Does IT Use by the Police Keep the City's Finest Safer?

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Abstract

Police officers perform their duty every day under a constant threat of violence, and each year, as many as 50 police officers in the United States lose their lives in the line of duty. This study examines how IT could help prevent violence against police officers. Specifically, we examine the relationship between IT use by the police and the number of police officers killed or assaulted in the line of duty. Integrating the literature on IT-enabled organizational capabilities with the criminology research, we theorize that police IT use helps develop two key law enforcement capabilities – ***intelligence-led policing*** *and* ***community-oriented policing*** *– which in turn help reduce violence against police officers. Our empirical analysis of 3,921 U.S. police departments shows that the IT use for crime analysis, dispatch, and the Internet is significantly associated with a decrease in the deaths of police officers, an effect that is found to be more pronounced in communities with a higher economic divide. Besides contributing to the nascent literature on the business value of IT in the public sector and the broader societal impact of IT, we also expand the scope of the IS literature by theorizing and empirically demonstrating the role of IT for occupational safety in organizations that operate in unpredictable and dangerous environments.*

Keywords: Public safety, Police IT use, Analytics, Real-time response, Officer safety, Police-induced homicides.

The policeman is a peacetime soldier always at war.
- Inscription inside the National Law Enforcement Officers' Memorial, Washington, D.C.

1. Introduction

Each year, as many as 50 police officers in the United States lose their lives in the line of duty, and more than 50,000 officers suffer from assaults. Policing is one of the few professions that performs its duty under a constant threat of violence and threat of lives in peacetime. Distrust and animosity that the public may hold against police officers, which we witnessed from recent upheavals in cities across the U.S., pose extra risks to police officers. An officer's death is not only tragic in itself but also it is a tremendous loss, because the public would lose the skills, experience, and ties with the community that the police officer has accumulated over the years. Injuries to officers are likewise painful to them and their families, but also they are costly to the public since the police department has to compensate the officers if they become disabled for an extended period of time.[1] Hence, besides the society's moral obligation, it is in the community's best interest to ensure the police officers' safety.

Like many organizations, law enforcement agencies rely heavily on information technology (IT) for a variety of purposes, such as intelligence gathering, crime investigation, and personnel and equipment management (e.g. Weisburd et al. 1994, Maguire 2000, Manning 2001, Chan 2004). Police departments are increasingly adopting analytics technologies to analyze crime information, such as crime-scene reports, on-street intelligence, potential suspects, and crime patterns (Weisburd et al. 2003, Cope 2004). They are also using real-time response technologies, such as computer-aided dispatch, for real-time communication, swift responses to incidents, and rapid deployment of police units (e.g., Sherman and Weisburd 1995, Institute for Law and Justice 2002). The Internet is a useful technology for the police to collect intelligence on crimes and interact with the community they serve in order to build strong ties with the community (e.g., Crump 2011, *Government Technology* 2013c). In this study, we seek to examine the role of IT use in

[1] For instance, the Los Angeles Police Department pays more than $30 million every year since 2009 for injury compensation. Please see: http://www.latimes.com/local/cityhall/la-me-sworn-injury-leave-20140928-story.html, accessed on Nov. 20, 2015

the occupational safety of police officers. Accordingly, our research question is: Does the use of IT by the police keep police officers safer?

This study investigates the relationship between IT use and violence against police officers in U.S. local police departments. Integrating the IS literature on IT-enabled organizational capabilities (e.g., Sambamurthy et al. 2003, Ravichandran and Lertwongsatien 2005, Pavlou and El Sawy 2006, 2010, Rai et al. 2006, Chi et al. 2010) with the criminology literature (e.g., Weisburd et al. 1994, Jacobs and Carmichael 2002, Hahn and Jeffries 2003, Rosenfeld et al. 2005), we propose that in order to reduce violence against police officers, police departments must develop two key law enforcement capabilities – *intelligence-led policing* (Maguire 2000, Cope 2004, Carter and Carter 2009) and *community-oriented policing* (Thurman and Reisig 1996, Adams et al. 2005, Dantzker 2010, Cordner 2014). Second, we theorize that the use of the technologies listed in Table 1 can help the police develop these capabilities. Analytics technologies provide the police with necessary intelligence for informed, targeted law enforcement. Real-time response technologies enable rapid responses to critical incidents, in which a few seconds could make a life-or-death difference. Finally, Internet use by the police facilitates strong ties and cohesive bonds with the community, which are essential for community-oriented policing.

Table 1. Description of Police IT Use and Corresponding Functionalities

Technology	Functionalities	Description of Functionalities
Analytics Technologies	Crime Analysis	Analyzing data on past crimes, incidents, offenders and other community information
	Crime Mapping	Geographically visualizing past crime occurrences to understand which neighborhood is most susceptible to crimes
	Hotspot Identification	Identifying areas where crimes are most likely to occur in the near future
Real-Time Response Technologies	Computer-Aided Dispatch	Responding to 911 calls, identifying the call locations, and deploying the nearest patrol units
	In-Field Communication	Communicating between police officers, digitally transmitting intelligence to officers in the field
	In-Field Report Writing	Writing incident reports in field, remotely submitting reports to the central repository
Internet		Collecting intelligence from the community and interacting with citizens

To test the relationship between IT use and violence against the police (deaths and assaults), we conducted an empirical analysis with a large-scale panel dataset from U.S. local police departments. We obtained data on police deaths and assaults from the Federal Bureau of Investigation (FBI). We also acquired data on police IT use and other operational information from the U.S. Bureau of Justice Statistics (BJS). We also collected data on demographic and socioeconomic indicators of localities from the U.S. Census Bureau. Combining these three data sources, we built a panel dataset of 3,912 local law enforcement agencies in 2003 and 2007. For an additional analysis, we also used a more recent dataset from 2013, which provides more detailed measures for IT use.

Our results show that IT use for crime analysis and computer-aided dispatch is significantly associated with fewer deaths of police officers. Internet use is also negatively associated with police deaths. Also, IT use for dispatch and in-field report writing is negatively related to assaults to officers. To corroborate our finding that police IT use contributes to a reduction in violence, we estimated the impact of IT use on the number of criminal offenders killed by police officers. We obtained a similar finding that the use of three IT functionalities (crime analysis, computer-aided dispatch, and the Internet) is related to a significant decrease in police-caused homicides of offenders. However, we also found that IT use for crime mapping and hotspot identification leads to more killings of offenders by the police. Additionally, we found that the relationship between police IT use and deaths of both police officers and offenders is stronger in municipalities with a higher economic divide.

To the best of our knowledge, this is one of the first studies, if any, to examine the role of IT for occupational safety in organizations that operate in turbulent and dangerous environments. We seek to contribute to the IS literature by showing that IT use can lead to an improvement in the safety of workers (police officers in this case) who perform risky, high-stake functions in violent settings. We believe that our results can be generalized to several other occupations that operate in hazardous conditions, such as the military, firefighters, emergency responders, intelligence agents, or workers in nuclear plants. This study addresses the broader challenging question as to how to ensure the safety of personnel, perhaps the most important resource for the success of any organization (Becker and Gerhart 1996, Collins and Clark 2003). We show that IT can be an indispensable tool for such organizations in identifying, avoiding, and responding to critical risks to their human resources.

2. Theoretical Development

2.1. Prior Work

Prior research in the criminology literature has looked at how IT adoption and use by the police facilitates law enforcement (e.g., Silverman and O'Connell 1999, Chan 2004, Manning 2001, Ratcliffe 2002, Ratcliffe and Guidetti 2008, Cope 2004, Willis et al. 1994). However, in this literature stream, quantitative empirical studies with large-scale data are scarce. Among such studies, Garicano and Heaton (2010) found that IT use by the police does not have a significant impact on crime occurrence and clearance rates, but it is significantly related to increases in education requirements and training hours for newly hired officers. Nunn (2001) showed that more computerized police departments are associated with higher expenditures, but with fewer sworn officers. Rosenfeld et al. (2005) claimed that after the introduction of Compstat, a data-driven policing program, in the New York City Police Department (NYPD) in 1994, homicide rates decreased to a greater (but marginal) extent than other large U.S. cities. Weisburd et al. (2006) showed that police departments that implemented Compstat-like policing were associated with higher organizational flexibility and more decentralized decision authority than others. Our study differentiates from these prior studies by looking at the effect of IT use on officer safety, using large-scale archival datasets from multiple data sources, which only a few prior studies in the IS or the criminology literature have examined.

The criminology literature has identified the key factors that affect violence against police officers. Prior studies posit that social instability, political division, and resource deprivation in the community are significantly associated with police homicides and assaults. For example, Jacobs and Carmichael (2002) and Kent (2010) showed that violent crime rates and income disparity between white and black populations are associated with police officer deaths. Kaminski et al. (2003) and Batton and Wilson (2006) showed that police officers are in more danger in economically deprived places with higher poverty and unemployment rates. Kaminski (2008) showed that social instability indicators, such as divorce rates, are associated with more violence against the police. Nonetheless, to the best of our knowledge, our study is one of the first, if any, to examine how IT use by the police influences violence against police officers.

2.2. Law Enforcement Capabilities and Violence against Police Officers

Extending the criminology literature by integrating with IS research on organizational capabilities, we theorize that two types of organizational capabilities in law enforcement – *intelligence-led policing* capability and *community-oriented policing* capability – help reduce violence against police officers.

2.2.1. Intelligence-Led Policing Capability

An intelligence-led policing capability is defined as the ability to collect and analyze "information related to crime and conditions that contributed to crime, resulting in an actionable intelligence product intended to aid law enforcement in development tactical responses to threats and/or strategic planning" (Carter and Carter 2009, p. 317). Intelligence-led policing initially originated from Compstat, a signature police management program introduced by the NYPD in 1994 (Weisburd et al. 1994, Rosenfeld et al. 2005). It was one of the first data-driven strategic policing initiatives (Skogan and Frydl 2004), in which the NYPD analyzes crime patterns to better understand underlying community problems based on granular crime statistics at the precinct level and other information such as complaints, summons, and victims. The NYPD is one of the first police departments to use electronic crime mapping, conduct "crime-spike" analyses and responses, and evaluate rank-and-file police officers (e.g. captains and commanders) based on crime statistics (Weisburd et al. 1994).

The police rely on a wide range of intelligence to identify and solve crimes (Chan 2004). Typically, to identify a suspect, police officers begin an investigation with information and evidence obtained from crime scenes, conduct interviews with victims, witnesses, and neighbors, and sift through the records of previous crimes, convicted offenders, and suspects. After identifying a person of interest, they collect intelligence on the suspect, such as his/her residence, behavior, personality, and *modus operandi*, all of which they use to apprehend and convict the suspect. Without such intelligence, police officers would have to rely only on their instincts, hunches, or gut feelings and try to apprehend offenders in a serendipitous, uninformed, or "flying-blind" manner (Weisburd et al. 2003). Without a systematic data-driven approach, it would take more time for the police to identify culpable suspects, or they might chase and apprehend innocent people, wasting time and goodwill with the community.

Intelligence-led policing also helps the police reduce the likelihood of violent encounters with criminal offenders in the following ways. First, with credible intelligence on suspected criminals (e.g., types of weapons that they are likely to use or potential locations they hide), police officers can adjust their approach in a manner to reduce violence during arrests. For instance, if police officers who try to apprehend a suspect have intelligence that the suspect is armed and dangerous, they will exercise extra caution in approaching the suspect by equipping themselves with necessary firearms and wearing protective gears (*The Washington Post* 2016). With such intelligence, the police can prioritize resource allocation (e.g., officers, patrol cars, and weapons) (Weisburd et al 2003, Cope 2004). When a violent encounter is expected, the police can deploy more officers and firepower to subdue criminals more swiftly with less violence. Also, a targeted, intelligence-driven approach in finding and apprehending suspects can reduce the chance of encounters with innocent, yet potentially violent suspects who may resist search or questioning more forcefully when they believe they are not culpable of crimes and are unfairly targeted by the police.

Intelligence-led policing also enables police officers to control crimes more proactively rather than responding to crimes that already occurred reactively (e.g. Gianakis and Davis 1998, Chan 2004, Ratcliffe 2002, Ratcliffe and Guidetti 2008). By being proactive, it means that the police can anticipate and deter crimes before they take place. For instance, the police use intelligence to forecast future crime occurances, an approach called "predictive policing" (Bachner 2013, *Government Technology* 2014c). The police can pinpoint areas where crimes are most likely to occur in the future (Sherman et al. 1989, Manning 2001, Skogan and Frydl 2004, *Government Technology* 2013c). Other intelligence used for predictive policing includes movement of organized crime members, trades of weapons and drugs, conflicts among criminal groups or gangs, and other socioeconomic conditions in unstable neighborhoods (Carter and Carter 2009). With such intelligence, the police can deploy necessary resources to such violent-prone areas, helping suppress criminal activities as well as violent encounters between police officers and criminals. Based on these theoretical arguments and practical examples, we offer the following proposition on reducing violence against police officers.

Proposition 1. *Intelligence-led policing leads to a reduction in violence against police officers.*

2.2.2. Community-Oriented Policing Capability

The criminology literature also puts forth that for effective law enforcement, a strong relationship with the public is a prerequisite (Hahn and Jeffries 2003, Skogan and Frydl 2004). This logic is motivated by the findings that increases in police budgets and manpower do not necessarily lead to a reduction in crimes, but a cooperative relationship with residents is more effective in crime control. Community-oriented policing aims to achieve this goal (Skolnick and Barley 1998, Adams et al. 2005). Dantzker (2010, p. 205) defines a community-oriented policing capability as "an approach to providing police services with a focus on improving the quality of life in a community," arguing that one of the requirements for this particular policing approach is the ability to interact with citizens in a way that "information and responsibilities are shared." Trojanowicz and Bucqueroux (1994, p. 2) propose that community-oriented policing requires a capability of working together with the community "to identify, prioritize, and solve contemporary problems such as crime, drugs, social and physical disorder…"

Law enforcement is a unique setting, in that the public are considered both consumers of public safety services and subjects of law enforcement (Hahn and Jeffries 2003). Unlike a traditional policing approach that emphasizes the latter, community-oriented policing requires the police not to view the community only as a target of law enforcement but as a partner and a co-producer of public safety (Thurman and Reisig 1996). It is emphasized that rather than playing a role of the enforcer of social order, the police become part of the community by engaging with residents and building rapport with them (Greene 1993, Mastrofski et al. 1995, Adams et al. 2005, Cordner 2014). According to this view, it is advised that the police be more responsive to residents' everyday concerns regarding safety and play a more active role in improving the community's conditions. Rather than reactively responding to crimes after they occur, the police are expected to proactively participate in the community's problem-solving efforts in challenging economic issues such as poverty, drugs, or poor education (e.g. Goldstein 1987, Mastrofski et al. 1995, Thurman and Reisig 1996, Gianakis and Davis 1998, Dantzker 2010), all of which are prone to crimes and violence against the police.

