metropolitan statistical area) fixed-effects to account for potential *unobserved heterogeneity* in terms of local economic conditions or regional law enforcement practices. Second, regional unobserved heterogeneity could be correlated with each other among neighboring localities. One possible source is spatial contagion of crimes and violence. As criminals are unlikely to restrict their behaviors into a single local area or jurisdiction, unobserved factors in one municipality are likely to be correlated with those in neighboring municipalities. In addition, unobserved economic and societal circumstances or policing practices could be similar among jurisdictions in one region. In order to account for this possibility, we adopted generalized spatial two-stage least-square (GS2SLS) estimators for spatial-autoregressive residuals (Kelejian and Prucha 2010, Arraiz et al. 2010, Drukker et al. 2013). To do so, we estimated the following specification.

Table 5. Descriptive Statistics (N = 2,657)

Variable		Mean	Std. Dev.	Minimum	Maximum
Civilian Killed	(1)	0.2149	0.9031	0	21
Records	(2)	6.9289	1.7311	0	8
Statistical Analyses	(3)	0.6692	0.4706	0	1
Access	(4)	4.3963	2.1841	0	6
Smartphone	(5)	0.6282	0.4834	0	1
Dash Camera	(6)	0.7166	0.4507	0	1
Body Camera	(7)	0.2744	0.4463	0	1
Crime Occurrence	(8)	6.7237	2.3912	0	12.8498
Crime Clearance	(9)	0.3050	0.1862	0	1.1906
Officer Assaults	(10)	1.0349	1.6426	0	7.5914
Population	(11)	10.1265	1.6995	5.2781	16.1144
Miles	(12)	3.3963	2.2579	-1.8420	9.9061
MSA Core City	(13)	0.1656	0.3718	0	1
Operational Budget	(14)	4.8754	1.4601	0	8.9258
Education Requirements	(15)	1.2303	0.7020	0	4
White Officer	(16)	0.8253	0.2381	0	1
Female Officer	(17)	0.0930	0.0775	0	0.6250
Weapon	(18)	9.4919	2.1031	0	12
Special Units	(19)	3.3007	3.8007	0	14
Community Policing	(20)	1.3429	1.2651	0	3
Male	(21)	0.4889	0.0263	0.3458	0.8163
White	(22)	0.7794	0.1819	0.0017	1
Young	(23)	0.1401	0.0542	0.0145	0.7850
High School	(24)	0.2026	0.0637	0.0140	0.4842
Income	(25)	51.3251	20.1283	15.1020	207.2220
Inequality	(26)	0.4403	0.0481	0.2762	0.6311
Vacant Homes	(27)	0.0671	0.1093	0	3.0694
Moved	(28)	0.1678	0.0626	0.0251	0.5833
Female Household Head	(29)	0.0542	0.0276	0	0.2758
Two Parent Household	(30)	0.1497	0.0454	0.0106	0.4375

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \text{ and } \mathbf{u} = \rho\mathbf{M}\mathbf{u} + \boldsymbol{\epsilon} \tag{5}$$

In this model, **M** is a spatial-weighting matrix in which non-diagonal elements are inverses of the Euclidean distance between two municipalities and the diagonal elements are zero. In other words, the correlation in unobserved factor (**u**) between two localities is inversely related to the distance between the two. This is a reasonable assumption; it is well-known in the public economics literature that in policy implementation and delivery of public services, neighboring local governments imitate each other (Besley and Case 1995, Figlio et al. 1999, Baicker 2005). Hence, jurisdiction-specific unobserved heterogeneity that may affect police use of force is likely to be spatially correlated. While our dataset is cross-sectional, this GS2SLS approach enables us to tease out unobserved heterogeneity (**u**) from residuals by taking advantage of the distance among the jurisdictions. Monte Carlo simulations show that estimates from Equation 5 are consistent and exhibit very little bias even in small samples (Kelejian and Prucha 2010). This proposed method has widely been used by many recent studies in urban and regional economics (e.g. Holly et al. 2011, Breustedt and Habermann 2011, Van Duijn and Rouwendal 2013).

Third, in order to control for observable heterogeneity of localities, the model includes several control variables that may affect police use of lethal force (Tables 4A and 4B). We controlled for the number of occurrences in violent and property crimes and the crime clearance rate (percentage of crimes cleared) in 2013 and 2014.[3] The more frequently crimes occur or the more vigorously the police attempt to clear crimes, the more frequently they are likely to use deadly force (Alpert and MacDonald 2001, Jacobs and Carmichael 2002, McElvain and Kposowa 2008). We also controlled for the number of police officers killed and assaulted in the line of duty, since police officers are more likely to use lethal force when they are in danger. The data for crimes and officer deaths/assaults were obtained from the UCR. Other control variables also include basic locality information such as population, geographic size, and whether the department covers the core city in an MSA.

Our estimation also controlled for several indicators for police operations and personnel that the criminology literature suggests to affect crimes and violence (Jacobs and O'Brian 1998, Adams et al. 2005, Kaminski 2008, McElvain and Kposowa 2008, Fridell et al. 2009, Kaminski and Stucky 2009, Cordner 2014). These variables include the size of operational budget, educational requirements for officers, the share of white and female officers, the types of weapons authorized to use, the number of specialized units, and community-oriented policing trainings. The data for these measures were obtained from the LEMAS (Table 4A). We also controlled for demographic, economic, and societal indicators in localities, utilizing data from the American Community Survey by the U.S. Census Bureau (Table 4B). The demographic indicators are the share of male, White, and young (15-34) and level of educational

[3] Crime occurrence and clearance data in 2015 from the UCR is not available at the time of our data collection.

attainment. We use these variables to measure the share of most crime-prone population (e.g. Miethe et al. 1991, Baumer et al. 1998, Baller et al. 2006, Kaminski 2008, Kent 2010, Garicano and Heaton 2010). The economic measures are median household income, income inequality, and share of vacant homes, following the criminology literature that economic distress is significantly related to crimes and violence (e.g. Baumer 1994, Baumer et al. 1998, Batton and Wilson 2006, Garicano and Heaton 2010). Finally, social disorganization theory suggests that social instability is strongly related to crimes and violence (e,g, Land et al. 1990, Baumer et al. 1998, Baumer 1994, Baller et al. 2006). To measure social instability, we used societal indicators for population movement and household characteristics.

Fourth, *reverse causality* could be a concern in this study; the use of video cameras could be motivated by frequent occurrences of police use-of-force incidents. In the following section, we present a series of robustness checks such as falsification tests and Heckman (1989) estimations for *self-selection*, in which we address endogeneity problems due to reverse causality. To do so, we utilize the data on criminal deaths by the police prior 2013 from the UCR.

Fifth, *measurement error* in the dependent variable is unlikely to be a problem. We believe that the Washington Post provides the most comprehensive records of fatal shootings by the police. Even though there could be unreported incidents in use of deadly force, such cases are believed to be rare (Jacobs and O'Brien 1998), since it is very difficult and politically risky for the police to cover up officer-involved homicide cases. Measurement errors in the technology use variables could be a concern, in that we regressed fatal shootings in 2015 on technology use in 2013. It is possible that technology use in 2015 could be different from 2013. To alleviate this concern, we will present estimations with alternative data sources such as killedbypolice.net and the UCR for civilian deaths in 2013 and 2014.

Table 6. The Baseline Estimation Results

Dependent Variable	**Log(Civilian Killed + 1)**			
Method	Spatial Autoregressive Regression			
Data Source	The Washington Post	killedbypolice.net	The Washington Post & killedbypolice.net	UCR
Year	2015	2013-2014	2013-2015	2013-2014
	(1)	(2)	(3)	(4)
Records	-0.0023 (0.0027)	-0.0009 (0.0032)	-0.0026 (0.0038)	-0.0026 (0.0028)
Statistical Analyses	**-0.0256*** (0.0098)**	**-0.0380*** (0.0125)**	**-0.0375** (0.0147)**	**-0.0363*** (0.0099)**
Access	0.0010 (0.0022)	-0.0021 (0.0027)	-0.0013 (0.0032)	-0.0031 (0.0023)
Smartphone	**-0.0249** (0.0107)**	**-0.0240* (0.0129)**	**-0.0404*** (0.0149)**	**-0.0016 (0.0112)**
Dash Camera	-0.0060 (0.0142)	0.0069 (0.0163)	-0.0045 (0.0190)	-0.0048 (0.0148)
Body Camera	**0.0358*** (0.0138)**	**-0.0018 (0.0156)**	**0.0173 (0.0179)**	**0.0117 (0.0144)**
Crime Occurrence	0.0049 (0.0039)	0.0126*** (0.0038)	0.0156*** (0.0050)	0.0079*** (0.0028)
Crime Clearance	-0.0507** (0.0255)	-0.0857*** (0.0317)	-0.1082*** (0.0371)	-0.0864*** (0.0255)
Officer Assaults	0.0482*** (0.0089)	0.0657*** (0.0112)	0.0815*** (0.0121)	0.0664*** (0.0113)
Population	0.0382*** (0.0080)	0.0563*** (0.0102)	0.0739*** (0.0117)	0.0283*** (0.0078)
Miles	0.0027 (0.0033)	0.0015 (0.0043)	0.0035 (0.0050)	-0.0075** (0.0034)
MSA Core City	0.1620*** (0.0255)	0.1820*** (0.0308)	0.2698*** (0.0348)	0.1866*** (0.0287)
Operation Budget	0.0102*** (0.0029)	0.0131*** (0.0037)	0.0176*** (0.0042)	0.0075*** (0.0029)
Education Req	0.0139 (0.0090)	-0.0001 (0.0108)	0.0078 (0.0126)	0.0049 (0.0097)
White Officer	-0.0079 (0.0253)	-0.0230 (0.0336)	-0.0246 (0.0393)	-0.0475* (0.0254)
Female Officer	-0.0418 (0.0532)	0.0960 (0.0728)	0.0126 (0.0825)	0.0485 (0.0651)
Weapon	-0.0113*** (0.0025)	-0.0100*** (0.0031)	-0.0127*** (0.0036)	-0.0093*** (0.0027)
Special Units	0.0104*** (0.0018)	0.0123*** (0.0023)	0.0162*** (0.0026)	0.0090*** (0.0020)
Community Poli	0.0026 (0.0041)	0.0035 (0.0049)	0.0004 (0.0057)	0.0101** (0.0045)
Male	-0.1551 (0.1539)	-0.1573 (0.1704)	-0.2295 (0.2166)	-0.1109 (0.1541)
White	0.0395 (0.0453)	-0.0073 (0.0508)	0.0206 (0.0628)	0.0305 (0.0447)
Young	-0.2640** (0.1244)	-0.2396* (0.1393)	-0.3503** (0.1686)	-0.1932 (0.1240)
High School	-0.0096 (0.1274)	0.1511 (0.1528)	0.1132 (0.1854)	-0.1056 (0.1268)
Income	-0.0011** (0.0004)	-0.0001 (0.0005)	-0.0007 (0.0006)	-0.0010** (0.0005)
Inequality	0.1683 (0.1204)	0.3472** (0.1499)	0.2851 (0.1740)	0.4662*** (0.1353)
Vacant Homes	0.0285 (0.0318)	0.0214 (0.0476)	0.0305 (0.0584)	0.0615** (0.0298)
Moved	-0.1092 (0.0998)	-0.1372 (0.1337)	-0.2028 (0.1504)	-0.4155*** (0.1106)
Female Head	0.0785 (0.2031)	0.1602 (0.2602)	0.2626 (0.3060)	0.0367 (0.2232)
Two Parent	-0.0137 (0.1556)	-0.2647 (0.1773)	-0.2969 (0.2161)	-0.0127 (0.1529)
ρ	-0.7704*** (0.2369)	-0.5307*** (0.1994)	-0.6212*** (0.2157)	-0.7844*** (0.2644)
Controls	State, MSA	State, MSA	State, MSA	State, MSA
Wald χ^2	$6.5\times10^{6***}$	$2.0\times10^{7***}$	$1.3\times10^{7***}$	$1.3\times10^{7***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.

5. Results

5.1. The Baseline Estimation Result

Table 6 presents the baseline estimates with spatial autoregressive regressions. In all columns, ρ is statistically significant, indicating that unobserved heterogeneity is significantly correlated across adjacent municipalities. It suggests that our use of spatial autoregressive model is appropriate.

The estimation with the Washington Post data in 2015 (Column 1) shows that the coefficients of *Statistical Analyses* and *Smartphone* are negative and statistically significant. It is predicted that in police departments that conduct statistical analyses with digital crime information, the number of fatal shootings by officers is 2.53%[4] fewer than in others. Smartphone use by officers is also associated with a 2.46% reduction in the shooting-deaths of civilians. This is consistent with our theoretical prediction (Proposition 1) that crime intelligence obtained by statistical analyses and access to the intelligence via smartphones lead to a decrease in fatal shootings by the police. In contrast, the number of crime records (*Records*) and the categories of data accessible by patrol officers (*Access*) are not significantly related to the incidents of civilian deaths.

Table 6, Column 1 also shows that the coefficient of *Body Camera* is positive and statistically significant. When officers wear video cameras on duty, they are 3.64% more likely to kill a suspect. Video cameras installed on patrol vehicles (*Dash Camera*) are not significantly associated with shootings of civilians by officers. This finding supports Proposition 2 that the use of evidence gathering technology (specifically wearable video cameras) reduces an officer's perceived risk of becoming liable for her use of deadly force. Expecting that a wearable video camera would provide evidence to justify the use of force, the officer becomes less reluctant to deploy deadly weapons.

Table 6, Columns 2-4 provide the consistent estimates with alternative data sources for police killings. In Column 2 with the killedbypolice.net data for 2013-2014, statistical analyses of crime data

[4] $1 - e^{-0.0256} = 0.0257$

and smartphone use by officers are associated with fewer deaths of civilians by the police. We found a similar finding from the estimation with a combine dataset of the Washington Post and killedbypolice.net in 2013-2015 (Column 3). The magnitude in the effects of statistical analyses and smartphone use is larger in Column 3 than in Column 1. Column 3 shows that smartphone usage is related to a 4% reduction in shooting-deaths. The coefficient of body cameras in Column 3 is again positive, albeit insignificant. Column 4 shows the estimation with the UCR dataset, that reports deaths of those who the police designate as felons. The coefficient of statistical analyses is also negative and significant.

Table 6 shows that the impact of wearable video cameras use in 2013 is significant only in 2015 (Column 1). It appears that there is a learning effect in the use of wearable video cameras. It could take a while for police officers to realize how helpful evidence from body cameras can be in justifying the use of lethal force. Anecdotal evidence suggests that some police officers who were initially skeptical of the effectiveness of body cameras have later embraced them after they learned how the use of cameras could lead to a reduction in the use-of-force complaints from citizens (Ariel et al. 2015) and how video recordings are used in use-of-force cases as evidence to exonerate officers involved (*The New York Times* 2013, *NBC News* 2016).