Strong partnerships with the community are critical in ensuring the safety of police officers (Moore 1992, Thurman and Reisig 1996). Without such a bond with the police, the community may recognize them as a ruler or an authoritarian figure that restrains the citizens' civil rights and suppresses their freedom in the name of safety (Kerley and Benson 2000, Adams et al. 2005). This is often the case in communities with large minority populations and White-majority police force (Hahn and Jeffries 2003). Under such an environment, law enforcement meets with more vehement resistance and opposition from the public. Viewing the police not as a partner but as the enemy, the community would be uncooperative with police investigations, inquiries, and requests for information (Dantzker 2010). The use of force by the police is more likely to be regarded as police brutality, not as justifiable police actions. Accordingly, feeling that the police treat citizens unjustly, criminal suspects would resist arrests or searches forcefully and aggressively, thereby posing more risks to police officers. On the other hand, effective community-oriented policing is likely to build trust and acceptance toward the police over time, thereby helping the police perform their role in public safety more effectively and reducing violence against police officers. This discussion leads us to offer the following proposition.[2]

Proposition 2.*Community-oriented policing leads to a reduction in violence against police officers.*

2.3. Hypotheses – Police IT Use and Violence against Police Officers

Drawing upon the propositions we put forth earlier, we propose our hypotheses that police use of three sets of technologies – *analytics*, *real-time response*, and *the Internet* (Table 1) – is associated with a reduction in violence against police officers. We make this link by building upon the perspective that the use of IT functionalities acts as an enabler of organizational capabilities (e.g., Pavlou and El Sawy 2006, Mishra et al. 2007, Rai et al. 2012; Im and Rai 2014, Angst et al. 2014, Liu and Ravichandran 2015). We adopt "IT use" as our theoretical construct of interest since the IS literature puts forth that actual IT use has a more concrete theoretical link with organizational resources and business value than IT spending or assets (e.g., Devaraj and Kohli 2003, Zhu and Kraemer 2005, Mishra and Agrawal 2010, Hsieh et al. 2011).

[2] In our dataset, the number of community policing policies are highly correlated with IT use variables (0.2627 – 0.5265).

2.3.1. Analytics Technologies

Analytics in law enforcement have been defined as the "process of identifying patterns and relationships between crime data and other relevant data sources to prioritize and target police activity" (Cope 2004, p. 188). In this study, we consider the use of analytics technologies for three functions – (a) *crime analysis*, (b) *crime mapping*, and (c) *hotspot identification* – all of which we argue can help develop intelligence-led and community-oriented policing capabilities in police departments.

Crime Analysis

As discussed earlier, by analyzing data on past crimes, behaviors of criminals, and underlying community conditions, the police cannot only gain necessary intelligence to identify and arrest criminal perpetuators, but also to better prioritize their limited resources (e.g. Weisburd et al. 2003, Cope 2004). Credible intelligence on criminals obtained from crime analyses, such as criminals' behavioral patterns, known associates, financial traits, and locations that they loiter helps the police apprehend them quickly and safely without violent resistance. As put forth in Proposition 1, such an informed targeting of offenders with crime analysis helps police officers avoid encounters with innocent, albeit potentially violent, citizens, thus reducing the occurrence of violent situations.

The use of analytics technologies for crime analysis can be a driver of the community-oriented policing as well. Swift crime clearance and effective crime control brought by intelligence can demonstrate that the police are a capable service provider and a problem solver that can address the needs and problems of the community (Moore 1992), thus enhancing the relationship between the police and the community. In addition, Cordner (2014, p. 158) emphasizes that for effective community-oriented policing at the granular neighborhood level, "there is a greater need for timely crime analysis and problem analysis with geographic information systems." With analyses of crimes and other demographic and socio-economic data, the police can identify and help solve chronic community problems, such as drugs, gangs, or tensions among ethnic groups, which create environments conducive to crimes and violence (Greene 1989, Moore 1992, Skogan and Frydl 2004). As put forth in Proposition 2, if the police can solve such deep-rooted socio-economic problems with crime analysis using analytics technologies, the community can embrace the legitimacy of police conduct (Moore 1992), thus helping to improve the relationship with the police and reducing violence against officers.

Crime Mapping and Hotspot Identification

The use of analytics technologies for crime mapping and hotspot identification also support predictive policing, a key part of intelligence-led policing. Crime mapping is used to visualize past crime occurrences on a map so that the police can have a clear understanding of which neighborhood is most susceptible to crimes and from what problems the community suffers (Manning 2001, Weisburd et al. 2003). With intelligence on gang behaviors, trades of guns or drugs, weather, and other factors that are conducive to crimes, the police can identify "hotspots" or areas where criminal incidents are most likely to occur in the near future (e.g. Sherman et al. 1989, Manning 2001, Skogan and Frydl 2004, *Government Technology* 2013c). The police can deploy more resources (officers, patrol cars, firearms) to the hotspots in a strategic, targeted manner (*Government Technology* 2014b). Such an increased level of police presence in hotspots sends a clear signal to criminals that there is a greater chance of getting arrested if they commit crimes. The criminology literature states that criminals generally act in a rational manner, and they are less willing to commit crimes if potential gains from crimes are outweighed by the risks of being apprehended and punished (Goel and Rich 1989, Ehrlich 1996, Machin and Meghir 2004). Sherman and Weisburd (1995) found that increased police presence in hotspots is associated with a reduction in crime and disorderly conduct. Guided by Proposition 1, we argue that intelligence-led policing supported by crime mapping and hotspot identification can lead to a decreased chance of police officers being attacked or killed by criminals.

Based on the forgoing theorization, we hypothesize that the use of analytics technologies supports intelligence-led and community-oriented policing, leading to a reduction in violence against police officers. In the empirical investigation to follow, we operationalize the use of analytic technologies with the three functionalities we mentioned above – *crime analysis, crime mapping, and hotspot identification*, while violence against police officers is measured by deaths and assaults of police officers.

Hypothesis 1. *Police IT use of analytic technologies is negatively associated with violence against police officers.*

2.3.2. Real-Time Response Technologies

We next put forth that the use of real-time response technologies help reduce violence against police officers by building both intelligence-led policing and community-oriented policing capabilities. Herein, we consider three functionalities in real-time response technologies – *computer-aided dispatch*, *in-field communication*, and *in-field report writing*.

Computer-Aided Dispatch

Computer-aided dispatch aims to automate crime response functions (Chan 2004, Institute for Law and Justice 2002, *Government Technology* 2014a). Traditionally, 911 operators had been using analog communication technologies to locate 911 callers and to deploy police officers. To locate where an incident takes place, the dispatch operators had to rely on what a 911 caller said to them over the telephone, but it is extremely difficult, in most cases, for the caller to describe where exactly he or she is at an emergency situation. In addition, with a traditional dispatch system, the dispatchers did not know where officers were patrolling and which patrol unit was closest to the incident location.

According to a survey by the BJS, on average, the police took approximately four minutes to arrive at an incident scene in 2007.[3] This responding time varied from less than one minute to a few hours across police departments. On the other hand, on average, a criminal incident ends in 90 seconds, [4] indicating that more often than not, the police missed a chance to stop the incident before the perpetuators ran away. A lengthy response time by the police can create a perception among citizens that the police are not concerned with the safety of the community, significantly degrading the relationship between the police and the community. Thus, swift responses to emergencies are important for effective community-oriented policing.

With computer-aided dispatch, the police dispatchers can immediately identify the precise location of a 911 call and find which patrol officers are closest to that location with a global positioning system (GPS). With this precision, police departments can shorten officers' response time to emergency situations. By doing so, the police can demonstrate that they are capable of crime response and deterrence, helping

[3] http://www.bjs.gov/index.cfm?ty=pbdetail&iid=1743, accessed on Sep. 22, 2015
[4] http://freedomoutpost.com/2014/06/when-seconds-count-police-are-minutes-awayor-your-911-call-goes-to-voicemail/, accessed on Sep. 22, 2015

improve citizens' relationship with the police, a key goal of community-oriented policing (Moore 1992). Thus, following Proposition 2, we expect that the use of computer-aided dispatch by police departments helps prevent violence against police officers.

In-Field Communication

In-field communication technologies support the intelligence-led policing capability by digitizing the communication between the dispatch and officers as well as among responding police officers. The communication used to take place over voice-based analog radio systems, in which it was rather unreliable for the dispatchers to deliver specific incident information to the police officers in the field. Digitized communication enables immediate, reliable transmission of fine-grained information on ongoing incidents to responding units, such as suspects' location, victims' status, criminal histories, *modus operandi*, weapons being used, and other actionable intelligence. As argued in Proposition 1, with such real-time intelligence, responding police officers effectively adjust their approach and better coordinate with fellow responders in a way that reduces the risk of being assaulted or killed in the line of duty.

In-Field Report Writing

Responding officers in the field can also use digital communication technologies to write incident reports in the field (*Police Chief Magazine* 2011). This provides an effective tool for real-time intelligence gathering. Without such a tool, officers would have to go back to their precincts at the end of their shift and write incident reports based on their recollection after a long shift, or even after several days. Studies show that police officers suffer from chronic stress, fatigue, and burnouts (Hawkins 2001, Anderson et al. 2002, Zhao et al. 2002, Vila 1996, 2006), which lead to short-term memory loss and impairment in cognitive abilities (McDonald et al. 1993, de Quervain et al. 1998, Kuhlmann et al. 2005, Henckens et al. 2009, Neu et al. 2011). Hence, it is difficult for them to provide an accurate account of what happened in the field. IT use for in-field report writing enables responding officers to produce more fresh, unadulterated incident information on the spot while their memory is clear, offering real-time actionable intelligence for arresting and convicting the criminals and thereby supporting intelligence-led policing. In addition, information produced by the responding officers immediately after an incident carries greater currency and provides more valuable intelligence than if they have to write reports much later at their precinct. Detectives can initiate investigations and identify perpetuators faster with on-the-spot incident reports. It is emphasized that "automating the transmission of incident reports is a critical element in building timely, accurate information and information-sharing capabilities" (*Police Chief Magazine* 2011, p. 1). Hence, based on the logic of Proposition 1, we propose that IT use for in-field report writing is associated with a decrease in police officer deaths and assaults.

The aforementioned discussion so far leads us to hypothesize that the use of real-time response technologies helps the police reduce violence against police officers.

Hypothesis 2. *Police IT use of real-time response technologies is negatively associated with violence against police officers.*

2.3.3. Internet Use

We propose that Internet use by the police leads to less violence against officers in two ways. First, the Internet is used to collect intelligence needed for crime solving and analyses. For instance, police departments can search social media sites such as Facebook, Twitter, or Pinterest to obtain intelligence on persons of interest (*Government Technology* 2013a). In addition, police departments "crowdsource" intelligence from citizens, who provide "tips" such as witness accounts, whereabouts of persons of interest, or other information on suspicious activities by sending emails, posting on Twitter, or submitting information to the department websites (*Government Technology* 2011, 2012). Such on-street information gathered from the public enables intelligence-led policing (Carter and Carter 2009). As discussed in Proposition 1, this informed, targeted approach leads the police to solve and control crimes more effectively as well as in a manner that reduces the chance of violent encounters with criminals or even with innocent bystanders.

Second, the Internet is an important tool for the police to advance its community-oriented policing capability. Dantzker (2010, p. 205) emphasizes that "police-citizen interactions where information and responsibilities are shared" are a prerequisite to community-oriented policing. The police can use the Internet as an interaction and communication tool with the community. The police use public websites and social media to publish crime trends, crime alerts, crime-deterrence activities, and other information that could keep the community informed and safe. In doing so, the police can demonstrate transparency and accountability in its law enforcement actions (*Government Technology* 2013b). These Internet-enabled efforts educate citizens on how to avoid areas where crimes take place and protect their properties and lives from criminals (Goldstein 1987).

The Internet can also be utilized as a channel for residents to participate in law enforcement. Using the Internet, the police can anonymously solicit the citizens' concerns, questions, or feedback on police activities and public safety. Cordner (2014) points out that citizen input and involvement in policing is one of the key philosophical elements in community-oriented policing. By instituting two-way communication channels over the Internet (Carter and Carter 2009), the police can be viewed not as a passive bureaucrat or an authoritative ruler, but as a genuine, trusted partner who aims to improve the quality of the community and daily lives (Thurman and Reisig 1996, Adams et al. 2005). Therefore, continuous interactions and close engagement via the Internet can help the community accept police activities as legitimate law enforcement efforts (Moore 1992, Kerley and Benson 2000, Hahn and Jeffries 2003). As noted in Proposition 2, a close relationship between the police and the community is essential in reducing violence against police officers. In addition, strong ties between the police and the community enable citizens to become more forthcoming in providing credible, reliable information needed for solving crimes. If citizens do not have much trust in the police, they would discourage each other from cooperating with the police, who in turn would have difficulty in collecting necessary intelligence from the community.

In summary, we propose that Internet use by the police improves the two key policing capabilities in terms of both intelligence-led and community-oriented policing, thereby helping reduce violence (deaths and assaults) against police officers.

Hypothesis 3*. Police IT use of the Internet is negatively associated with violence against police officers.*

3. Research Methodology

3.1. Data

We tested our hypotheses in the context of U.S. local police departments located in cities, counties, or townships. We collected data on police IT use and other operational information from the Law Enforcement Management and Administrative Statistics (LEMAS) published by the BJS, which conducted surveys in 2003 and 2007 on a random sample of 2,800 law enforcement agencies, such as local police departments, state police, and specialized police agencies. We excluded state law enforcement and specialized agencies (e.g., campus, transit, or park) since their duties differ from local agencies and their jurisdiction is either too wide or too narrow, respectively, compared to local police departments.[5] We obtained data on violence against police officers from the Uniform Crime Reports (UCR) database published by the FBI. The UCR covers annual crime statistics and other public safety data from more than 18,000 law enforcement agencies. It also annually publishes the number of police officers killed or assaulted in the line of duty in each agency. Combining the LEMAS and the UCR datasets, our sample consists of 4,950 observations from 3,921 police departments in two years (2003 and 2007).

Table 2 describes the profiles of the police departments in the sample. One-sample *t*-tests showed that the police departments in our sample are not significantly different from others in terms of population, crime occurrence and clearance rates. Other indicators such as median household income, ethnicity, or educational attainment in our localities are similar to the national averages.

Table 2. Profiles of Police Departments in Our Sample

Population	**Number of Departments**
> 1,000,000	40
500,000 – 1,000,000	81
200,000 – 500,000	189
100,000 – 200,000	307
50,000 – 100,000	521
20,000 – 50,000	863
10,000 – 20,000	657
< 10,000	1,263
Urban/Rural	Number of Departments
Urban [1)]	2,221

[5] During 1999-2013, 96.6% of the law enforcement agents who were killed in the line of duty were police officers in ***local*** police departments. 98.7% of the attacks were occurred against ***local*** police officers.