Table 7. Estimation by Victim Characteristics

Dependent Variable	Log(Civilian Killed + 1)								
Method	Spatial Autoregressive Regression								
Data Source	The Washington Post (2015)								
Subgroup	Armed with Gun	Armed with Other Weapons	Unarmed	White and Asian	Black and Hispanic	Male	Female	Age ≤ 31	Age > 31
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Records	-0.0021	-0.0007	0.0010	-0.0014	-0.0023	-0.0013	-0.0012	-0.0015	-0.0015
	(0.0021)	(0.0015)	(0.0007)	(0.0019)	(0.0019)	(0.0026)	(0.0009)	(0.0016)	(0.0022)
Statistical Analyses	**-0.0201*****	**-0.0123****	**-0.0090****	**-0.0115**	**-0.0227*****	**-0.0235****	**-0.0041***	**-0.0144****	**-0.0219*****
	(0.0077)	**(0.0060)**	**(0.0036)**	**(0.0075)**	**(0.0068)**	**(0.0096)**	**(0.0023)**	**(0.0064)**	**(0.0077)**
Access	0.0005	0.0000	0.0001	0.0008	0.0004	0.0009	0.0000	0.0028**	-0.0017
	(0.0017)	(0.0012)	(0.0007)	(0.0016)	(0.0015)	(0.0021)	(0.0005)	(0.0014)	(0.0017)
Smartphone	**-0.0193****	**-0.0066**	**0.0000**	**-0.0083**	**-0.0169****	**-0.0250****	**0.0001**	**-0.0181****	**-0.0083**
	(0.0087)	**(0.0063)**	**(0.0037)**	**(0.0077)**	**(0.0080)**	**(0.0105)**	**(0.0029)**	**(0.0077)**	**(0.0084)**
Dash Camera	0.0098	-0.0089	0.0017	-0.0009	-0.0004	-0.0044	0.0001	-0.0002	0.0009
	(0.0108)	(0.0094)	(0.0053)	(0.0102)	(0.0109)	(0.0139)	(0.0041)	(0.0101)	(0.0112)
Body Camera	**0.0305*****	**0.0187****	**0.0024**	**0.0067**	**0.0368*****	**0.0393*****	**0.0009**	**0.0307*****	**0.0181***
	(0.0111)	**(0.0084)**	**(0.0049)**	**(0.0098)**	**(0.0108)**	**(0.0134)**	**(0.0041)**	**(0.0096)**	**(0.0110)**
Crime Occurrence	0.0047*	-0.0008	0.0011	0.0000	0.0046**	0.0042	0.0010	0.0047*	-0.0002
	(0.0026)	(0.0030)	(0.0012)	(0.0029)	(0.0023)	(0.0039)	(0.0007)	(0.0025)	(0.0030)
Crime Clearance	-0.0358*	-0.0274**	-0.0041	0.0145	-0.0674***	-0.0468*	-0.0123*	-0.0625***	-0.0032
	(0.0212)	(0.0136)	(0.0093)	(0.0200)	(0.0183)	(0.0253)	(0.0066)	(0.0174)	(0.0207)
Officer Assaults	0.0350***	0.0231***	0.0071**	0.0239***	0.0345***	0.0457***	0.0069***	0.0318***	0.0314***
	(0.0071)	(0.0056)	(0.0036)	(0.0060)	(0.0076)	(0.0088)	(0.0022)	(0.0067)	(0.0070)
Population	0.0246***	0.0198***	0.0041	0.0268***	0.0199***	0.0395**	-0.0010	0.0200***	0.0284***
	(0.0058)	(0.0056)	(0.0029)	(0.0055)	(0.0061)	(0.0080)	(0.0016)	(0.0055)	(0.0063)
Miles	0.0015	-0.0023	0.0027**	-0.0003	0.0020	0.0014	0.0014*	-0.0005	0.0016
	(0.0026)	(0.0019)	(0.0011)	(0.0024)	(0.0024)	(0.0033)	(0.0008)	(0.0021)	(0.0026)
MSA Core City	0.0989***	0.0696***	0.0326***	0.0717***	0.1135***	0.1631***	0.0059	0.1101***	0.0784***
	(0.0196)	(0.0165)	(0.0104)	(0.0174)	(0.0204)	(0.0249)	(0.0072)	(0.0186)	(0.0196)
ρ	-0.5806***	-1.4049***	-2.1115***	-0.6928**	-0.9707***	-0.6783***	-1.4195**	-1.5276***	-0.6898***
	(0.2015)	(0.3519)	(0.4449)	(0.2998)	(0.3005)	(0.2281)	(0.6305)	(0.4749)	(0.2377)
Controls	State, MSA	State, MSA	State, MSA	State, MSA	State, MSA	State, MSA	State, MSA	State, MSA	State, MSA
Wald χ^2	$1.4\times10^{7***}$	$8.7\times10^{5***}$	$1.9\times10^{7***}$	$7.3\times10^{6***}$	$6.0\times10^{6***}$	$8.4\times10^{6***}$	$7.7\times10^{6***}$	$5.4\times10^{5***}$	$1.7\times10^{7***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.; Other control variables are omitted for brevity.

5.2. Additional Analyses with Victim Characteristics

The Washington Post database provides several characteristics of shooting victims such as race, age, gender, and whether or not they were armed. We dug deeper with this information to find how the impact of technology use varies by victim characteristics and incident circumstances. Table 7, Columns 1-3 show that the impact of statistical analyses, smartphone, and wearable video cameras is more pronounced when the victims are armed with guns (Column 1) than otherwise (Columns 2-3).[5] Compared to deaths of unarmed civilians (Column 3), the effect of technology use is stronger for civilians with less-lethal weapons such as knives or hatchets (Column 2). In other words, the more threatening a civilian target is, the stronger effect the technology use has on fatal shootings by the police.

According to Proposition 1-(ii), it seems that the use of technologies for intelligence reduces the ambiguity (σ) that an officer faces during a dangerous encounter, but not to an extent that the officer fully discerns between noise and signal without much risk so easily (Proposition 1-iii, $\sigma < \frac{1}{\sqrt{-2\log w}}$). This result illustrates that with statistical analyses and smartphone use, police officers are able to obtain real-time intelligence on potential suspects (e.g. how violent they would be or what kind of weapons they would use) and take appropriate measures to subdue them without lethal force. Consistently with Lemma 4-(a), with an expectation that video recordings would be used as substantiating evidence, police officers become less hesitant to deploy lethal force when they perceive the presence of deadly threats from suspects, leading to more correct hits (Column 1). While Lemma 4-(b) also predicts that the use of video cameras can also increase the likelihood of shootings to unarmed citizens (false alarms), its effect is found be positive but insignificant (Table 7, Column 3).

Table 7, Columns 4-9 present intriguing and potentially disturbing findings. The coefficients of statistical analyses, smartphone, and video cameras are more negative and significant when shooting

[5] The difference in the coefficients of smartphones and body cameras between Columns 1 and 3 is statistically significant ($p < 0.05$), but not for statistical analyses.

victims are African Americans or Hispanics (Column 5),[6] male (Column 6), and younger than 31 years old (Column 8).[7] Surprisingly, the impact of all three technologies is found to be insignificant for White and Asian deaths (Column 4), even though these two groups constitute 51.4% of the shooting victims by the police in 2015. Table A1 in Appendix A presents a similar result from the estimation that combines the data from the Washington Post and killedbypolice.net for 2013-2015, which corresponds to Table 6, Column 3. Note that while the coefficient of body cameras is insignificant in Table 6, Column 3, it becomes significant for African Americans and Hispanics (Table A1, Column 2). Prior literature in police shootings puts forth the existence of a racial prejudice in which African Americans and Hispanics are perceived to be more violent than Whites and Asians (e.g. Correll et al. 2007a, Salder et al. 2012). Correll et al. (2014) argued that people "interpret ambiguous behavior as more violent when the actor is Black rather than White" (p. 202). Correll et al. (2006) conducted neurological experiments and found that the participants perceive more threats from African Americans than from Whites, as measured by their event-related brain potentials.

According to our theoretical model, when confronted with an African American or a Hispanic suspect, a police officer may perceive more uncertainty (σ) in distinguishing between signal and noise. Correll et al. (2002) found that the experiment participants use a lower criterion (λ) to shoot Black targets than Whites targets. Lemma 1 shows that the higher uncertainty (σ) the police officer faces, the lower criterion (λ) she uses in shooting ($\frac{\partial \lambda^*}{\partial \sigma} < 0$). From Lemma 1, $\frac{\partial^2 \lambda^*}{\partial \sigma^2} = 2 \log w < 0$, indicating that the impact of uncertainty reduction on the criterion (λ) is greater when σ is higher. This explains that the uncertainty reduction effect from statistical analyses and smartphone use is stronger when the officer is confronted by a suspect who has stereotypical characteristics associated with violence (non-White, male, and youth). Likewise, $\frac{\partial^2 \lambda^*}{\partial \sigma \partial w} = \frac{2\sigma}{\mathrm{w}} > 0$, indicating that the positive impact of evidence gathering

[6] The difference in the coefficient of body cameras between Columns 4 and 5 is statistically significant ($p < 0.05$), but not for statistical analyses and smartphones.
[7] The median age of the civilians killed by the police in 2015 is 31.

technology use (wearable video cameras) on shooting criterion (Lemma 3) is magnified under higher uncertainty. This explains the higher coefficients of video cameras in Table 7, Columns 5, 6, and 8.

5.3. Robustness Tests

We have conducted several robustness checks as follows. First, with respect to unobserved heterogeneity, we conducted falsification tests to rule out potential alternative explanations for police use of force. Specifically, the impact of technology use on fatal shootings by the police could be compounded by unobserved general trends that reduce crimes and violence. To address this concern, we ran our estimations with alternative dependent variables – the number of murders and manslaughters reported to police in 2013 and 2014, excluding homicides by the police. As the results in Table 8 show, the coefficients of technology use are estimated to be insignificant (Columns 1-2). In addition, while it is unlikely that the deaths of criminals in 2007-2011[8] would directly cause fatal shootings in 2015, we nonetheless included this variable as additional control variable. Table 9, Column 1 provides a very similar result to our baseline estimate in Table 6, Column 1. While we noted in the previous section that the UCR only reports the deaths of civilians who the police designate as felons, too many deaths of offenders in 2007-2011 could still motivate police departments to adopt technologies in 2012, particularly video cameras, and to begin using them in 2013. Table 9, Column 1 shows that controlling for the number of criminal deaths by the police prior 2013, our primary findings remain consistent.

[8] We use different time frames for this analysis, such as 2009-2011 or 2010-2012, but did not obtain different results.

Table 8. Falsification Tests

Dependent Variable	Log (Murder + 1)		Log (Murder + Manslaughter + 1)		Log (Criminal Death + 1)	
Method	Spatial Autoregressive Regression					
Data Source	UCR					
Year	2013-2014		2013-2014		2007-2011	
	(1)		(2)		(3)	
Records	0.0104	(0.0081)	0.0097	(0.0081)	-0.0005	(0.0037)
Statistical Analyses	0.0322	(0.0288)	0.0393	(0.0290)	-0.0336**	(0.0140)
Access	-0.0019	(0.0066)	-0.0002	(0.0066)	-0.0043	(0.0035)
Smartphone	-0.0082	(0.0274)	-0.0089	(0.0274)	0.0028	(0.0158)
Dash Camera	0.0206	(0.0335)	0.0255	(0.0337)	-0.0094	(0.0195)
Body Camera	0.0429	(0.0308)	0.0441	(0.0309)	0.0249	(0.0193)
Crime Occurrence					0.0049	(0.0043)
Crime Clearance	-0.3234***	(0.0754)	-0.3154***	(0.0761)	-0.0994**	(0.0435)
Officer Assaults	0.1796***	(0.0181)	0.1782***	(0.0180)	0.1038***	(0.0128)
Population	0.2405***	(0.0203)	0.2446***	(0.0204)	0.0471***	(0.0098)
Miles	-0.0061	(0.0090)	-0.0046	(0.0092)	-0.0009	(0.0044)
MSA Core City	0.7343***	(0.0559)	0.7362***	(0.0553)	0.2711***	(0.0389)
Operational Budget	0.0341***	(0.0085)	0.0369***	(0.0085)	0.0051	(0.0041)
Education Req	-0.0152	(0.0237)	-0.0128	(0.0239)	0.0030	(0.0134)
White Officer	-0.1741**	(0.0680)	-0.1760**	(0.0685)	-0.0774**	(0.0365)
Female Officer	0.1529	(0.1707)	0.1581	(0.1713)	0.1225	(0.0879)
Weapon	-0.0099	(0.0066)	-0.0089	(0.0066)	-0.0175***	(0.0037)
Special Units	0.0341***	(0.0046)	0.0342***	(0.0046)	0.0137***	(0.0026)
Community Policing	-0.0179*	(0.0104)	-0.0166	(0.0104)	0.0129**	(0.0064)
Male	1.0115**	(0.4251)	0.9613**	(0.4248)	0.0351	(0.2138)
White	-0.9701***	(0.1215)	-0.9682***	(0.1219)	-0.0353	(0.0703)
Young	-0.0215	(0.3216)	0.0263	(0.3226)	-0.3374*	(0.1733)
High School	0.2833	(0.3614)	0.3030	(0.3626)	-0.1807	(0.1843)
Income	-0.0051***	(0.0014)	-0.0052***	(0.0014)	-0.0013**	(0.0007)
Inequality	0.6265*	(0.3374)	0.5850*	(0.3355)	0.6528***	(0.1891)
Vacant Homes	0.3198***	(0.1144)	0.3201***	(0.1156)	0.1145**	(0.0475)
Moved	-0.1951	(0.3045)	-0.1666	(0.3045)	-0.4480***	(0.1480)
Female Household Head	3.4142***	(0.6480)	3.4481***	(0.6453)	0.1177	(0.3338)
Two Parent Household	0.1708	(0.4011)	0.2244	(0.4027)	-0.4622**	(0.2079)
ρ	-1.4676***	(0.4437)	-1.2241***	(0.3746)	-1.3422***	(0.3670)
Controls	State, MSA		State, MSA		State, MSA	
Wald χ^2	$1.1\times10^{7***}$		$8.9\times10^{7***}$		$7.1\times10^{6***}$	

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.