Rural	1,691
Share of White Population	Number of Departments
> 90%	1,437
70% - 90%	1,529
50% - 70%	609
< 50%	337
Median Household Income	Number of Departments
> $70,000	499
$50,000 - $70,000	999
$30,000 - $50,000	2,124
< $30,000	290

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

Table 3A. Variable Definitions and Data Sources (Main Variables)

Variable	Definition	Data Sources
Dependent Variable		
Officer Killed	Number of officers killed in the line of duty	Uniform Crime Reports (UCR) from the FBI
Officer Assaulted	Number of officers assaulted in the line of duty	
Offender Killed	Number of offenders killed by police	
Independent Variables – Police IT Use		
Crime Analysis (H1)	1 = Agency uses computer for crime analysis; 0 = otherwise	Law Enforcement Management and Administration Survey (LEMAS) from the BJS
Crime Mapping (H1)	1 = Uses computer for crime mapping	
Hotspot Identification (H1)	1 = Uses computer for hotspot identification	
Dispatch (H2)	1 = Uses computer for dispatch	
In-Field Communication (H2)	1 = Uses computer for in-field communication	
In-Field Report Writing (H2)	1 = Uses computer for in-field report writing	
Internet (H3)	1 = Uses computer for Internet	
Control Variables – Crime Occurrence and Clearance		
Crime Occurrence	Log (# of crimes known to police)	UCR
Crime Clearance	Share of crimes cleared to crimes known	
Control Variables – Basic Locality Information		
Population	Log (population)	UCR
Miles	Log (square-miles covered by agency)	
MSA Core City	1 = core city of metropolitan area; 0 = otherwise	
Control Variables – Police Operation		
Operational Budget	Log (operational budget ($) per capita)	LEMAS
Education Requirement	Educational requirements for new officers (1 = no requirement, 5 = high school or higher)	
White Officer	Share of White officers to total officers with arrest powers	
Female Officer	Share of female officers	
Training	# of training hours required for new officers (in 1,000)	
Weapon	# of types of sidearm (e.g. 10mm) allowed in duty	
Policy	# of instituted officer conduct policy	
Community Policing	# of community policing initiatives	

Table 3B. Variable Definitions (Demographic and Socio-Economic Conditions)

Variable	Definition
Data Sources - American Community Survey from the U.S. Census Bureau	
Control Variables – Demographic Information (Miethe et al. 1991, Baller et al. 2006, Kaminski 2008, Garicano and Heaton 2010)	
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 (Baumer et al. 1998, Batton and Wilson 2006, Baller et al. 2006, Kent 2010)	
Income	Median household income ($ thousand)
Poverty	Share of population below poverty level
Vacant Homes	Number of vacant homes per capita
Inequality	Gini coefficient for income inequality
Control Variables – Social Conditions (Land et al. 1990, Miethe et al. 1991, Baumer 1994, Kaminski et al. 2003, Kaminski and Stucky 2009)	
Moved	Share of population who moved within one year
Public Transportation	Share of workers using public transit
Female Workers	Share of female workers
Female Household Head	Share of female household heads (a single mother or a single grandmother)
Two Parent Household	Share of households with two parents

3.2. Measurement

Tables 3A and 3B list our measures and definitions. We used police IT use indicators from the LEMAS datasets in 2003 and 2007, which measure whether a police department uses computers in 18 functions such as record management, personnel management, or resource allocation, as of June 30, 2003 and September 30, 2007, respectively. Our independent variables measure IT use in seven functionalities – crime analysis, crime mapping, hotspot identification, dispatch, in-field communication, in-field report writing, and Internet access. As an additional analysis, we used a more recent LEMAS dataset collected in 2013, which includes additional measures for Internet use by police departments.

We measured violence against police officers with the number of police officers killed or assaulted in the line of duty in a three-year period (2003-2005 and 2007-2009). We regressed officer deaths and assaults in 2003-2005 and 2007-2009 on IT use in 2003 and 2007, respectively. As robustness checks, we changed this three-year window to a one-year or a two-year window, and we did not obtain substantially different results. To further validate our theoretical discussion, we also used the number of offenders killed by officers as another dependent variable, obtained from the UCR Supplementary Homicide Reports (Jacobs and O'Brien 1998, Smith 2003, 2004, McElvain and Kposowa 2008).

We controlled for several factors that could affect violence against the police in our estimations. Since police officers are at a greater danger when crimes are more prevalent or the police enforce laws more aggressively, we controlled for the *number of crimes occurred* and the *share of crimes cleared by the police* in our estimation (Jacobs and Carmichael 2002, Kaminski et al. 2003, Batton and Wilson 2006, Fridell et al. 2009, Kent 2010, Garicano and Heaton 2010). The crimes occurred and cleared include violent crimes (e.g., murders, manslaughters, rapes, robberies, assaults) and property crimes (e.g., burglaries, larcenies, vehicle thefts). We controlled for basic locality information, such as *population* and *size of jurisdiction*. We added a dummy variable (MSA Core) that is equal to one if a department serves the largest city in metropolitan statistical areas (MSA) as defined by the U.S. Census Bureau.[6] Our control variables also include several indicators for police operations and personnel. We controlled for *operational budget per capita* as an indicator for the size of police departments. As measures for personnel characteristics, we controlled for *education requirement* and *training hours* for new recruits (McElvain and Kposowa 2008, Fridell et al. 2009, Garicano and Heaton 2010). Since the criminology literature points out that violence against police officers depends on officers' race and gender, we controlled for the share of *white and female officers* to total sworn officers with arrest power (e.g. Smith 2003, McElvain and Kposowa 2008, Kaminski and Stucky 2009). As for police operations, we included *the type of firearms* (e.g. revolver, semi-automatic) allowed and *the number of police conduct policies* as control variables (e.g., Kaminski 2008, Fridell et al. 2009, Garicano and Heaton 2010). Since violence against the police is also affected by the relationship between the police and the community, we also controlled for *the number of formal community-oriented policing initiatives*, such as collaborative problem-solving partnerships or involvement of citizens in policing (Greene 1989, Moore 1992, Cordner 2014).

[6] For example, Dallas is the core city in the Dallas-Fort Worth-Arlington, Texas, metropolitan area.

Following the criminology literature (e.g., Land et al. 1990, Miethe et al. 1991, Baller et al. 2006, Kaminski 2008), we also controlled for several *demographic* and *socioeconomic factors* that indicate propensity to crimes and violence, using data from the American Community Survey conducted by the U.S. Census Bureau (Table 3B). Table 4 and Table A1 (Online Supplementary Appendix A) show the descriptive statistics and correlation among the key variables, respectively.

Table 4. Descriptive Statistics (*N* = 4,950)

Variable		Mean	Std. Dev.	Minimum	Maximum
Officer Killed	(1)	0.0426	0.2793	0	6
Officer Assaulted	(2)	45.7950	202.4326	0	5019
Offender Killed	(3)	0.4293	2.5984	0	66
Crime Analysis	(4)	0.5683	0.4954	0	1
Crime Mapping	(5)	0.4566	0.4982	0	1
Hotspot Identification	(6)	0.2887	0.4532	0	1
Dispatch	(7)	0.7083	0.4546	0	1
In-Field Communication	(8)	0.4463	0.4972	0	1
In-Field Report Writing	(9)	0.5168	0.4998	0	1
Internet	(10)	0.9014	0.2981	0	1
Crime Occurrence	(11)	7.6820	1.9651	0	13.2823
Crime Clearance	(12)	0.2959	0.1524	0	1.3333
Population	(13)	10.2411	1.6589	4.1271	16.1052
Miles	(14)	3.7336	2.3042	-1.9260	11.3943
MSA Core	(15)	0.1798	0.3841	0	1
Operational Budget	(16)	4.9875	0.7417	1.2398	8.4440
Education Requirement	(17)	2.9533	1.7615	1	5
White Officer	(18)	0.8673	0.1799	0	1
Female Officer	(19)	0.0825	0.0731	0	1
Training	(20)	1.0935	0.5235	0	9.7800
Weapon	(21)	2.2826	2.2806	0	9
Policy	(22)	3.6434	0.6557	0	4
Community	(23)	2.9838	2.4006	0	8
Male	(24)	0.4886	0.0253	0.2333	0.8894
White	(25)	0.7798	0.1830	0.0142	1
Young	(26)	0.1421	0.0515	0	0.7586
High School	(27)	0.2055	0.0631	0	0.4815
Income	(28)	50.5777	20.1052	10.8020	242.1880
Poverty	(29)	0.1513	0.0778	0	0.6147
Vacant Homes	(30)	0.0681	0.1267	0	3.5202
Inequality	(31)	0.4359	0.0478	0.0800	0.6445
Moved	(32)	0.1755	0.0610	0	0.6586
Public Transportation	(33)	0.0264	0.0507	0	0.5604
Female Workers	(34)	0.4682	0.0652	0.1733	0.8250
Female Household Head	(35)	0.0535	0.0270	0	0.2596
Two Parent Household	(36)	0.1559	0.0431	0	0.4360

3.3. Estimation Approach and Identification Strategy

We estimated the model with a random-effects regression[7] and controlled for state, metropolitan area, and year fixed-effects. As robustness checks, we used negative binomial regression and spatial autocorrelation models as alternative estimation methods (Arraiz et al. 2010).

We do not have a strong reason to believe that endogeneity is of major concern in our setting. Prior literature argues that IT use in police departments is primarily driven by the need to control and reduce crimes or to improve productivity in police operations (Manning 2001, Nunn 2001, Chan 2004, Garicano and Heaton 2010). Thus, we do not expect *reverse causality* to create substantial bias in our estimation. In addition, we controlled for a variety of factors in police operations, officer characteristics, demographics, and socio-economic conditions of neighborhoods (Table 3A) in order to minimize *simultaneity* in our estimations as much as possible. For example, one may point out that IT use leads to a decrease in violence against police officers by reducing crime occurrence rates, a factor that is controlled in our estimation. Alternatively, IT use is associated with an increase in educational requirements for police officers (Garicano and Heaton 2010), who could become more apt in avoiding violence against themselves. We controlled for the educational requirements in order to rule out this possibility. *Measurement error* in our dependent variables is not of concern since it is difficult to conceal deaths and assaults of police officers (Jacobs and O'Brien 1998). However, measurement error in the independent variables could cause bias in our estimations because the self-reported IT use variables may differ from actual IT use. However, our additional analysis with the LEMAS 2013 dataset with more detailed measures for IT use renders support to our measurement.

Still, there might be *unobserved heterogeneity* that affects both IT use and officer deaths/assaults. Ideally, we would use instrumental variables to account for unobserved heterogeneity, but given that we have seven independent variables for IT use, it would be virtually impossible to identify an enough

[7] We chose not to use a fixed-effect estimation for the following reason. In our panel dataset, only 1,079 out of 3,921 police departments in our sample appear in both 2003 and 2007. Thus, with fixed-effects estimations (i.e. adding 3,921 dummy variables to the sample of 4,950 observations), the model would lose too many degrees of freedom.

number of suitable instruments. Therefore, we alternatively used the approach of Shaver (1998) for correction of endogeneity, which was developed based on Lee (1978) and Heckman (1979). This approach was adopted by subsequent studies such as Pollock and Rindova (2003), Cantwell and Mudambi (2005), Sampson (2007), and Bharadwaj et al. (2007).

4. Results

4.1. Hypothesis Testing

Table 5 presents our baseline estimation results. Column 1 shows that IT use for crime analysis (H1) and computer-aided dispatch (H2) is significantly related to fewer killings of police officers. The coefficients indicate that crime analysis and computer-aided dispatch are associated with a 1.45% and 0.9% reduction, respectively, in officer deaths. Given the tragedy and economic loss of a police officer's death, we believe that this represents a significant improvement in officer safety. Column 1 also shows that Internet use (H3) is significantly associated with a reduction in deaths of police officers.

Table 5, Column 2 demonstrates that IT use for dispatch and in-field report writing (H2) is significantly related to fewer assaults to police officers. In particular, IT use for in-field report writing is associated with a 10.17% reduction in assaults to police officers. As argued in H2, with the use of in-field report writing technologies, responding officers can produce fresh, unadulterated intelligence on the spot, helping other officers capture offenders with less violence and thereby fewer assaults of police officers.

To buttress our proposition that police IT use affects violence between officers and criminals, we examined the effect of IT use on the number of offenders killed by police officers. Table 5, Column 3 presents similar results as Column 1. IT use for crime analysis, computer-aided dispatch, and Internet use is negatively associated with deaths of offenders, affirming our finding in Column 1. In particular, IT use for crime analysis and dispatch is associated with a 3.0% and a 5.73% reduction in criminals' deaths, respectively. This is an encouraging result; a homicide by the police, whether it is warranted or not, could cause a costly, time-consuming litigation by the family of the deceased and deteriorate the relationship with the community (Cheh 1996, Smith and Holmes 2003), as vividly shown in recent community turmoil in Ferguson, Missouri, and Baltimore, Maryland.

Table 5. The Baseline Estimation Results

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0146*** (0.0040)	0.0226 (0.0413)	-0.0303*** (0.0112)
Crime Mapping	0.0083* (0.0045)	0.0582 (0.0447)	0.0228* (0.0127)
Hotspot Identification	0.0086 (0.0068)	0.0219 (0.0451)	0.0560*** (0.0178)
Dispatch	-0.0090** (0.0042)	-0.0732* (0.0411)	-0.0590*** (0.0117)
In-Field Communication	0.0078 (0.0056)	0.0796* (0.0442)	0.0011 (0.0143)
In-Field Report Writing	-0.0020 (0.0052)	-0.1073*** (0.0376)	0.0012 (0.0124)
Internet	-0.0129** (0.0060)	-0.0689 (0.0535)	-0.0308* (0.0162)
Crime Occurrence	0.0077*** (0.0023)	0.2082*** (0.0234)	0.0360*** (0.0068)
Crime Clearance	-0.0108 (0.0130)	0.4314*** (0.1281)	-0.0204 (0.0345)
Population	0.0114*** (0.0043)	0.2843*** (0.0352)	0.0595*** (0.0111)
Miles	0.0039*** (0.0014)	-0.0262* (0.0140)	0.0018 (0.0038)
MSA Core	0.0163 (0.0104)	0.4786*** (0.0763)	0.2230*** (0.0303)
Operational Budget	0.0188*** (0.0047)	0.1748*** (0.0340)	0.0652*** (0.0122)
Education Requirement	-0.0061** (0.0027)	-0.0181 (0.0230)	-0.0127* (0.0072)
White Officer	-0.0467*** (0.0167)	-0.0696 (0.1453)	-0.1168** (0.0479)
Female Officer	0.0202 (0.0264)	-0.0865 (0.2422)	0.0476 (0.0763)
Training	0.0001 (0.0057)	0.0568* (0.0332)	0.0417*** (0.0142)
Weapon	0.0007 (0.0012)	0.0330*** (0.0085)	0.0019 (0.0034)
Policy	0.0014 (0.0026)	-0.0183 (0.0249)	-0.0008 (0.0071)
Community	-0.0018 (0.0013)	-0.0006 (0.0097)	-0.0125*** (0.0037)
Male	0.0076 (0.0760)	0.5394 (0.6373)	0.2468 (0.1954)
White	0.0199 (0.0206)	-0.0152 (0.1884)	-0.0840 (0.0644)
Young	-0.1305** (0.0516)	-0.7769 (0.5038)	-0.0175 (0.1554)
High School	0.0330 (0.0458)	0.8343 (0.5162)	0.2129 (0.1403)
Income	-0.0004** (0.0002)	-0.0053*** (0.0019)	-0.0010* (0.0005)
Poverty	0.0937* (0.0501)	0.7126 (0.4569)	0.0441 (0.1356)
Vacant Homes	-0.0013 (0.0121)	0.1687 (0.1514)	0.0535 (0.0445)
Inequality	0.1421*** (0.0516)	0.5284 (0.4600)	0.2498 (0.1554)
Moved	-0.0464 (0.0483)	-0.7872* (0.4229)	-0.6664*** (0.1308)
Public Transportation	0.1268 (0.0981)	0.9931 (0.8431)	0.9237*** (0.3321)
Female Workers	0.0040 (0.0425)	0.6061 (0.3810)	-0.1575 (0.1175)
Female Household Head	-0.0981 (0.0979)	0.9783 (0.9997)	-0.3266 (0.3125)
Two Parent Household	0.0564 (0.0747)	0.1295 (0.5608)	0.0712 (0.1612)
Controls	State, MSA[1)], Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.1814	0.6993	0.4293
Wald χ^2	50186.46***	83367.14***	1.0×10^5***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 4,950; # of Groups = 3,921; Robust standard errors are in parentheses.