Table 9. Estimations to Address Endogeneity Concerns

Dependent Variable	**Log(Civilian Killed + 1)**		
Method	Spatial Autoregressive Regression		
Data Source	The Washington Post (2015)		
	(1)	(2)	(3)
Records	-0.0021 (0.0025)	-0.0016 (0.0027)	-0.0027 (0.0027)
Statistical Analyses	**-0.0199** (0.0090)**	**-0.0216** (0.0097)**	**-0.0235** (0.0097)**
Access	0.0021 (0.0020)	0.0010 (0.0021)	0.0011 (0.0021)
Smartphone	**-0.0243** (0.0102)**	**-0.0240** (0.0107)**	**-0.0234** (0.0108)**
Dash Camera	-0.0040 (0.0132)	-0.0019 (0.0143)	-0.0049 (0.0141)
Body Camera	**0.0300** (0.0125)**	**0.0346** (0.0137)**	**0.0358***(0.0137)**
Criminal Deaths in 07-11	0.2239***(0.0286)		
Crime Occurrence	0.0013 (0.0038)	0.0262***(0.0051)	0.0089** (0.0040)
Crime Clearance	-0.0162 (0.0243)	-0.0607** (0.0259)	-0.1528***(0.0338)
Officer Assaults	0.0265***(0.0082)	0.0492***(0.0088)	0.0564***(0.0095)
Population	0.0283***(0.0075)	0.0397***(0.0081)	0.0410***(0.0082)
Miles	0.0029 (0.0032)	0.0026 (0.0033)	0.0021 (0.0033)
MSA Core City	0.0997***(0.0252)	0.1559***(0.0253)	0.1547***(0.0252)
Operation Budget	0.0087***(0.0027)	0.0108***(0.0028)	0.0103***(0.0028)
Education Req	0.0128 (0.0088)	0.0135 (0.0089)	0.0150* (0.0091)
White Officer	0.0073 (0.0243)	-0.0036 (0.0251)	-0.0084 (0.0254)
Female Officer	-0.0741 (0.0501)	-0.0344 (0.0531)	-0.0623 (0.0533)
Weapon	-0.0073***(0.0023)	-0.0106***(0.0025)	-0.0111***(0.0025)
Special Units	0.0075***(0.0017)	0.0098***(0.0018)	0.0099***(0.0018)
Community Policing	-0.0004 (0.0038)	0.0022 (0.0040)	0.0015 (0.0040)
Male	-0.1579 (0.1379)	-0.1355 (0.1549)	-0.1520 (0.1539)
White	0.0451 (0.0431)	0.0365 (0.0452)	0.0417 (0.0454)
Young	-0.1856* (0.1122)	-0.2763** (0.1243)	-0.2521** (0.1226)
High School	0.0267 (0.1180)	-0.0065 (0.1264)	-0.0198 (0.1279)
Income	-0.0007** (0.0004)	-0.0011***(0.0004)	-0.0012***(0.0004)
Inequality	0.0519 (0.1060)	0.1803 (0.1198)	0.1734 (0.1193)
Vacant Homes	0.0079 (0.0292)	0.0256 (0.0325)	0.0301 (0.0319)
Moved	-0.0093 (0.0936)	-0.0750 (0.0992)	-0.1086 (0.1001)
Female Head	0.0471 (0.1932)	0.1254 (0.2017)	0.1173 (0.2038)
Two Parent	0.0845 (0.1448)	0.0029 (0.1554)	-0.0152 (0.1550)
Inverse Mills Ratio for Statistical Analyses		0.1657***(0.0289)	
Inverse Mills Ratio for Body Camera			-0.4755***(0.1056)
ρ	-0.822***(0.2571)	-0.7714***(0.2359)	-0.7606***(0.2347)
Controls	State, MSA	State, MSA	State, MSA
Wald χ^2	$7.8\times10^{6***}$	$7.5\times10^{6***}$	$5.2\times10^{7***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.

Second, in regard to reverse causality, we also conducted another falsification test, in which we regressed the number of criminal offenders killed by officers in 2007-2011, which was collected from the UCR, on the explanatory variables (Table 8, Column 3). Table 8, Column 3 shows that such a reverse casualty concern is unlikely to be serious for the use of smartphones and wearable body cameras. Indeed, the correlation between criminal deaths in 2007-2011 and body-camera use in 2013 is -0.006. However, the negative and significant coefficient of statistical analyses in Table 8, Column 3 may indicate the presence of reverse causality. While the primary motivation for technology use in law enforcement is to reduce crime rates and clear more crimes (Manning 2001, Nunn 2001, Garicano and Heaton 2010), it might be the case that police departments whose officers kill more offenders in 2007-2011 are more likely to conduct statistical analyses in 2013 to prevent civilian deaths.

To further address this endogeneity concern, we followed the approach of Heckman (1979) and Shaver (1998) by obtaining inverse Mills ratios for statistical analyses and body cameras. We first ran Probit regressions in which each of the two variables was regressed to the number of criminals killed, crime occurrences, crime clearance rates, and the number of officers killed and assaulted in 2007-2011 (Table A2 in Appendix). Table A2, Column 2 indicates that the number of criminals killed in 2007-2011 do not have a significant influence on the use of wearable body cameras in 2013. Then we added the inverse Mills ratios from the Probit regressions to the spatial-autocorrelation model (Eq. 5) as an additional control variable. As Table 9, Columns 2-3 demonstrate, while the coefficients of the ratios are significant, the overall results are consistent with our primary estimations in Table 6, Column 1.

Third, in terms of measurement error, the baseline analyses only consider civilian deaths by fatal shootings, but there are other ways in which the police can kill civilians, such as Tasers or vehicle accidents. According to the Guardian, 20 people in the U.S. were killed in 2015 by police officers with Tasers (*The Guardian* 2015), which cause electronic shocks and muscle contractions to a target. We did not include them in our main analyses since it is not typically considered to be a lethal weapon[9] (*Governing* 2015). Unlike Tasers, guns are used by the police with an explicit aim to subdue violent targets by killing them. Nevertheless, to demonstrate the robustness of our analysis, we tested the impact of technology use on civilian deaths caused by both lethal (guns) and non-lethal (Taser) weapons, with additional data from the Guardian and killedbypolice.net. This estimation presented in Table A3 produces very similar findings to those in Table 6.

Fourth, with respect to alternative empirical specifications, since the dependent variable is in fact a count variable (the number of civilians killed), one could argue that non-linear models such as Poisson or negative binomial regressions would be more appropriate than linear models. However, Greene (2002) pointed out inconsistency in non-linear models that include fixed-effects. In addition, the spatial autoregressive model allows us to account for unobserved heterogeneity correlated with peer jurisdictions. Nonetheless, we estimated the model with Poisson regressions as shown in Table A4 to demonstrate the robustness of our findings. Column 1 with the Washington Post data shows that the effect of wearable video camera use is positive and significant. Columns 2 and 3 with killedbypolice.net data for 2013 and 2014 show that the use of smartphones is still negatively associated with deadly shootings by the police. It could be the case that deadly shooting incidents by the police are not independent with each other, leading us to run a negative binomial regression as in Table A4, Column 4. This regression produced a similar result to Column 1.

Finally, we addressed any other potential unobserved heterogeneity concerns as follows. While we controlled for a variety of factors that drive technology use and fatal shootings by the police, we used alternative control variables to further rule out alternative effects. First, one might argue that violent crimes (murders, manslaughters, robberies, and assaults) are more likely to be related to deadly shootings to civilians than other crimes. In Table A5, Column 1, we show the estimation with violent crime

[9] The U.S. Department of Defense categorizes a Taser as a non-lethal weapon. http://jnlwp.defense.gov/CurrentNonLethalWeapons/X26Taser.aspx, accessed on May 16, 2016.

occurrence and clearance rates as alternative control variables, instead of total crimes that include property crimes (burglaries, larcenies, and auto thefts). The main result does not change. In our baseline estimation (Table 6), we did not include the size of police force as a control variable, as it is highly correlated with the amount of operational budget. However, frequent fatal shootings could be driven by a large size of police officers. In Table A5, Column 2, we controlled for the number of sworn full-time officers per capita. The estimate remains consistent. Finally, in Table A5, Column 3, we control for poverty rate (share of population below a poverty line), instead of the median household income. This estimation also provides similar results.