1) Metropolitan Statistical Areas

Table 5 demonstrates that in our empirical estimation, reverse causality is not of serious concern. We do not have a strong reason to believe that deaths of criminals (Column 3) would lead the police to substantially increase their IT use. Provided that IT use negatively affects deaths of both police officers and criminals, if reverse causality or other endogeneity issues create large downward bias in Column 1, the coefficients of IT use in Column 3 would have been insignificant.

Surprisingly, however, IT use for crime mapping and hotspot identification is related to significantly more killings of offenders by police officers (Column 3). IT use for crime mapping is also marginally associated with more deaths of officers (Column 1). The literature indicates that many crime incidents go unnoticed by the police because victims do not always report them (e.g., Willis 1983, Kennedy 1988). Victims or witnesses are often afraid to go to the police because of fear of retaliation by the perpetuators. We interpret that crime mapping and hotspot identification help the police discover crimes that otherwise would have not been known to them, resulting in more aggressive interactions with criminals and thus more use of deadly force by police officers.[8]

Table 6. Estimation by Income Inequality (Full Results in Table A2)

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Killed + 1)**	**Log(Offender Killed + 1)**	**Log(Offender Killed + 1)**
Method	Random Effects			
	Inequality ≥ Median[1)]	Inequality < Median	Inequality ≥ Median	Inequality < Median
	(1)	(2)	(3)	(4)
Crime Analysis	-0.0156** (0.0074)	-0.0056 (0.0041)	-0.0417** (0.0206)	-0.0091 (0.0105)
Crime Mapping	0.0169** (0.0084)	0.0007 (0.0055)	0.0187 (0.0232)	0.0162 (0.0133)
Hotspot Ident.	0.0115 (0.0114)	-0.0007 (0.0085)	0.0647** (0.0261)	0.0461** (0.0229)
Dispatch	-0.0083 (0.0069)	0.0015 (0.0043)	-0.0546***(0.0194)	-0.0292** (0.0121)
In-Field Comm.	0.0104 (0.0107)	0.0048 (0.0057)	0.0265 (0.0236)	-0.0105 (0.0153)
In-Field Report	-0.0016 (0.0094)	-0.0052 (0.0058)	-0.0102 (0.0211)	0.0022 (0.0131)
Internet	-0.0302***(0.0110)	-0.0015 (0.0063)	-0.0741***(0.0275)	-0.0285* (0.0172)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year	State, MSA, Year
N	2,497	2,453	2,497	2,453
# of Groups	1,938	2,078	1,938	2,078
Overall R^2	0.2710	0.1664	0.5472	0.4154
Wald χ^2	$2.7\times10^{6***}$	$2.9\times10^{6***}$	$3.3\times10^{5***}$	$6.1\times10^{5***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors are in parentheses. ; [1)] Median = 0.432

[8] Indeed, IT use for crime mapping and hotspot identification in 2003 and 2007 is positively correlated with violent crime occurrence per capita in 2005 and 2009, respectively. The correlation ranges between 0.27 and 0.22.

Table 7. Estimation by Racial Disparity (Full Results in Table A3)

Dependent Variable	**Log(Offender Killed + 1)**	
Method	Random Effects	
	Racial Gap = | White Population – White Officer |	
	Racial Gap ≥ Median[1)]	Racial Gap < Median
	(1)	(2)
Crime Analysis	-0.0518***(0.0197)	-0.0146 (0.0140)
Crime Mapping	0.0315 (0.0204)	0.0176 (0.0171)
Hotspot Identification	0.0556** (0.0258)	0.0286 (0.0250)
Dispatch	-0.0654***(0.0205)	-0.0547***(0.0138)
In-Field Communication	0.0214 (0.0216)	-0.0285 (0.0199)
In-Field Report Writing	-0.0029 (0.0202)	0.0191 (0.0160)
Internet	-0.0534* (0.0283)	-0.0168 (0.0188)
Controls	State, MSA, Year	State, MSA, Year
N	2,475	2,475
# of Groups	1,980	2,110
Overall R^2	0.4510	0.5320
Wald χ^2	87270.83***	$3.8{\times}10^{6***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors are in parentheses.
[1)] Median = 0.0927, Mean = 0.1345, Min = 0, Max = 0.9888

4.2. Moderating Effects

In order to reinforce the validity of our theoretical mechanisms, we examine three moderating effects – (1) *income inequality*, (2) *racial disparity between the police and the public*, and (3) *the quality of the relationship between the public and the police*.

The criminology literature argues that violence against police officers can be explained by the economic and power structures of society (Jacobs and Carmichael 2002, Karminsky and Stucky 2009, Kent 2010). If a group of the population is disfranchised economically or politically, such a divide is conducive to aggression toward those who dominate the power, such as police officers. We examine how income inequality and racial disparity between the police and the overall population affect the relationship between police IT use and violence against the police. These two moderating factors represent an economic and a political division, respectively. The community is more unstable and susceptible to crimes and violence when there exists a greater economic division. Also, if the racial gap between the police (the enforcer of the law) and the community (the subject of enforcement) is large, the community is more likely to regard the police as an unruly power holder who suppresses their rights, possibly creating more tension and deepening distrust between the community and the police.

Table 6 first shows the estimation results with two subsamples divided by income inequality (the full estimation results are available in Table A2 in Appendix A). Columns 1 and 3 show the estimations with localities whose Gini coefficient is higher than the median (0.432), while Columns 2 and 4 are with Gini coefficients below the median. Comparing Columns 1 and 2, we find that IT use for crime analysis and the Internet is associated with police deaths more negatively when income inequality is higher. The coefficient of crime mapping is positive and significant in Column 1, but not in Column 2. This shows that the role of police IT use in violence against the police is more profound when the community they serve is more economically unequal and divided. We obtain more intriguing outcomes from Columns 3 and 4, which estimate the effect on criminals killed by the police. The impact of IT use for crime analysis, dispatch, and Internet on police-caused deaths is more negative in Column 3 than in Column 4. We conducted a similar sub-sample analysis with respect to assaults to police officers, but the impact of income equality is not as salient as in Table 6.

Table 8. Estimation by Citizen Complaints (Full Results in Table A4)

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Killed + 1)**	**Log(Offender Killed + 1)**	**Log(Offender Killed + 1)**
Method	Random Effects			
	Complaint ≥ Median[1)]	Complaint < Median	Complaint ≥ Median	Complaint < Median
	(1)	(2)	(3)	(4)
Crime Analysis	-0.0448^{***} (0.0155)	-0.0126^{*} (0.0068)	-0.1054^{***} (0.0396)	0.0000 (0.0162)
Crime Mapping	0.0229 (0.0153)	0.0006 (0.0064)	0.0520 (0.0402)	0.0138 (0.0176)
Hotspot Ident.	0.0076 (0.0167)	0.0109 (0.0114)	0.0356 (0.0386)	0.0411 (0.0264)
Dispatch	-0.0055 (0.0176)	-0.0083 (0.0066)	-0.0911^{**} (0.0451)	-0.0195 (0.0150)
In-Field Comm.	0.0073 (0.0158)	0.0111 (0.0093)	0.0518 (0.0364)	-0.0169 (0.0206)
In-Field Report	-0.0127 (0.0173)	0.0051 (0.0080)	0.0172 (0.0368)	-0.0092 (0.0183)
Internet	-0.0197 (0.0248)	-0.0126 (0.0121)	-0.0828 (0.0635)	-0.0245 (0.0186)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year	State, MSA, Year
N	1,592	1,592	1,592	1,592
# of Groups	1,229	1,490	1,229	1,490
Overall R^2	0.3064	0.2737	0.5472	0.4528
Wald χ^2	47470.17^{***}	40.86	$1.1\times10^{5***}$	97228.80^{***}

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors are in parentheses. ;
[1)] The number of citizen complaints on police use of force per 10,000 population,
Median = 0.016, Mean = 0.188; Min = 0, Max = 1.696

We also obtained an interesting result with respect to *racial disparity*, which is measured by the absolute difference between the share of white population and that of white police officers. We found that while racial disparity does not affect the relationship between IT use and officer deaths and assaults significantly, it does have an impact with respect to police killings of offenders (Table 7). The coefficient of crime analysis is significantly more negative in Column 1 than in Column 2. Also, the coefficient of hotspot identification is positive and significant in Column 1, but not in Column 2. These findings illustrate that police IT use affects police-caused deaths of criminals more significantly when the racial disparity is larger, that is, when a violent conflict between the police and the community is more likely to occur.

As we explained above, violence between police officers and criminals is also affected by the relationship between the police and the community; police officers are likely to be in more danger when citizens have distrust and acrimony against them. We examine how the relationship with the community affects the role of police IT use. The LEMAS data in 2003 and 2007 report the number of complaints filed by citizens regarding police use of force. We divided the sample by the number of complaints per 10,000 people. Table 8, Columns 1 and 2 show that the effect of crime analysis on officer deaths is more negative when the number of complaints is larger than the median. Likewise, the coefficient of crime analysis and dispatch with respect to criminals' deaths is more negative in Column 3 than in Column 4. This result shows that IT use can be more effective in reducing violence with criminals in areas with a poor relationship between the police and the community.

4.3. Robustness Tests

We conducted a series of robustness checks in order to address the concerns of endogeneity, unobserved heterogeneity, and omitted variable bias. In doing so, we adopted alternative estimation approaches, different sets of subsamples, varied lagged effects, and alternative control variables.

In order to address a concern of potential endogeneity, we followed Shaver (1998) and Bharadwaj et al. (2007). Specifically, we created a dummy variable that is equal to one if the sum of the seven IT use measures is greater than the mean. Then, we obtained inverse Mills ratios from a Probit regression of the dummy on several factors that drive police IT use (Table A5). These factors include IT use variables that are related to the management of internal resources (e.g. fleet management, resource allocation, automated booking). Then we added the inverse Mills ratios for each observation to our random-effects regressions. As shown in Table A6, while the coefficient of the ratio is significant in Column 1 and 3, this robustness check produces very similar results with our baseline estimation in Table 5.

A possible source of unobserved heterogeneity is spatial contagion of violence. The criminology literature theorizes that crimes and violence are contagious, as criminals do not honor jurisdictional boundaries (Baller et al. 2006). As such, crime occurrences in one locality are likely to be correlated with nearby ones, and we expect that it is the case with violence against police officers. In order to account for this, we estimate the model with a spatial-autoregressive model for a cross-sectional dataset (Arraiz et al. 2010, Kelejian and Prucha 2010, Drukker et al. 2013). Specifically, it is modeled as:

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

where $\mathbf{M}$ is a spatial-weighting matrix with 0 diagonal elements for spatial autoregressive disturbances. In $\mathbf{M}$, the weight between two localities (non-diagonal elements) is the inverse of the distance between the two. This model is estimated by a generalized two-stage estimation approach. Tables A7 and A8 show that this spatial autoregressive estimation produces similar results as Table 5.

As Table 2 shows, our sample includes both large metropolitan cities (e.g. New York, Chicago) and also small municipalities in rural areas. One might argue that the presence of rural areas in our sample where officer deaths and assaults rarely occur may create a downward bias in our estimations. While we believe that police officers in small communities also perform risky, dangerous duties, and our estimations controlled for population and crime occurrences, one might wonder how police IT use affects officer safety in large cities or large metropolitan areas. In Table A9 (Appendix A), we estimated the model with a sub-sample of large localities with populations above 50,000. In Table A10, we also used a sub-sample of municipalities located in metropolitan areas with population of 500,000 or more (e.g. Madison, Wisconsin or Des Moines, Iowa metropolitan areas). Tables A10 and A11 present consistent results with Table 5. IT use for crime analysis is associated with fewer killings of officers in large cities and metropolitan areas. IT use for in-field report writing is also negatively related to the number of assaults to officers. We also estimated the model with a sub-sample of high-crime areas (more than 100 crime occurrences per thousand population per year) (Table A12). This analysis does not produce substantially different results.

Since our two dependent variables (the number of officers killed or assaulted) are count variables, we estimated our model with negative binomial regressions as an alternative specification. We believe a negative binomial regression is preferred to a Poisson regression because officer deaths and assaults are not events that are independent of each other; multiple officers could be killed or assaulted by a single perpetuator or a single group of criminals. Indeed, Pearson goodness of fit tests do not support fit with a Poisson distribution. Table A12 presents the negative binomial regression results. Crime analysis is still associated with a decrease in officer killings. IT use for dispatch, in-field report writing, and the Internet is associated with fewer assaults to police officers.

As we explained above, we used a three-year window in measuring officer deaths and assaults (officer deaths and assaults in 2003-2005 and 2007-2009 were regressed on IT use in 2003 and 2007, respectively). Tables A13 and A14 offer robustness checks with a one-year and a two-year window, respectively, which produce similar results with our baseline estimation in Table 5.

Lastly, violence against police officers could depend more on occurrences of violent crimes, such as murders and rapes, not on property crimes, such as burglaries. In addition, one could argue that IT use leads to fewer officer deaths or assaults simply by reducing the number of violent crimes via more effective policing or by cutting the size of the police force via automation. In our baseline estimation (Table 5), we did not control for the size of the police force because it is highly correlated with the amount of its operational budget (ρ = 0.78). As a robustness check, we estimated with alternative control variables (violence crime occurrence/clearance rates in lieu of overall crimes and the number of police officers instead of operational budget). As shown in Table A15, this robustness check with alternative control variables does not generate widely different results.

4.4. Estimation with 2013 Data

The BJS collected the LEMAS dataset in 2013 with substantially revised questionnaires, particularly for police IT use. Unlike the 2003 and 2007 surveys that measured Internet use only with one yes-or-no question, the 2013 survey introduced several new questions that measure Internet use in more detail. With this dataset, we conducted an OLS estimation with state and metropolitan fixed-effects as shown in Table 9 (see Table A16 in Appendix A for the full results). The dependent variables are the number of police officers killed/assaulted and offenders killed by the police in 2013.[9]

Table 9. Estimation with 2013 Data (Full Result in Table A14)

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	OLS		
	(1)	(2)	(3)
Statistical Analysis	0.0003 (0.0028)	-0.0863** (0.0437)	-0.0284** (0.0132)
Web Site	-0.0016 (0.0036)	-0.1719***(0.0584)	-0.0582***(0.0171)
Crime Info	0.0040 (0.0027)	0.0243 (0.0497)	-0.0069 (0.0129)
Crime Reporting	-0.0018* (0.0011)	-0.0086 (0.0214)	0.0071 (0.0052)
Crime Alert	-0.0009 (0.0026)	-0.0350 (0.0466)	-0.0099 (0.0122)
Social Media	0.0005 (0.0010)	0.0363* (0.0212)	0.0158***(0.0049)
Controls	State, MSA	State, MSA	State, MSA
R^2	0.3330	0.6778	0.3791
Adjusted R^2	0.1928	0.6101	0.2485
F	2.37***	1089.77***	709.30***
MSE	0.0497	0.8856	0.2364

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; N = 2,499; Robust standard errors are in parentheses.
Statistical Analysis = 1 if an agency conducts research or statistical analyses using computerized reports of criminal incidents as of Jan 1, 2013, 0 otherwise
Web Site = 1 if the agency has a Web site, 0 otherwise
Crime Info = 1 if the agency publishes crime statistics via its Web site, 0 otherwise
Crime Reporting = 1 if the agency receives crime reporting from citizens via its Web site, 0 otherwise
Alert = 1 if the agency sends out crime alerts to the public via emails, text messages, or other electronic means.
Social Media = the number of social media sites that the agency uses – Twitter, Facebook, YouTube, and others.

The 2013 LEMAS survey asked whether a police department conducts research or statistical analyses using computerized reports of criminal incidents as of Jan 1, 2013 (Statistical Analysis). 66.9% of the sample departments responded that they conduct statistical analyses. Table 9 shows that the coefficient of Statistical Analysis is negative and significant for officer assaults (Column 2) and criminal deaths (Column 3). A police department that conducts statistical analyses with crime data experiences an 8.3% reduction in assaults to police officers and a 2.8% decrease in offenders killed by officers, further substantiating our main findings. The 2013 survey also asked whether the police department operates its own website, to which 79.5% of the sample responded affirmatively. Table 9 shows that police departments that do have websites report significantly fewer assaults to their officers as well as fewer deaths of criminals. The 2013 survey also asked if citizens were able to report crimes via the department's

[9] At the time of our analysis, police officer deaths and assaults data are not available for 2014 and 2015.

website (Crime Reporting). Table 9, Column 1 shows that the citizen's crime reporting to the police is marginally associated with a reduction in officer deaths.

Finally, the 2013 survey asked how many social media sites (e.g. Facebook, Twitter, YouTube) a police department had used as of Jan 1, 2013 (Social Media). 25.9% of the sample departments reported that they did not use any social media, and the rest of the respondents used 2.15 sites, on average. Strikingly, Table 9 shows that the number of social media sites used is significantly associated with more assaults to police officers (Column 2) and more killings of criminals (Column 3). This provides a consistent finding that IT use for predictive policing may lead to discovery of more crimes and thereby more violent encounters with offenders. Recent reports suggest that many police departments use social media sites not only to obtain crime intelligence but also to predict future crime occurrences (*Governing* 2013, *The Economist* 2013, *The New York Times* 2015, *The Washington Post* 2016).

5. Discussion and Conclusion

5.1. Key Findings

In this study, we offer empirical evidence that demonstrates significant effects of police IT use on violence against the police. We found that IT use for crime analysis, computer-aided dispatch, and the Internet in 2003 and 2007 is negatively associated with both the number of police officers killed in the line of duty and offenders killed by the police. Computer-aided dispatch and in-field report writing are negatively related to assaults to officers. Unexpectedly, however, we found that IT use for crime mapping and hotspot identification is associated with an increase in deaths of criminals. It appears that predictive analytics, which attempts to forecast when crime will happen in the future, may have different effects on violence between criminals and officers from reactive analytics, which analyzes what occurred in the past. We also found that the effects of police IT use on violence become more paramount in places with higher income inequality or a larger racial disparity between the police and the community.

5.2. Contributions and Implications for Theory

To the best of our knowledge, the IS literature has paid scant attention to how an organization can use IT to improve the safety of its human resources, one of the most important organizational assets (e.g., Becker and Gerhart 1996, Collins and Clark 2003). Considering that the capability of personnel is one of the key prerequisites to organizational success, we believe that keeping employees safe is a critical challenge for many organizations, either in the private or the public sector. We thus contribute to the IS literature by proposing theoretical mechanisms that explain how IT enables an organization to discover and lessen serious risks that endanger its workers in violent and life-threatening environments.

This study also expands the burgeoning literature on the business value of IT in the public sector (e.g., Garicano and Heaton 2010, Pang et al. 2014a, 2014b, 2015) and the broader societal impact of IT (e.g., Angst et al. 2011, Bhargava and Mishra 2014, Chan and Ghose 2014, Ganju et al. 2015, Greenwood and Wattal 2015). The public sector has remained a blind spot in the IS discipline in general, and in the IT business value research in particular, compared to the sheer number of IT value studies in traditional business settings. While public organizations spend a considerable amount of tax dollars in IT to offer public services, we do not have sufficient understanding of how IT in the public sector creates value to the society. While Pang et al. (2014b, 2015) found that IT investments in state governments are related to improved financial performance, few prior studies, if any, have focused on the business value of IT at a public-service level (e.g., public safety or welfare). One could argue that since a government in most cases is a monopoly supplier of public services within its jurisdiction and not under direct competitive pressures, the government hardly has an incentive to effectively use IT to improve its performance or to deliver greater value to the public. In contrast, our research shows that this may not necessarily be the case, and we instead demonstrate that IT use by police departments can create value and fulfill the interests of the community by keeping the personnel safe.

5.3. Contributions and Implications for Practice and Public Policy

This study provides managerial implications for practitioners and public officials in law enforcement. Like many firms in the for-profit sector, police departments heavily invest in training their new hires as well as incumbent officers, since effective law enforcement requires capable, professional police officers who are robust both physically and intellectually (Hahn and Jefferies 2003, Dantzker 2010). Thus, it is critical for police departments to ensure the safety of their officers. The police are expected to take sufficient measures to reduce the risk of duty, and we show that IT can be one such measure to achieve this goal.

This study illustrates that police departments can use analytics technologies to identify potential risks and institute appropriate precautions. We also found that the use of real-time response technologies, such as computer-aided dispatch and in-field report writing, helps the police reduce a chance of violent encounters with criminals that could put officers in danger. Police departments, particularly in municipalities with limited tax revenues, will be able to use our findings to justify their investments in advanced digital technologies. We also showed that the Internet is an important tool for the police for intelligence gathering, crime solving, and maintaining a close relationship with the community, all of which are associated with improved safety of police officers. However, the police are advised to be mindful of our finding that predictive policing enabled by the use of crime mapping, hotspot identification, and social media can pose extra dangers to police officers by uncovering more dangerous crime incidents.

5.4. Limitations and Suggestions for Future Research

This study carries a few limitations as follows. We acknowledge that IT use measures are not comprehensive. Also, we were not able to obtain more granular data on, for example, what kind of data each police department in our sample uses in crime analysis, how it identifies hotspots, or how the police interact with citizens via the Internet. While we obtained supplementary results from the LEMAS 2013 dataset, future research can explore IT use and its impacts in law enforcement with more comprehensive datasets or in-depth qualitative evidence. Also, the UCR database does not offer much information on circumstances of police officer deaths and assaults (e.g., how many officers were killed, by whom, and their ranks and duties). Such data would have allowed us to conduct more in-depth analyses and obtain deeper insights on police safety.

Public safety provides IS researchers with various opportunities for future research. First, they can examine how IT affects the effectiveness of law enforcement. For instance, with predictive analytics, will police officers be able to catch offenders quickly and clear more crimes? Can police departments, armed with advanced IT, suppress crimes with fewer officers or weapons? Second, future research can examine how intelligence-led and the community-oriented policing capabilities enabled by IT help improve the citizens' relationship with the police. Third, IS researchers can investigate how IT can be used to protect lives in other public safety or military settings and to prevent terrorism or other risks to national security. By doing so, the IS discipline will be able to expand its research horizon to an unchartered territory and bring new audiences from the public sector. Lastly, in the public administration discipline, the literature on network governance (e.g., Klitgaard and Treverton 2004, Alford and Hughes 2008) emphasizes that effective delivery of public services such as public safety increasingly requires collaboration and cooperation among peer law enforcement agencies (e.g. local, state, and federal agencies) as well as between the police and other organizations (not-for-profit organizations, neighborhood watch groups). IS researchers can examine how IT capabilities such as inter-organizational integration or information sharing facilitate such network governance structures for law enforcement.

5.5. Concluding Remarks

Law enforcement is a unique and interesting setting for IS research. The police are required to fulfill diverse, conflicting objectives (Hahn and Jeffries 2003, Pang et al. 2014a); advancing one goal may come at the expense of another. The primary mandate in law enforcement is to protect citizens' lives and properties from crimes and disorders. Fulfilling this mandate, however, requires risk taking and sacrifices of police officers. We reiterate that it is in the police's best interest to keep the finest sound and safe. Furthermore, in enforcing laws, the police are expected to preserve the rights and freedom of citizens who are subject to law enforcement, be they are culpable or innocent. These objectives are in many situations incompatible with each other, posing significant challenges to law enforcement. Our study illustrates that police IT use has the potential to lessen these conflicts in values and enable the police to achieve their multiple objectives in concert. We believe that the use of IT can help to create a substantial social good, even if it can help to save a single person's life.

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Online Supplementary Appendix A – Additional Tables

Table A1. Correlation Table (*N* = 4,950)[1]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	1															
(2)	0.3260	1														
(3)	0.3792	0.4291	1													
(4)	0.1011	0.2949	0.2167	1												
(5)	0.1364	0.3212	0.2627	0.6319	1											
(6)	0.1450	0.2990	0.2579	0.4851	0.5438	1										
(7)	0.0883	0.2421	0.1514	0.3334	0.3545	0.2745	1									
(8)	0.1030	0.2607	0.1877	0.3878	0.4328	0.4002	0.3768	1								
(9)	0.0326	0.1118	0.0765	0.2166	0.2695	0.2012	0.1967	0.4062	1							
(10)	0.0102	0.0563	0.0462	0.1851	0.1684	0.1329	0.1903	0.1333	0.1114	1						
(11)	0.2475	0.5768	0.4313	0.4822	0.5173	0.4450	0.4453	0.4051	0.1954	0.1521	1					
(12)	-0.0371	0.0330	-0.0790	-0.0713	-0.0861	-0.0519	-0.0682	-0.0405	0.0081	0.0105	-0.1465	1				
(13)	0.2354	0.5143	0.4062	0.4056	0.4463	0.3920	0.4494	0.3937	0.1860	0.1525	0.7917	-0.1028	1			
(14)	0.1027	0.1206	0.1362	0.0438	0.0626	0.0647	0.1692	0.0354	0.0134	0.0615	0.1883	-0.0352	0.5460	1		
(15)	0.1496	0.3483	0.3334	0.3019	0.3513	0.3367	0.2241	0.2527	0.0885	0.0878	0.5307	-0.0694	0.3670	-0.0234	1	
(16)	0.0791	0.2106	0.1491	0.2545	0.2539	0.1883	0.1976	0.2243	0.1201	0.0507	0.2912	-0.0546	-0.0620	-0.3968	0.2558	1

[1] The full correlation table is available from the authors.

Table A2. Estimation by Income Inequality

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Killed + 1)	Log(Offender Killed + 1)	Log(Offender Killed + 1)
Method	Random Effects			
	Inequality ≥ Median[1)]	Inequality < Median	Inequality ≥ Median	Inequality < Median
	(1)	(2)	(3)	(4)
Crime Analysis	-0.0156** (0.0074)	-0.0056 (0.0041)	-0.0417** (0.0206)	-0.0091 (0.0105)
Crime Mapping	0.0169** (0.0084)	0.0007 (0.0055)	0.0187 (0.0232)	0.0162 (0.0133)
Hotspot Ident.	0.0115 (0.0114)	-0.0007 (0.0085)	0.0647** (0.0261)	0.0461** (0.0229)
Dispatch	-0.0083 (0.0069)	0.0015 (0.0043)	-0.0546***(0.0194)	-0.0292** (0.0121)
In-Field Comm.	0.0104 (0.0107)	0.0048 (0.0057)	0.0265 (0.0236)	-0.0105 (0.0153)
In-Field Report	-0.0016 (0.0094)	-0.0052 (0.0058)	-0.0102 (0.0211)	0.0022 (0.0131)
Internet	-0.0302***(0.0110)	-0.0015 (0.0063)	-0.0741***(0.0275)	-0.0285* (0.0172)
Crime Occurrence	0.0112***(0.0041)	0.0050* (0.0028)	0.0532***(0.0114)	0.0218***(0.0077)
Crime Clearance	-0.0134 (0.0246)	-0.0065 (0.0137)	-0.0011 (0.0564)	-0.0787* (0.0424)
Population	0.0136* (0.0072)	0.0020 (0.0036)	0.0554***(0.0186)	0.0368***(0.0114)
Miles	0.0084***(0.0026)	0.0016 (0.0014)	0.0154** (0.0070)	-0.0049 (0.0040)
MSA Core	0.0215 (0.0154)	-0.0243* (0.0124)	0.2566***(0.0384)	0.1310***(0.0447)
Operational Budget	0.0261***(0.0079)	0.0039 (0.0037)	0.0661***(0.0181)	0.0275** (0.0121)
Education Req.	-0.0102* (0.0053)	-0.0010 (0.0028)	-0.0152 (0.0130)	-0.0132* (0.0077)
White Officer	-0.0319 (0.0255)	-0.0122 (0.0144)	-0.0866 (0.0660)	-0.0144 (0.0591)
Female Officer	0.0447 (0.0482)	-0.0031 (0.0243)	0.1098 (0.1348)	-0.0343 (0.0574)
Training	-0.0050 (0.0095)	0.0031 (0.0053)	0.0633***(0.0242)	0.0102 (0.0104)
Weapon	0.0011 (0.0021)	-0.0011 (0.0013)	0.0041 (0.0053)	0.0022 (0.0039)
Policy	0.0033 (0.0048)	0.0011 (0.0026)	0.0117 (0.0126)	-0.0055 (0.0076)
Community	-0.0035 (0.0023)	0.0011 (0.0015)	-0.0214***(0.0058)	0.0009 (0.0036)
Male	-0.0684 (0.1241)	0.0002 (0.1392)	0.1775 (0.3374)	0.1080 (0.2535)
White	-0.0145 (0.0346)	0.0038 (0.0185)	-0.1050 (0.0974)	-0.1844** (0.0803)
Young	-0.0611 (0.0942)	-0.0472 (0.0617)	0.0358 (0.2719)	0.3715** (0.1787)
High School	0.0115 (0.0907)	0.0269 (0.0413)	0.1813 (0.2762)	0.0746 (0.1373)
Income	-0.0004 (0.0003)	-0.0003* (0.0002)	-0.0012 (0.0008)	-0.0012* (0.0007)
Poverty	0.1222 (0.0860)	0.0121 (0.0544)	0.0020 (0.2329)	0.0962 (0.1367)
Vacant Homes	0.0186 (0.0185)	0.0061 (0.0175)	0.0974 (0.0601)	0.0683** (0.0346)
Inequality	0.2518* (0.1390)	0.0549 (0.0581)	0.8561** (0.3702)	-0.2379 (0.1975)
Moved	-0.0893 (0.0843)	0.0659 (0.0577)	-0.6578***(0.2228)	-0.3649***(0.1403)
Public Tranport.	0.2750* (0.1502)	-0.1212 (0.0736)	1.0484** (0.4472)	-0.1771 (0.1996)
Female Workers	-0.0620 (0.0768)	-0.0374 (0.0529)	-0.2833 (0.2245)	-0.1046 (0.1174)
Female Head	-0.0602 (0.1882)	-0.1510 (0.1040)	-0.3174 (0.5275)	-0.3466 (0.3260)
Two Parent House	0.2706* (0.1419)	-0.0386 (0.0831)	0.1870 (0.3281)	0.2187 (0.1736)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year	State, MSA, Year
N	2,497	2,453	2,497	2,453
# of Groups	1,938	2,078	1,938	2,078
Overall R^2	0.2710	0.1664	0.5472	0.4154
Wald χ^2	$2.7\times10^{6***}$	$2.9\times10^{6***}$	$3.3\times10^{5***}$	$6.1\times10^{5***}$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors are in parentheses. ; [1)] Median = 0.432