6. Discussion and Conclusion

6.1. Key Findings

This study addresses one of the most controversial societal challenges in the U.S – fatal shootings to civilians by the police. The police are mandated to protect the lives of all citizens, be they criminals or otherwise. At the same time, however, they should often make a critical, high-stake decision in an uncertain and violent setting – whether or not to shoot and kill a civilian to save others and themselves. This decision carries a considerable risk; failing to shoot could put innocent people and the officers themselves in danger, but there is always a possibility that the target is innocent or unarmed, an outcome that the officers could be held responsible for. In this study, we ask the following question that no prior IS study has shed light on: how does technology use by the police affect a decision to deploy deadly force?

Our analysis with the dataset that combines multiple data sources from both governments (the FBI and the DOJ) and media (the Washington Post) produced several interesting findings. We obtained an encouraging finding that the use of technology for intelligence (statistical analyses and smartphones) is significantly associated with fewer fatal shootings by the police. It illustrates that technology use for intelligence analyses and access helps police officers make more informed decisions in using lethal force. We obtained similar results from the analyses with alternative data on civilian deaths (killedbypolice.net and the UCR), demonstrating the robustness of our findings. We found, however, that the use of wearable body cameras is associated with an increase in shooting-deaths of civilians. This contradicts the expectation of many law enforcement officials and policymakers that video cameras would reduce incidents of use of deadly force. We explain this surprising finding in a sense that police officers may believe that the video footages that record encounters with violent civilians would help justify their use of force and exonerate themselves in case of criminal conviction. Based on signal detection theory, we explain that this expectation leads them to put more emphasis on the lives of the innocent in their shooting decisions, becoming less reluctant to use lethal force against suspects.

We also find that the impact of technology use – statistical analyses, smartphones, and body cameras – is more pronounced for suspects who are armed with more lethal weapons. In addition, the relationship between technology use and fatal shootings is stronger for civilians who are minorities (African American or Hispanic), male, or younger than 31 years old. Surprisingly, the technology impact is found to be insignificant for Whites or Asians, who make up of 51% of the shooting victims in 2015. According to our analytical model, it seems that technology use influences an officer’s decision to fire more profoundly under greater uncertainty.

6.2. Contribution to the Literature

We contribute to the evolving literature on the societal impacts of IS (Chan and Ghose 2016, Greenwood and Wattal 2016, Jha et al. 2016, Venkatesh et al. 2016) by developing a simple, stylized model that depicts a police officer’s behavior in a life-threatening encounter. To our knowledge, this is one of the first attempts in the IS literature to examine the effect of technology in uncertain, turbulent, and life-threatening circumstances. To do so, we adopted a new interdisciplinary approach integrating IS, criminology, and psychology literatures. This study differentiates itself from prior IS research by discovering the significant effect of ethnicity in technology use and its impacts. By studying one of the most politically charged societal problems, we extend the boundary of the IS literature toward the public policy arena, an effort to expand the relevance and influence of IS research.

6.3. Implications for Public Policy

This study delivers both encouraging and cautionary messages to law enforcement officials and policymakers. As mentioned in the Chicago shooting case in the Introduction, the adoption of wearable video cameras is one of the most widely-adopted policies to reduce deadly incidents. It is believed that the use of video cameras can restrain both excessive use of force by the police and violent resists by civilians (Harris 2010, Ariel et al. 2015). This is why the U.S. Congress is considering the Police CAMERA Act,[10] which would authorize the federal government to provide monetary grants to local governments for the purchase of video cameras. Our study shows that this expectation could be misguided. While it is a silver lining that the use of body cameras does not have a significant impact on deaths of unarmed civilians (Table 7, Column 3), it is concerning to law enforcement that it is more significantly related to the fatal shootings of African American and Hispanic victims than Whites and Asians (Table 7, Columns 4 and 5). This paper demonstrates that technology use for intelligence analyses and real-time intelligence access by officers can be much more effective in reducing police-caused homicides. Accordingly, we advise law enforcement officials that the use of video cameras be accompanied with technology for intelligence access and more extensive training for police officers that would help them overcome cognitive racial bias (Correll et al. 2007, 2014).

6.4. Limitations and Future Research

There are a few limitations in our study. Since the LEMAS in 2013 is the most recent data available for police IT use, we were able to build only a cross-sectional dataset. Still, we overcame this limitation by building a large-scale dataset with more than 2,600 departments and devising a sound estimation and identification strategy. In addition, the LEMAS survey does not provide in-depth, granular

[10] CAMERA stands for "Creating Accountability by Making Effective Recording Available." The U.S. Senate bill S.877 https://www.congress.gov/bill/114th-congress/senate-bill/877 and House Bill H.R.1680 https://www.congress.gov/bill/114th-congress/house-bill/1680 , accessed on May 16, 2016.

information on how the police utilize technology. For instance, we were not able to obtain information on, for example, what kind of intelligence police departments obtain from statistical analyses of crime data or for what specific activities they utilize the intelligence. Also, due to data limitation, we were not able to examine how technology use affects warranted and unwarranted shootings differently. This is because it is very challenging to unequivocally judge whether use of deadly force is justified, due to limited evidence and conflicting accounts. Also, the determination of warranty is inherently subjective and depends heavily on judgement of investigators, prosecutors, or judges, each of which can have different interpretations of evidence and laws. In many cases, the results of internal investigations by the police or prosecutors are not available to the public. We believe that our estimation with more objective information on whether the victims were armed or unarmed (Table 7, Columns 1-3) sheds some light on this matter.

Law enforcement provides IS researchers with abundant opportunities for future research. It would be interesting to study how police departments can utilize digital technologies in improving the relationship between the community. The criminology literature stresses that a close relationship with the public is imperative for effective law enforcement (Mastrofski et al. 1995, Skolnick and Barley 1998, Kerley and Benson 2000, Adams et al. 2005). The Internet has become an essential tool for the police to communicate and engage with citizens they serve (*Government Technology* 2012, 2013). Future research can look at how this effort helps the police maintain a symbiotic relationship with the community and affects their response to police use of force incidents. It would be worthwhile to investigate what factors influence the adoption and use of law enforcement technologies. In particular, since the political nature of law enforcement and its impact, we expect that political circumstances in municipalities have a significant impact on technology use in the police. To the best of our knowledge, the IS literature has paid little attention on political impacts on IS (Pang 2016). Future research can also examine how social media affects police practices. In particular, there is a growing concern among law enforcement officials on a so-called “viral video effect” or “YouTube effect” (*The Washington Post* 2015, *Reuter* 2016), in which police officers become less reluctant to deal with violence in a fear that their behaviors are being videotaped and could be viral on the Internet. Is this really the case? We believe it would be an intriguing IS research question.

6.5. Concluding Remarks

Whenever a civilian is killed by the police, be it justified or not, it causes emotional distress and tension, damaging the relationship between the police and the community. Yet, it is often inevitable for police officers to deploy deadly force in order to protect others and themselves. Our study suggests that technology use for intelligence analyses and access could be an effective means to prevent the loss of lives. This is particularly the case for unarmed suspects who may not pose an imminent threat as well as for African Americans and Hispanics, who believe that they have unfairly suffered from police brutality. This is an encouraging result, given that the U.S. history is with century-long struggles and fights for the civil rights, which many people believe are still on-going (e.g. Hall 2005, *CBS News* 2014, *USA Today* 2014). While there have been substantial advances in the civil right movement for the last several decades, police use of force is still a politically contentious issue that is significant to all political spectrums. This research provides important insights to the on-going discourses in public safety and civil rights and influence formulation and implementation of the public safety policies in technology adoption.

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Appendix – Additional Estimation Tables

Table A1. Estimations by Race in 2013-2015

Dependent Variable	**Log (Civilian Killed + 1)**	
Method	Spatial Autoregressive Regression	
Data Source and Year	The Washington Post and killedbypolice.net (2013-2015)	
Race	White and Asian	Black and Hispanic
	(1)	(2)
Records	0.0009 (0.0028)	-0.0023 (0.0026)
Statistical Analyses	**-0.0246** (0.0110)**	**-0.0239** (0.0095)**
Access	-0.0018 (0.0024)	-0.0003 (0.0021)
Smartphone	**-0.0163 (0.0112)**	**-0.0337*** (0.0110)**
Dash Camera	0.0060 (0.0141)	-0.0060 (0.0142)
Body Camera	**-0.0105 (0.0138)**	**0.0338*** (0.0127)**
Crime Occurrence	0.0055 (0.0037)	0.0101*** (0.0033)
Crime Clearance	-0.0015 (0.0269)	-0.1226*** (0.0264)
Officer Assaults	0.0405*** (0.0087)	0.0532*** (0.0104)
Population	0.0520*** (0.0081)	0.0281*** (0.0085)
Miles	0.0023 (0.0036)	0.0017 (0.0033)
MSA Core City	0.1160*** (0.0256)	0.1696*** (0.0259)
Operational Budget	0.0117*** (0.0031)	0.0051* (0.0028)
Education Req	0.0083 (0.0085)	0.0026 (0.0097)
White Officer	0.0023 (0.0300)	-0.0236 (0.0232)
Female Officer	-0.0739 (0.0568)	0.0975 (0.0642)
Weapon	-0.0092*** (0.0027)	-0.0076*** (0.0025)
Special Units	0.0104*** (0.0020)	0.0105*** (0.0018)
Community Policing	-0.0017 (0.0043)	0.0007 (0.0040)
Male	-0.1015 (0.1528)	-0.1401 (0.1310)
White	0.1324*** (0.0434)	-0.1268*** (0.0444)
Young	-0.1407 (0.1215)	-0.2875** (0.1191)
High School	0.1311 (0.1341)	-0.0148 (0.1234)
Income	0.0002 (0.0005)	-0.0011*** (0.0004)
Inequality	0.0456 (0.1229)	0.4594*** (0.1285)
Vacant Homes	-0.0066 (0.0434)	0.0587** (0.0298)
Moved	-0.1129 (0.1108)	-0.1471 (0.1055)
Female Household Head	0.0883 (0.2182)	0.0703 (0.2140)
Two Parent Household	-0.3544** (0.1619)	0.0186 (0.1446)
ρ	-0.8054*** (0.2459)	-0.7785*** (0.2355)
Controls	State, MSA	State, MSA
Wald χ^2	$6.2\times10^{6***}$	$6.0\times10^{6***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.

Table A2. Probit Regressions to Obtain Inverse Mill's Ratios

Dependent Variable	Statistical Analyses	Body Camera
Method	Probit Regression	
	(1)	(2)
Criminal Deaths in 2007-2011	0.2768** (0.1080)	0.0841 (0.0562)
Crime Occurrence in 2007-2011	0.2522*** (0.0149)	-0.0014 (0.0133)
Crime Clearance in 2007-2011	-0.2765* (0.1662)	0.6428*** (0.1617)
Officer Assaults in 2007-2011	0.0485*** (0.0192)	-0.0397** (0.0163)
Constant	-1.4611*** (0.1127)	-0.6339*** (0.1032)
Pseudo R^2	0.1757	0.0075
Log L	-1390.2816	-1549.4117
Wald χ^2	592.56***	23.45***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; $N = 2{,}657$; Robust standard errors are in parentheses.

Table A3. Estimations with Deaths by Guns and Tasers

Dependent Variable	**Log (Civilian Killed + 1)**	
Method	Spatial Autoregressive Regression	
Data Source	The Washington Post The Guardian	The Washington Post The Guardian killedbypolice.net
Year	2015	2013-2015
	(1)	(2)
Records	-0.0022 (0.0027)	-0.0018 (0.0038)
Statistical Analyses	**-0.0248** (0.0100)**	**-0.0354** (0.0149)**
Access	0.0012 (0.0022)	-0.0013 (0.0032)
Smartphone	**-0.0243** (0.0108)**	**-0.0423*** (0.0150)**
Dash Camera	-0.0057 (0.0144)	-0.0061 (0.0193)
Body Camera	**0.0325** (0.0137)**	**0.0103 (0.0182)**
Crime Occurrence	0.0036 (0.0042)	0.0153*** (0.0052)
Crime Clearance	-0.0567** (0.0256)	-0.1147*** (0.0378)
Officer Assaults	0.0527*** (0.0089)	0.0841*** (0.0123)
Population	0.0411*** (0.0085)	0.0784*** (0.0119)
Miles	0.0020 (0.0034)	0.0030 (0.0051)
MSA Core City	0.1724*** (0.0256)	0.2749*** (0.0350)
Operational Budget	0.0104*** (0.0029)	0.0181*** (0.0043)
Education Req	0.0116 (0.0092)	0.0019 (0.0127)
White Officer	-0.0048 (0.0256)	-0.0213 (0.0394)
Female Officer	-0.0556 (0.0539)	0.0026 (0.0832)
Weapon	-0.0112*** (0.0026)	-0.0119*** (0.0037)
Special Units	0.0106*** (0.0019)	0.0163*** (0.0026)
Community Policing	0.0014 (0.0041)	-0.0025 (0.0057)
Male	-0.1370 (0.1526)	-0.2240 (0.2168)
White	0.0358 (0.0459)	0.0100 (0.0639)
Young	-0.2722** (0.1252)	-0.3489** (0.1707)
High School	0.0027 (0.1289)	0.1614 (0.1883)
Income	-0.0010** (0.0004)	-0.0006 (0.0006)
Inequality	0.1885 (0.1220)	0.2971* (0.1768)
Vacant Homes	0.0345 (0.0319)	0.0386 (0.0574)
Moved	-0.1119 (0.1015)	-0.2081 (0.1542)
Female Household Head	0.1462 (0.2035)	0.3661 (0.3109)
Two Parent Household	-0.0174 (0.1559)	-0.2965 (0.2192)
ρ	-0.7379*** (0.2298)	-0.6584*** (0.2215)
Controls	State, MSA	State, MSA
Wald χ^2	$1.4\times10^{7***}$	$1.2\times10^{7***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.