Table A3. Estimation by Racial Gap

Dependent Variable	**Log(Offender Killed + 1)**	
Method	Random Effects	
	Racial Gap = | White Population – White Officer |	
	Racial Gap ≥ Median[1)]	Racial Gap < Median
	(1)	(2)
Crime Analysis	-0.0518*** (0.0197)	-0.0146 (0.0140)
Crime Mapping	0.0315 (0.0204)	0.0176 (0.0171)
Hotspot Identification	0.0556** (0.0258)	0.0286 (0.0250)
Dispatch	-0.0654*** (0.0205)	-0.0547*** (0.0138)
In-Field Communication	0.0214 (0.0216)	-0.0285 (0.0199)
In-Field Report Writing	-0.0029 (0.0202)	0.0191 (0.0160)
Internet	-0.0534* (0.0283)	-0.0168 (0.0188)
Crime Occurrence	0.0695*** (0.0119)	0.0111 (0.0087)
Crime Clearance	-0.0225 (0.0643)	-0.0428 (0.0409)
Population	0.0379** (0.0160)	0.0768*** (0.0180)
Miles	0.0130* (0.0070)	-0.0097* (0.0050)
MSA Core	0.2001*** (0.0382)	0.2681*** (0.0583)
Operational Budget	0.0646*** (0.0177)	0.0616*** (0.0174)
Education Requirement	-0.0265** (0.0121)	0.0042 (0.0097)
White Officer	-0.0498 (0.0559)	-0.0127 (0.2488)
Female Officer	0.2851* (0.1616)	-0.1819** (0.0801)
Training	0.0493** (0.0203)	0.0255 (0.0209)
Weapon	-0.0016 (0.0052)	0.0075 (0.0049)
Policy	-0.0020 (0.0130)	-0.0006 (0.0081)
Community	-0.0159*** (0.0052)	-0.0080 (0.0055)
Male	0.0966 (0.2877)	0.8981*** (0.3271)
White	-0.0123 (0.0911)	-0.4942* (0.2670)
Young	0.0628 (0.2528)	-0.0182 (0.2004)
High School	0.0800 (0.2563)	0.2313 (0.1637)
Income	-0.0009 (0.0009)	-0.0013* (0.0007)
Poverty	0.0871 (0.2208)	0.0410 (0.1923)
Vacant Homes	0.1404* (0.0809)	0.0692* (0.0415)
Inequality	0.0448 (0.2321)	0.3596* (0.1995)
Moved	-0.7540*** (0.2093)	-0.6883*** (0.1771)
Public Transportation	0.8427* (0.4991)	0.9836*** (0.3483)
Female Workers	-0.2932 (0.2114)	-0.1606 (0.1535)
Female Household Head	-0.5174 (0.5010)	0.4285 (0.3614)
Two Parent Household	0.0280 (0.2742)	0.3266 (0.2286)
Controls	State, MSA, Year	State, MSA, Year
N	2,475	2,475
# of Groups	1,980	2,110
Overall R^2	0.4510	0.5320
Wald χ^2	87270.83***	3.8×10^{6}***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors are in parentheses.
1) Median = 0.0927, Mean = 0.1345, Min = 0, Max = 0.9888

Table A4. Estimation by Citizen Complaints

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Killed + 1)**	**Log(Offender Killed + 1)**	**Log(Offender Killed + 1)**
Method	Random Effects			
	Complaint ≥ Median[1]	Complaint < Median	Complaint ≥ Median	Complaint < Median
	(1)	(2)	(3)	(4)
Crime Analysis	-0.0448*** (0.0155)	-0.0126* (0.0068)	-0.1054*** (0.0396)	0.0000 (0.0162)
Crime Mapping	0.0229 (0.0153)	0.0006 (0.0064)	0.0520 (0.0402)	0.0138 (0.0176)
Hotspot Ident.	0.0076 (0.0167)	0.0109 (0.0114)	0.0356 (0.0386)	0.0411 (0.0264)
Dispatch	-0.0055 (0.0176)	-0.0083 (0.0066)	-0.0911** (0.0451)	-0.0195 (0.0150)
In-Field Comm.	0.0073 (0.0158)	0.0111 (0.0093)	0.0518 (0.0364)	-0.0169 (0.0206)
In-Field Report	-0.0127 (0.0173)	0.0051 (0.0080)	0.0172 (0.0368)	-0.0092 (0.0183)
Internet	-0.0197 (0.0248)	-0.0126 (0.0121)	-0.0828 (0.0635)	-0.0245 (0.0186)
Crime Occurrence	0.0204** (0.0098)	0.0083** (0.0036)	0.1050*** (0.0270)	0.0190** (0.0079)
Crime Clearance	-0.0303 (0.0516)	0.0022 (0.0196)	0.0235 (0.1370)	-0.0759 (0.0469)
Population	0.0272* (0.0153)	0.0064 (0.0067)	0.1074*** (0.0399)	0.0394** (0.0158)
Miles	0.0083 (0.0055)	-0.0015 (0.0022)	0.0096 (0.0160)	-0.0066 (0.0056)
MSA Core	0.0029 (0.0171)	-0.0146 (0.0354)	0.1806*** (0.0477)	0.0765 (0.0881)
Operational Budget	0.0414*** (0.0125)	0.0034 (0.0085)	0.1380*** (0.0312)	0.0203 (0.0154)
Education Req.	-0.0127 (0.0084)	-0.0013 (0.0039)	-0.0022 (0.0211)	-0.0073 (0.0092)
White Officer	-0.1132* (0.0676)	-0.0186 (0.0195)	-0.6203*** (0.1674)	-0.0017 (0.0457)
Female Officer	0.0070 (0.1256)	-0.0388 (0.0445)	-0.2444 (0.3504)	-0.0441 (0.0722)
Training	-0.0063 (0.0179)	0.0039 (0.0143)	0.0500 (0.0398)	0.0172 (0.0294)
Weapon	-0.0021 (0.0036)	0.0026 (0.0026)	-0.0088 (0.0095)	0.0042 (0.0068)
Policy	0.0023 (0.0142)	0.0036 (0.0038)	-0.0352 (0.0365)	0.0129 (0.0086)
Community	-0.0035 (0.0038)	-0.0006 (0.0022)	-0.0208** (0.0082)	0.0066 (0.0052)
Male	0.4111 (0.2649)	-0.1304 (0.1589)	0.9615 (0.5856)	0.5882* (0.3461)
White	0.0209 (0.0642)	0.0425 (0.0340)	0.0495 (0.1791)	-0.0674 (0.0818)
Young	-0.1632 (0.2047)	-0.1048 (0.0875)	0.5883 (0.5836)	-0.0364 (0.2116)
High School	0.1131 (0.2186)	0.0559 (0.0695)	0.0691 (0.6592)	0.0059 (0.1692)
Income	-0.0006 (0.0007)	-0.0003 (0.0003)	-0.0020 (0.0021)	-0.0004 (0.0006)
Poverty	0.0391 (0.2190)	0.0815 (0.0992)	0.5598 (0.5453)	-0.1870 (0.2051)
Vacant Homes	-0.0133 (0.0363)	0.0152 (0.0240)	0.0632 (0.1575)	-0.0118 (0.0430)
Inequality	0.3202* (0.1926)	0.2132*** (0.0774)	0.3997 (0.5137)	-0.1470 (0.1812)
Moved	0.0526 (0.2337)	0.0561 (0.0798)	-1.5941*** (0.5071)	-0.2828 (0.1832)
Public Tranport.	0.0878 (0.2163)	-0.0490 (0.0856)	0.6716 (0.6321)	0.3754* (0.2166)
Female Workers	-0.1311 (0.2183)	-0.0373 (0.0925)	-0.4988 (0.4900)	-0.2816* (0.1663)
Female Head	-0.3795 (0.3831)	0.0032 (0.2251)	-1.2398 (1.1160)	0.1995 (0.3258)
Two Parent House	0.1129 (0.2938)	0.1891 (0.1682)	-0.1249 (0.7312)	0.0145 (0.2383)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year	State, MSA, Year
N	1,592	1,592	1,592	1,592
# of Groups	1,229	1,490	1,229	1,490
Overall R^2	0.3064	0.2737	0.5472	0.4528
Wald χ^2	47470.17***	40.86	1.1×10^{5}***	97228.80***

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; Robust standard errors are in parentheses.
[1] The number of citizen complaints on police use of force per 10,000 population,
Median = 0.016, Mean = 0.188; Min = 0, Max = 1.696

Table A5. Probit Regression for Inverse Mills Ratio

Dependent Variable	High IT Use Dummy
Method	Probit Regression
IT Use for Booking	0.2558***(0.0462)
IT Use for Fleet Management	0.3375***(0.0481)
IT Use for Personnel Management	0.2182***(0.0499)
IT Use for Record Management	0.3409***(0.0725)
IT Use for Resource Allocation	0.7866***(0.0560)
Crime Occurrences in Prior Year	0.1746***(0.0228)
Population	0.2231***(0.0270)
Operational Budget	0.3947***(0.0373)
Education Requirement	-0.0854***(0.0128)
Training	0.1386***(0.0443)
Constant	-6.2566***(0.2986)
N	4,950
Pseudo R^2	0.3783
Log Likelihood	-2121.2413
LR χ^2	2581.57***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Robust standard errors are in parentheses.
High IT Use Dummy is equal to one if the sum of seven IT use variables is greater than mean (3.58); zero otherwise.

Table A6. Estimation with Inverse Mill's Ratio

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0173*** (0.0045)	0.0138 (0.0432)	-0.0368*** (0.0121)
Crime Mapping	0.0041 (0.0049)	0.0447 (0.0463)	0.0126 (0.0136)
Hotspot Identification	0.0082 (0.0068)	0.0209 (0.0451)	0.0550*** (0.0178)
Dispatch	-0.0110** (0.0045)	-0.0795* (0.0422)	-0.0638*** (0.0123)
In-Field Communication	0.0045 (0.0060)	0.0697 (0.0458)	-0.0067 (0.0155)
In-Field Report Writing	-0.0043 (0.0056)	-0.1145*** (0.0390)	-0.0042 (0.0131)
Internet	-0.0133** (0.0060)	-0.0702 (0.0534)	-0.0318* (0.0163)
Crime Occurrence	0.0083*** (0.0024)	0.2103*** (0.0235)	0.0374*** (0.0069)
Crime Clearance	-0.0101 (0.0130)	0.4338*** (0.1282)	-0.0189 (0.0346)
Population	0.0125*** (0.0045)	0.2875*** (0.0355)	0.0620*** (0.0116)
Miles	0.0040*** (0.0014)	-0.0260* (0.0140)	0.0019 (0.0038)
MSA Core	0.0162 (0.0104)	0.4782*** (0.0763)	0.2228*** (0.0303)
Operational Budget	0.0204*** (0.0049)	0.1798*** (0.0347)	0.0691*** (0.0129)
Education Requirement	-0.0065** (0.0027)	-0.0195 (0.0232)	-0.0137* (0.0074)
White Officer	-0.0454*** (0.0166)	-0.0662 (0.1451)	-0.1135** (0.0475)
Female Officer	0.0193 (0.0263)	-0.0877 (0.2423)	0.0453 (0.0758)
Training	0.0008 (0.0058)	0.0594* (0.0337)	0.0435*** (0.0144)
Weapon	0.0008 (0.0012)	0.0332*** (0.0084)	0.0020 (0.0034)
Policy	0.0017 (0.0026)	-0.0175 (0.0249)	-0.0002 (0.0071)
Community	-0.0017 (0.0013)	-0.0004 (0.0097)	-0.0124*** (0.0037)
Male	0.0106 (0.0760)	0.5469 (0.6366)	0.2539 (0.1949)
White	0.0201 (0.0206)	-0.0140 (0.1882)	-0.0836 (0.0643)
Young	-0.1312** (0.0516)	-0.7809 (0.5042)	-0.0193 (0.1554)
High School	0.0330 (0.0458)	0.8345 (0.5164)	0.2130 (0.1399)
Income	-0.0004** (0.0002)	-0.0053*** (0.0019)	-0.0010* (0.0005)
Poverty	0.0948* (0.0502)	0.7165 (0.4573)	0.0467 (0.1359)
Vacant Homes	-0.0020 (0.0121)	0.1667 (0.1512)	0.0518 (0.0443)
Inequality	0.1418*** (0.0514)	0.5270 (0.4598)	0.2490 (0.1551)
Moved	-0.0473 (0.0483)	-0.7897* (0.4230)	-0.6683*** (0.1310)
Public Transportation	0.1253 (0.0979)	0.9889 (0.8432)	0.9201*** (0.3307)
Female Workers	0.0033 (0.0425)	0.6049 (0.3811)	-0.1592 (0.1174)
Female Household Head	-0.1000 (0.0979)	0.9713 (1.0013)	-0.3313 (0.3130)
Two Parent Household	0.0576 (0.0744)	0.1324 (0.5607)	0.0739 (0.1612)
Inverse Mills Ratio	0.0087** (0.0041)	0.0276 (0.0338)	0.0209* (0.0113)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.1820	0.6993	0.4297
Wald χ^2	47234.21***	2.0×10^5***	50068.18***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 4,950; # of Groups = 3,921; Robust standard errors are in parentheses.

Table A7. Robustness Checks with Spatial Autocorrelation Regression (2003)

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Assaulted + 1)**	**Log(Offender Killed + 1)**
Method	Spatial Autocorrelation Regression		
	(1)	(2)	(3)
Crime Analysis	-0.0079 (0.0052)	0.0095 (0.0610)	-0.0298** (0.0145)
Crime Mapping	0.0161** (0.0071)	0.1181* (0.0684)	0.0339* (0.0182)
Hotspot Identification	0.0070 (0.0097)	0.0511 (0.0719)	0.0702***(0.0233)
Dispatch	-0.0217***(0.0061)	-0.0651 (0.0562)	-0.0891***(0.0145)
In-Field Communication	0.0119 (0.0084)	0.0236 (0.0642)	-0.0092 (0.0196)
In-Field Report Writing	0.0036 (0.0079)	-0.0733 (0.0511)	0.0174 (0.0168)
Internet	-0.0038 (0.0064)	-0.1383* (0.0714)	-0.0262 (0.0180)
Crime Occurrence	0.0063** (0.0031)	0.2550***(0.0319)	0.0499***(0.0077)
Crime Clearance	-0.0051 (0.0185)	0.5292***(0.1803)	-0.1444***(0.0383)
Population	0.0125***(0.0048)	0.3287***(0.0459)	0.0499***(0.0121)
Miles	0.0066***(0.0018)	-0.0240 (0.0184)	0.0050 (0.0046)
MSA Core	0.0204 (0.0134)	0.5263***(0.0829)	0.1904***(0.0319)
Operational Budget	0.0258***(0.0061)	0.1926***(0.0490)	0.0708***(0.0155)
Education Requirement	-0.0084 (0.0062)	0.0100 (0.0519)	-0.0237 (0.0154)
White Officer	-0.0080 (0.0301)	-0.4740* (0.2646)	-0.1585** (0.0742)
Female Officer	-0.0162 (0.0324)	-0.2268 (0.3137)	-0.0223 (0.0911)
Training	-0.0034 (0.0072)	0.0866** (0.0363)	0.0234** (0.0119)
Weapon	0.0018 (0.0015)	0.0384***(0.0111)	-0.0031 (0.0033)
Policy	-0.0038 (0.0039)	-0.0576* (0.0332)	-0.0237***(0.0087)
Community	-0.0022 (0.0018)	-0.0228* (0.0135)	-0.0126***(0.0045)
Male	-0.0695 (0.0859)	0.3729 (0.9305)	-0.1723 (0.2621)
White	-0.0399 (0.0290)	0.4907** (0.2470)	-0.0554 (0.0769)
Young	-0.0904 (0.0688)	-1.0600 (0.7109)	-0.1070 (0.1929)
High School	0.0904 (0.0675)	0.8491 (0.7260)	0.4280** (0.1736)
Income	-0.0004* (0.0002)	-0.0066***(0.0024)	-0.0009 (0.0006)
Poverty	0.0997 (0.0633)	1.1974** (0.6057)	0.1340 (0.1559)
Vacant Homes	0.0115 (0.0151)	0.4497***(0.1435)	0.0604 (0.0658)
Inequality	0.1552** (0.0682)	0.4559 (0.6476)	0.4065** (0.1821)
Moved	-0.0713 (0.0496)	-0.5022 (0.5734)	-0.6043***(0.1490)
Public Transportation	0.1779 (0.1395)	1.7453** (0.8105)	0.9397***(0.2978)
Female Workers	0.0411 (0.0485)	0.5072 (0.4750)	0.1012 (0.1319)
Female Household Head	-0.1050 (0.1216)	1.5284 (1.3848)	-0.5004 (0.3732)
Two Parent Household	0.1254 (0.0791)	-0.0882 (0.7572)	0.4091** (0.2034)
Controls	State, MSA	State, MSA	State, MSA
ρ	2.09×10^{-6}	1.22×10^{-5}	-9.9×10^{-6}

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,393; Robust standard errors are in parentheses.

Table A8. Robustness Checks with Spatial Autocorrelation Regression (2007)

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Assaulted + 1)**	**Log(Offender Killed + 1)**
Method	Spatial Autocorrelation Regression		
	(1)	(2)	(3)
Crime Analysis	-0.0180*** (0.0055)	-0.0132 (0.0584)	-0.0100 (0.0154)
Crime Mapping	0.0002 (0.0055)	0.0674 (0.0632)	0.0068 (0.0170)
Hotspot Identification	0.0099 (0.0084)	0.0957 (0.0657)	0.0523** (0.0232)
Dispatch	-0.0001 (0.0062)	-0.1614*** (0.0591)	-0.0549*** (0.0169)
In-Field Communication	0.0037 (0.0075)	0.0789 (0.0598)	-0.0210 (0.0192)
In-Field Report Writing	-0.0107 (0.0066)	-0.1342** (0.0539)	-0.0133 (0.0179)
Internet	-0.0230** (0.0110)	0.0148 (0.0813)	-0.0383 (0.0287)
Crime Occurrence	0.0133*** (0.0031)	0.2612*** (0.0305)	0.0672*** (0.0100)
Crime Clearance	-0.0258 (0.0182)	0.3250* (0.1734)	-0.1842*** (0.0548)
Population	0.0082 (0.0059)	0.1665*** (0.0467)	0.0321** (0.0159)
Miles	0.0035* (0.0019)	-0.0078 (0.0179)	0.0098* (0.0052)
MSA Core	0.0066 (0.0132)	0.1735* (0.0904)	0.2116*** (0.0389)
Operational Budget	0.0244*** (0.0065)	0.2367*** (0.0482)	0.1019*** (0.0172)
Education Requirement	-0.0061* (0.0032)	0.0038 (0.0313)	-0.0210** (0.0099)
White Officer	-0.0688*** (0.0211)	0.0303 (0.1768)	-0.1144** (0.0556)
Female Officer	0.0139 (0.0440)	0.1314 (0.3409)	0.0144 (0.1076)
Training	0.0079 (0.0105)	0.0181 (0.0625)	0.0559** (0.0281)
Weapon	-0.0004 (0.0022)	0.0889*** (0.0166)	0.0043 (0.0066)
Policy	0.0080** (0.0037)	-0.0322 (0.0369)	0.0096 (0.0111)
Community	-0.0003 (0.0016)	0.0179 (0.0149)	-0.0080 (0.0050)
Male	0.0761 (0.1219)	1.5274* (0.8066)	0.7889*** (0.2460)
White	0.0756*** (0.0259)	-0.2162 (0.2373)	-0.0042 (0.0767)
Young	-0.0638 (0.0658)	0.1505 (0.6457)	0.2626 (0.1988)
High School	-0.0108 (0.0638)	0.8300 (0.6732)	-0.1247 (0.1903)
Income	-0.0004 (0.0002)	-0.0058** (0.0025)	-0.0010* (0.0006)
Poverty	0.0628 (0.0677)	-0.2551 (0.6404)	0.0089 (0.1855)
Vacant Homes	-0.0055 (0.0172)	-0.1997 (0.1662)	0.0114 (0.0406)
Inequality	0.1580** (0.0686)	0.8121 (0.5845)	0.0013 (0.1923)
Moved	-0.0672 (0.0819)	-1.2103** (0.5789)	-0.9743*** (0.1835)
Public Transportation	0.0863 (0.1331)	0.6506 (1.1011)	0.8655** (0.4053)
Female Workers	-0.0739 (0.0721)	0.5882 (0.5351)	-0.4126** (0.1666)
Female Household Head	-0.0324 (0.1513)	1.1573 (1.3473)	-0.1609 (0.3897)
Two Parent Household	-0.0102 (0.1288)	0.4367 (0.7164)	-0.1873 (0.2185)
Controls	State, MSA	State, MSA	State, MSA
ρ	$3.23\times10^{-5*}$	$6.08\times10^{-5**}$	3.53×10^{-5}

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,556; Robust standard errors are in parentheses.

Table A9. Estimation with Large Municipalities (Population > 50,000)

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0367^{**} (0.0158)	-0.0157 (0.1135)	-0.1047^{***} (0.0369)
Crime Mapping	0.0202 (0.0146)	0.0878 (0.0957)	0.0343 (0.0358)
Hotspot Identification	0.0051 (0.0149)	-0.0081 (0.0698)	0.0554^{*} (0.0321)
Dispatch	0.0132 (0.0154)	0.1316 (0.1332)	0.0277 (0.0480)
In-Field Communication	0.0030 (0.0144)	0.0442 (0.0886)	0.0023 (0.0329)
In-Field Report Writing	-0.0076 (0.0149)	-0.1558^{*} (0.0832)	0.0039 (0.0318)
Internet	0.0120 (0.0256)	-0.3037^{*} (0.1614)	-0.1103^{*} (0.0572)
Crime Occurrence	0.0370^{***} (0.0077)	0.4203^{***} (0.0522)	0.1508^{***} (0.0176)
Crime Clearance	0.0392 (0.0593)	0.5671 (0.4392)	0.0420 (0.1387)
Population	0.0299^{*} (0.0160)	0.4637^{***} (0.0978)	0.1896^{***} (0.0369)
Miles	0.0173^{**} (0.0081)	-0.0382 (0.0559)	0.0130 (0.0198)
MSA Core	0.0104 (0.0192)	0.2294^{*} (0.1372)	0.2173^{***} (0.0539)
Operational Budget	0.0303^{**} (0.0135)	0.2284^{***} (0.0796)	0.1053^{***} (0.0291)
Education Requirement	-0.0115 (0.0074)	-0.0770 (0.0479)	-0.0130 (0.0192)
White Officer	-0.1075 (0.0680)	-0.6325 (0.4705)	-0.1491 (0.1556)
Female Officer	0.0984 (0.1310)	-0.2841 (1.0151)	-0.0220 (0.2995)
Training	-0.0009 (0.0168)	0.0667 (0.0853)	0.0814^{**} (0.0357)
Weapon	-0.0017 (0.0025)	0.0187 (0.0148)	-0.0117^{*} (0.0063)
Policy	0.0108 (0.0106)	-0.0119 (0.0783)	0.0054 (0.0273)
Community	0.0007 (0.0034)	0.0060 (0.0180)	-0.0096 (0.0074)
Male	0.8707 (0.5457)	-0.6623 (3.8753)	2.8752^{**} (1.4310)
White	-0.0363 (0.0705)	0.5674 (0.5685)	-0.2211 (0.2181)
Young	-0.3729 (0.3040)	-2.5804 (2.1355)	0.6579 (0.7897)
High School	0.4450 (0.3793)	1.9123 (2.8799)	0.0726 (1.0601)
Income	-0.0021^{*} (0.0013)	-0.0041 (0.0091)	-0.0074^{**} (0.0033)
Poverty	0.0179 (0.3464)	2.6917 (2.2293)	-0.3262 (0.8484)
Vacant Homes	-0.1689 (0.3274)	-1.7076 (1.7938)	0.8402 (0.5723)
Inequality	0.9222^{***} (0.3047)	0.1372 (2.1909)	0.7925 (0.7645)
Moved	0.1396 (0.2576)	-0.8326 (1.7236)	-2.3111^{***} (0.6738)
Public Transportation	0.0358 (0.2749)	-1.5228 (2.7764)	0.6987 (0.9641)
Female Workers	0.5046^{*} (0.2966)	3.2920^{*} (1.7031)	0.3093 (0.6967)
Female Household Head	-0.2371 (0.6693)	-1.1617 (4.5393)	0.0991 (1.8998)
Two Parent Household	1.0220^{***} (0.3657)	-0.0157 (0.1135)	1.1378 (0.9420)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.3099	0.7741	0.5998
Wald χ^2	$1.2\times10^{6***}$	$3.4\times10^{6***}$	51606.35^{***}

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 1,845; # of Groups = 1,133; Robust standard errors are in parentheses.

Table A10. Estimation with Large Metropolitan Areas (Population > 500,000)

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Assaulted + 1)**	**Log(Offender Killed + 1)**
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0243*** (0.0075)	-0.0117 (0.0706)	-0.0591*** (0.0210)
Crime Mapping	0.0099 (0.0071)	0.1168* (0.0700)	0.0315 (0.0207)
Hotspot Identification	0.0090 (0.0098)	-0.0097 (0.0609)	0.0509** (0.0250)
Dispatch	-0.0140 (0.0089)	-0.0965 (0.0777)	-0.1003*** (0.0239)
In-Field Communication	0.0104 (0.0085)	0.0970 (0.0621)	0.0208 (0.0217)
In-Field Report Writing	-0.0071 (0.0090)	-0.1898*** (0.0602)	-0.0060 (0.0211)
Internet	-0.0022 (0.0112)	-0.0460 (0.0955)	-0.0248 (0.0340)
Crime Occurrence	0.0184*** (0.0045)	0.3139*** (0.0395)	0.0863*** (0.0122)
Crime Clearance	-0.0313 (0.0270)	0.5618** (0.2555)	-0.0555 (0.0785)
Population	0.0078 (0.0066)	0.2716*** (0.0572)	0.0638*** (0.0179)
Miles	0.0085** (0.0037)	-0.0164 (0.0321)	0.0016 (0.0106)
MSA Core	0.0071 (0.0151)	0.3004*** (0.1059)	0.2397*** (0.0446)
Operational Budget	0.0248*** (0.0078)	0.1544*** (0.0511)	0.1031*** (0.0207)
Education Requirement	-0.0050 (0.0043)	-0.0027 (0.0332)	-0.0216* (0.0116)
White Officer	-0.1228*** (0.0348)	-0.5818** (0.2547)	-0.3379*** (0.0969)
Female Officer	0.0409 (0.0566)	-0.0965 (0.4762)	0.1746 (0.1727)
Training	0.0031 (0.0096)	0.0620 (0.0566)	0.0556** (0.0248)
Weapon	0.0006 (0.0020)	0.0242* (0.0127)	0.0013 (0.0055)
Policy	0.0063 (0.0073)	0.0105 (0.0536)	0.0232 (0.0189)
Community	-0.0032 (0.0021)	-0.0038 (0.0139)	-0.0186*** (0.0055)
Male	0.1352 (0.1943)	1.7195 (1.2613)	0.4053 (0.4488)
White	0.0510 (0.0327)	0.3245 (0.2962)	-0.0038 (0.1068)
Young	-0.1759* (0.0974)	-0.1709 (0.7885)	0.2013 (0.2885)
High School	0.0360 (0.0825)	1.4524* (0.8676)	0.0245 (0.2821)
Income	-0.0001 (0.0002)	0.0003 (0.0024)	-0.0004 (0.0007)
Poverty	0.3044*** (0.1063)	2.0366** (0.8162)	0.5355* (0.3051)
Vacant Homes	-0.0410 (0.0372)	-0.5315 (0.3820)	0.0824 (0.1038)
Inequality	0.2183** (0.0881)	1.6751** (0.7004)	0.5083* (0.2680)
Moved	-0.0795 (0.1037)	-1.5326** (0.7283)	-1.3460*** (0.2815)
Public Transportation	-0.0061 (0.1125)	0.1314 (0.9932)	0.4046 (0.3492)
Female Workers	0.0446 (0.0840)	1.3817** (0.6706)	-0.2073 (0.2355)
Female Household Head	-0.3133* (0.1839)	2.3465 (1.8654)	-0.9076 (0.6453)
Two Parent Household	0.1249 (0.1378)	-0.0628 (0.9083)	0.1548 (0.3233)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.1904	0.6926	0.4733
Wald χ^2	9.2×10^{11}***	1.4×10^{11}***	2.2×10^{11}***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,359; # of Groups = 1,750; Robust standard errors are in parentheses.