Table A4. Poisson and Negative Binomial Regressions

Dependent Variable	**Civilian Killed**							
Method	Poisson						Negative Binomial[1)]	
Data Source	The Washington Post		killedbypolice.net		The Washington Post & killedbypolice.net		The Washington Post	
Year	2015		2013-2014		2013-2015		2015	
	(1)		(2)		(3)		(4)	
Records	-0.0564	(0.0486)	-0.0412	(0.0399)	-0.0498*	(0.0296)	-0.0555	(0.0400)
Statistical Analyses	0.2406	(0.2106)	-0.2170	(0.2058)	-0.0098	(0.1564)	0.0809	(0.2112)
Access	0.0383	(0.0461)	0.0346	(0.0467)	0.0375	(0.0327)	0.0170	(0.0366)
Smartphone	-0.1767	(0.1264)	-0.2379**	(0.1116)	-0.2173**	(0.0850)	-0.1295	(0.1073)
Dash Camera	-0.1036	(0.1387)	0.0906	(0.1160)	0.0247	(0.0922)	-0.1833	(0.1118)
Body Camera	0.3215***	(0.1225)	-0.0811	(0.1164)	0.0785	(0.0832)	0.2602**	(0.1029)
Crime Occurrence	0.2605**	(0.1015)	0.5848***	(0.0968)	0.4294***	(0.1002)	0.2570*	(0.1532)
Crime Clearance	0.6687	(0.5634)	-0.1782	(0.5355)	0.1810	(0.4232)	0.0121	(0.4656)
Officer Assaults	0.0621	(0.0439)	0.0258	(0.0369)	0.0383	(0.0297)	0.0860***	(0.0229)
Population	0.5054***	(0.1290)	0.3929***	(0.1051)	0.4660***	(0.1073)	0.5170***	(0.1481)
Miles	0.1038	(0.0724)	0.1567***	(0.0544)	0.1233**	(0.0511)	0.0802	(0.0572)
MSA Core City	0.7682***	(0.1719)	0.2585*	(0.1528)	0.4696***	(0.1239)	0.5408***	(0.1759)
Operation Budget	0.1131	(0.0708)	0.1725**	(0.0705)	0.1499***	(0.0502)	0.1783*	(0.0958)
Education Req	0.0661	(0.0781)	-0.0970	(0.0770)	-0.0264	(0.0568)	-0.0196	(0.0623)
White Officer	0.2331	(0.3911)	0.1211	(0.2983)	0.1569	(0.2393)	-0.0263	(0.2573)
Female Officer	-1.5621	(1.1260)	-0.3161	(1.0828)	-0.7502	(0.8047)	-1.1571	(0.9805)
Weapon	-0.0846**	(0.0373)	0.0030	(0.0299)	-0.0300	(0.0235)	-0.0235	(0.0282)
Special Units	0.0246	(0.0195)	-0.0176	(0.0175)	-0.0005	(0.0142)	0.0397**	(0.0183)
Community Poli	-0.0701	(0.0502)	0.0234	(0.0380)	-0.0153	(0.0321)	-0.0291	(0.0385)
Male	-4.8195	(4.6486)	-2.2199	(3.4134)	-3.3263	(2.7735)	-1.4146	(3.7030)
White	-0.2787	(0.7257)	-0.7085	(0.6201)	-0.4705	(0.4654)	-0.5759	(0.4451)
Young	-4.3951	(2.7221)	-1.4522	(1.8951)	-2.6401	(1.6110)	-5.0911***	(1.7065)
High School	-2.0787	(3.4148)	3.3034	(2.8182)	1.3087	(2.3234)	-2.7467	(1.9289)
Income	-0.0227**	(0.0106)	0.0154*	(0.0093)	0.0002	(0.0081)	-0.0258***	(0.0069)
Inequality	-4.2908*	(2.5587)	0.3582	(2.1249)	-1.4797	(1.7099)	-4.0430**	(1.8942)
Vacant Homes	-0.8315	(1.5469)	-5.6027**	(2.2873)	-2.8724*	(1.4698)	-1.2988	(1.5087)
Moved	1.6874	(2.1090)	2.6145	(1.8868)	2.5089*	(1.3685)	3.5026**	(1.3649)
Female Head	-1.1981	(5.0581)	6.8264	(4.4183)	3.5027	(3.4847)	-7.0408*	(3.6357)
Two Parent	-0.8364	(2.9776)	-4.4500	(2.8482)	-2.8649	(2.0945)	2.1929	(2.0759)
Controls	State, MSA		State, MSA		State, MSA			
Pseudo L	-680.1627		-909.5409		-1257.2117		-905.7210	
Pseudo R^2	0.6175		0.6705		0.6855		0.3180	
Wald χ^2	$1.4\times10^{5***}$		$2.9\times10^{10***}$		$2.4\times10^{8***}$		1115.97***	

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.

1) Estimation with state and MSA fixed-effects failed to achieve convergence.

Table A5. Alternative Control Variables

Dependent Variable	**Log (Civilian Killed + 1)**		
Method	Spatial Autoregressive Regression		
Source	The Washington Post (2015)		
Alternative Control	Violent Crimes	Police Force Size	Poverty Rate
	(1)	(2)	(3)
Records	-0.0026 (0.0027)	-0.0023 (0.0027)	-0.0022 (0.0027)
Statistical Analyses	**-0.0274*** (0.0099)**	**-0.0229** (0.0097)**	**-0.0264*** (0.0098)**
Access	0.0010 (0.0022)	0.0008 (0.0021)	0.0009 (0.0022)
Smartphone	**-0.0255** (0.0107)**	**-0.0234** (0.0107)**	**-0.0244** (0.0107)**
Dash Camera	-0.0065 (0.0142)	-0.0015 (0.0142)	-0.0067 (0.0142)
Body Camera	**0.0355** (0.0138)**	**0.0352** (0.0136)**	**0.0357** (0.0138)**
Crime Occurrence		0.0056 (0.0038)	0.0050 (0.0039)
Crime Clearance		-0.0433* (0.0254)	-0.0465* (0.0254)
Violent Crime Occurrence	0.0096** (0.0045)		
Violent Crime Clearance	-0.0451** (0.0192)		
Officer Assaults	0.0473*** (0.0089)	0.0461*** (0.0088)	0.0487*** (0.0089)
Population	0.0340*** (0.0082)	0.0523*** (0.0094)	0.0400*** (0.0082)
Miles	0.0036 (0.0033)	0.0032 (0.0033)	0.0020 (0.0033)
MSA Core City	0.1585*** (0.0257)	0.1571*** (0.0254)	0.1616*** (0.0256)
Operational Budget	0.0100*** (0.0029)		0.0100*** (0.0029)
Officer		0.0199*** (0.0041)	
Education Req	0.0141 (0.0091)	0.0156* (0.0090)	0.0133 (0.0090)
White Officer	-0.0068 (0.0252)	0.0056 (0.0253)	-0.0097 (0.0253)
Female Officer	-0.0440 (0.0531)	-0.0671 (0.0530)	-0.0479 (0.0531)
Weapon	-0.0115*** (0.0025)	-0.0119*** (0.0025)	-0.0113*** (0.0025)
Special Units	0.0102*** (0.0018)	0.0095*** (0.0018)	0.0104*** (0.0018)
Community Policing	0.0032 (0.0041)	0.0030 (0.0040)	0.0024 (0.0041)
Male	-0.1529 (0.1542)	-0.1675 (0.1549)	-0.2054 (0.1503)
White	0.0428 (0.0454)	0.0477 (0.0450)	0.0343 (0.0459)
Young	-0.2701** (0.1244)	-0.2922** (0.1265)	-0.2353* (0.1257)
High School	-0.0187 (0.1277)	-0.0473 (0.1262)	0.1480 (0.1101)
Income	-0.0010** (0.0004)	-0.0012*** (0.0004)	
Poverty Level			0.1160 (0.0905)
Inequality	0.1841 (0.1203)	0.1011 (0.1180)	0.1259 (0.1242)
Vacant Homes	0.0275 (0.0316)	-0.1687*** (0.0634)	0.0375 (0.0320)
Moved	-0.1163 (0.1001)	-0.1867* (0.1038)	-0.0759 (0.0989)
Female Household Head	0.0408 (0.2029)	0.0403 (0.2062)	0.0788 (0.2139)
Two Parent Household	-0.0186 (0.1553)	-0.1154 (0.1625)	-0.0831 (0.1537)
ρ	-0.7695*** (0.2370)	-0.8017*** (0.2410)	-0.779*** (0.2397)
Controls	State, MSA	State, MSA	State, MSA
Wald χ^2	$9.9\times10^{6***}$	$6.0\times10^{6***}$	$6.4\times10^{6***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,657; Robust standard errors are in parentheses.