Table A11. Estimation with High Crime Areas (Crime Per Capita > 100)

Dependent Variable	**Log(Officer Killed + 1)**	**Log(Officer Assaulted + 1)**	**Log(Offender Killed + 1)**
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0342***(0.0082)	-0.0499 (0.0787)	-0.0702***(0.0234)
Crime Mapping	0.0008 (0.0079)	0.0406 (0.0779)	0.0036 (0.0231)
Hotspot Identification	0.0086 (0.0102)	0.0112 (0.0658)	0.0603** (0.0284)
Dispatch	-0.0146 (0.0089)	-0.0606 (0.0767)	-0.1020***(0.0252)
In-Field Communication	0.0085 (0.0101)	0.0527 (0.0739)	0.0098 (0.0260)
In-Field Report Writing	0.0030 (0.0101)	-0.1039 (0.0646)	0.0178 (0.0237)
Internet	-0.0279** (0.0138)	-0.1232 (0.1011)	-0.0587* (0.0346)
Crime Occurrence	0.0115 (0.0107)	0.3522***(0.0914)	0.0537* (0.0295)
Crime Clearance	0.0146 (0.0296)	0.7362***(0.2595)	0.0980 (0.0858)
Population	0.0219 (0.0134)	0.2737***(0.1035)	0.1317***(0.0355)
Miles	0.0095** (0.0040)	-0.0239 (0.0372)	0.0071 (0.0123)
MSA Core	0.0136 (0.0142)	0.4005***(0.1077)	0.1806***(0.0413)
Operational Budget	0.0281***(0.0096)	0.1874***(0.0642)	0.1041***(0.0256)
Education Requirement	-0.0105* (0.0054)	-0.0403 (0.0443)	-0.0274* (0.0151)
White Officer	-0.0828** (0.0337)	-0.1375 (0.2631)	-0.1156 (0.0886)
Female Officer	-0.0080 (0.0556)	0.0307 (0.5268)	0.1615 (0.1657)
Training	-0.0066 (0.0105)	0.0531 (0.0502)	0.0344 (0.0225)
Weapon	0.0008 (0.0020)	0.0260* (0.0134)	0.0016 (0.0057)
Policy	0.0059 (0.0066)	0.0497 (0.0555)	0.0080 (0.0184)
Community	-0.0040* (0.0023)	-0.0195 (0.0150)	-0.0252***(0.0061)
Male	0.0362 (0.1670)	1.5708 (1.0833)	0.1956 (0.3620)
White	0.0204 (0.0348)	-0.0462 (0.2973)	-0.0388 (0.1035)
Young	-0.1865* (0.0978)	-0.2304 (0.8627)	0.1496 (0.2955)
High School	0.1459 (0.1011)	1.2191 (0.9689)	0.4387 (0.3218)
Income	-0.0010* (0.0005)	-0.0079** (0.0035)	-0.0023 (0.0017)
Poverty	0.0376 (0.0997)	0.4586 (0.7784)	0.1276 (0.2767)
Vacant Homes	0.0106 (0.0209)	0.2922* (0.1574)	0.1159 (0.0858)
Inequality	0.2515** (0.1012)	0.4269 (0.8091)	0.2660 (0.3080)
Moved	-0.0351 (0.0841)	-0.5188 (0.6717)	-0.9975***(0.2153)
Public Transportation	0.2458 (0.1835)	-0.2831 (1.2209)	1.7337***(0.5548)
Female Workers	0.0516 (0.0843)	0.5482 (0.6216)	-0.2768 (0.2265)
Female Household Head	-0.0966 (0.1868)	-0.7511 (1.6340)	-0.5241 (0.5148)
Two Parent Household	0.0412 (0.1253)	-0.7286 (0.9302)	-0.0094 (0.3140)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.2569	0.7317	0.5221
Wald χ^2	78768.13***	$7.2\times10^{5***}$	13347.34***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,446; # of Groups = 1,874; Robust standard errors are in parentheses.

Table A12. Negative Binomial Estimation

Dependent Variable	Officer Killed	Officer Assaulted	Offender Killed
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.7799***(0.2757)	0.0183 (0.0705)	0.0827 (0.1686)
Crime Mapping	0.5823** (0.2855)	-0.0461 (0.0741)	0.2569* (0.1493)
Hotspot Identification	0.2059 (0.2261)	-0.0301 (0.0661)	0.2360***(0.0907)
Dispatch	0.4436 (0.3651)	-0.2093***(0.0719)	-0.0552 (0.1797)
In-Field Communication	0.1607 (0.2231)	0.0856 (0.0630)	-0.1036 (0.1031)
In-Field Report Writing	-0.0234 (0.2058)	-0.1385** (0.0563)	0.0149 (0.0933)
Internet	-0.4725 (0.3175)	-0.1756* (0.0905)	-0.1800 (0.1699)
Crime Occurrence	0.6353***(0.1583)	0.6091***(0.0335)	0.8408***(0.0822)
Crime Clearance	0.3876 (0.9176)	1.5554***(0.1967)	0.7024 (0.4578)
Population	0.1281 (0.1774)	0.5622***(0.0448)	0.2844***(0.1093)
Miles	0.1801** (0.0844)	-0.1026***(0.0215)	0.0873* (0.0472)
MSA Core	-0.1538 (0.2461)	0.3492***(0.0786)	0.2613** (0.1214)
Operational Budget	0.4356* (0.2294)	0.2706***(0.0490)	0.2845** (0.1265)
Education Requirement	-0.1921 (0.1483)	-0.0526 (0.0396)	-0.0506 (0.0604)
White Officer	0.0211 (0.7053)	0.0170 (0.1977)	0.7835** (0.3660)
Female Officer	0.7149 (2.0208)	0.6819 (0.4372)	-0.1416 (0.9520)
Training	-0.0318 (0.2047)	0.1038* (0.0620)	0.0524 (0.0869)
Weapon	-0.0101 (0.0377)	0.0367***(0.0125)	0.0034 (0.0177)
Policy	0.0681 (0.2531)	0.0826* (0.0492)	-0.0407 (0.0985)
Community	-0.0282 (0.0458)	-0.0186 (0.0142)	-0.0188 (0.0217)
Male	-0.3185 (12.771)	-0.3418 (1.2956)	6.3073 (3.9907)
White	-0.8943 (0.8700)	-0.1179 (0.2418)	-1.0993***(0.3971)
Young	-7.1108 (4.6531)	-0.2153 (0.8338)	1.3403 (1.8847)
High School	5.3501 (4.3813)	-0.0418 (0.9103)	-3.7510 (2.4037)
Income	-0.0187 (0.0155)	-0.0041 (0.0030)	-0.0204** (0.0079)
Poverty	1.2766 (5.0088)	1.7507** (0.8249)	-2.7669 (2.0451)
Vacant Homes	-3.3480 (4.2107)	0.3211 (0.2164)	-0.1717 (0.4364)
Inequality	4.5536 (3.3506)	-0.7034 (0.7903)	-2.1799 (2.4418)
Moved	6.0840 (3.9989)	-1.9814***(0.6793)	-4.7780***(1.4776)
Public Transportation	2.1763 (2.3684)	1.5607** (0.6739)	2.2575* (1.2126)
Female Workers	0.5103 (4.3194)	-0.3841 (0.6589)	-0.5540 (1.7353)
Female Household Head	-5.8160 (10.301)	-0.0953 (1.6818)	7.8997* (4.3836)
Two Parent Household	5.7095 (5.9841)	-1.4275 (0.9521)	-0.0209 (2.7901)
Controls	State, Year	State, Year	State, Year
Log Likelihood	-541.1634	-12639.445	-1740.2537
Pseudo R^2	0.3207	0.1757	0.3791
Wald χ^2	445.08***	5389.39***	29815.25***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 4,950; # of Groups = 3,921; Robust standard errors are in parentheses.

Table A13. Estimation with One-Year Window

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0058^{**} (0.0024)	0.0122 (0.0355)	-0.0147^{**} (0.0063)
Crime Mapping	0.0054^{**} (0.0026)	0.0359 (0.0384)	0.0089 (0.0072)
Hotspot Identification	0.0034 (0.0040)	0.0417 (0.0386)	0.0132 (0.0104)
Dispatch	-0.0048^{**} (0.0021)	-0.0573^{*} (0.0339)	-0.0322^{***} (0.0066)
In-Field Communication	-0.0011 (0.0034)	0.0593 (0.0361)	0.0014 (0.0093)
In-Field Report Writing	-0.0018 (0.0030)	-0.0811^{***} (0.0308)	-0.0015 (0.0079)
Internet	-0.0037 (0.0038)	-0.0178 (0.0461)	-0.0190 (0.0116)
Crime Occurrence	0.0011 (0.0013)	0.1538^{***} (0.0195)	0.0146^{***} (0.0038)
Crime Clearance	-0.0146^{**} (0.0072)	0.2675^{**} (0.1040)	0.0058 (0.0201)
Population	0.0081^{***} (0.0024)	0.2247^{***} (0.0291)	0.0350^{***} (0.0066)
Miles	0.0012^{*} (0.0006)	-0.0102 (0.0113)	0.0018 (0.0021)
MSA Core	0.0018 (0.0059)	0.4518^{***} (0.0670)	0.0961^{***} (0.0178)
Operational Budget	0.0108^{***} (0.0027)	0.1557^{***} (0.0289)	0.0405^{***} (0.0074)
Education Requirement	-0.0025 (0.0015)	-0.0116 (0.0181)	-0.0100^{**} (0.0043)
White Officer	-0.0219^{**} (0.0100)	-0.0885 (0.1222)	-0.0866^{***} (0.0287)
Female Officer	0.0250 (0.0163)	-0.0665 (0.2017)	0.0483 (0.0482)
Training	0.0004 (0.0028)	0.0603^{**} (0.0299)	0.0207^{**} (0.0097)
Weapon	-0.0001 (0.0007)	0.0238^{***} (0.0075)	-0.0022 (0.0021)
Policy	0.0006 (0.0014)	-0.0497^{**} (0.0212)	0.0011 (0.0041)
Community	0.0002 (0.0007)	0.0011 (0.0084)	-0.0069^{***} (0.0023)
Male	-0.0134 (0.0367)	0.3444 (0.5252)	-0.0222 (0.1058)
White	0.0112 (0.0126)	0.0852 (0.1583)	-0.0179 (0.0377)
Young	-0.0401 (0.0278)	-0.5106 (0.4184)	-0.0522 (0.0881)
High School	0.0518^{**} (0.0252)	0.5112 (0.4257)	0.1422^{*} (0.0807)
Income	-0.0001 (0.0001)	-0.0046^{***} (0.0016)	-0.0004 (0.0003)
Poverty	0.0519^{**} (0.0261)	0.5481 (0.3817)	0.0850 (0.0767)
Vacant Homes	0.0003 (0.0051)	0.1239 (0.1380)	0.0334 (0.0271)
Inequality	0.0320 (0.0290)	0.3822 (0.3815)	0.1293 (0.0912)
Moved	-0.0303 (0.0255)	-0.7747^{**} (0.3499)	-0.3414^{***} (0.0771)
Public Transportation	0.0854 (0.0584)	1.0358 (0.7122)	0.5372^{**} (0.2350)
Female Workers	0.0024 (0.0206)	0.3342 (0.3287)	-0.0416 (0.0668)
Female Household Head	-0.0527 (0.0455)	0.6372 (0.8411)	-0.2930 (0.1818)
Two Parent Household	0.0105 (0.0263)	0.0533 (0.4727)	0.0349 (0.0894)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.1003	0.7317	0.5221
Wald χ^2	$4.4\times10^{6***}$	$2.2\times10^{5***}$	74441.65^{***}

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 4,950; # of Groups = 3,910; Robust standard errors are in parentheses.

Table A14. Estimation with Two-Year Window

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0099***(0.0033)	0.0201 (0.0397)	-0.0254***(0.0092)
Crime Mapping	0.0051 (0.0037)	0.0635 (0.0432)	0.0140 (0.0101)
Hotspot Identification	0.0077 (0.0056)	0.0201 (0.0438)	0.0259* (0.0147)
Dispatch	-0.0082***(0.0032)	-0.0682* (0.0381)	-0.0430***(0.0091)
In-Field Communication	0.0036 (0.0048)	0.0704* (0.0416)	-0.0026 (0.0120)
In-Field Report Writing	-0.0061 (0.0042)	-0.1118***(0.0357)	0.0000 (0.0102)
Internet	-0.0056 (0.0048)	-0.0600 (0.0518)	-0.0267* (0.0142)
Crime Occurrence	0.0042** (0.0018)	0.1897***(0.0224)	0.0253***(0.0055)
Crime Clearance	-0.0133 (0.0102)	0.3931***(0.1192)	-0.0024 (0.0277)
Population	0.0104***(0.0034)	0.2658***(0.0334)	0.0461***(0.0091)
Miles	0.0021** (0.0009)	-0.0220* (0.0131)	0.0035 (0.0030)
MSA Core	0.0071 (0.0082)	0.4730***(0.0726)	0.1606***(0.0244)
Operational Budget	0.0133***(0.0038)	0.1735***(0.0323)	0.0529***(0.0102)
Education Requirement	-0.0043** (0.0020)	-0.0235 (0.0217)	-0.0174***(0.0057)
White Officer	-0.0243* (0.0131)	-0.0983 (0.1368)	-0.1153***(0.0385)
Female Officer	0.0276 (0.0216)	-0.0154 (0.2274)	0.0534 (0.0639)
Training	0.0044 (0.0047)	0.0585* (0.0319)	0.0344***(0.0117)
Weapon	0.0007 (0.0011)	0.0333***(0.0083)	-0.0004 (0.0028)
Policy	0.0002 (0.0020)	-0.0418* (0.0236)	-0.0032 (0.0057)
Community	-0.0006 (0.0011)	0.0010 (0.0095)	-0.0077** (0.0030)
Male	0.0109 (0.0456)	0.5675 (0.5915)	0.0063 (0.1455)
White	0.0068 (0.0174)	0.0422 (0.1778)	-0.0465 (0.0519)
Young	-0.0600 (0.0391)	-0.8258* (0.4705)	-0.0681 (0.1237)
High School	0.0461 (0.0349)	0.5763 (0.4844)	0.1646 (0.1119)
Income	-0.0003** (0.0001)	-0.0054***(0.0018)	-0.0007* (0.0004)
Poverty	0.0697* (0.0380)	0.7999* (0.4292)	0.0515 (0.1084)
Vacant Homes	0.0069 (0.0069)	0.1848 (0.1339)	0.0380 (0.0337)
Inequality	0.0788* (0.0406)	0.4004 (0.4338)	0.2460* (0.1260)
Moved	-0.0510 (0.0324)	-0.8812** (0.3983)	-0.5173***(0.1064)
Public Transportation	0.0643 (0.0708)	1.1496 (0.8007)	0.7743***(0.2956)
Female Workers	0.0093 (0.0279)	0.5393 (0.3616)	-0.0631 (0.0933)
Female Household Head	-0.0473 (0.0643)	0.5252 (0.9356)	-0.2710 (0.2505)
Two Parent Household	0.0876 (0.0557)	0.1231 (0.5258)	-0.0020 (0.1228)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.1229	0.6861	0.3858
Wald χ^2	$7.0\times10^{6***}$	$2.1\times10^{6***}$	3164.13***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 4,950; # of Groups = 3,910; Robust standard errors are in parentheses.

Table A15. Estimation Results with Alternative Control Variables

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	Random Effects		
	(1)	(2)	(3)
Crime Analysis	-0.0129*** (0.0040)	0.0395 (0.0414)	-0.0267** (0.0112)
Crime Mapping	0.0079* (0.0045)	0.0564 (0.0446)	0.0204 (0.0128)
Hotspot Identification	0.0082 (0.0068)	0.0183 (0.0451)	0.0548*** (0.0178)
Dispatch	-0.0074* (0.0042)	-0.0549 (0.0412)	-0.0559*** (0.0117)
In-Field Communication	0.0082 (0.0056)	0.0859* (0.0444)	0.0045 (0.0145)
In-Field Report Writing	-0.0025 (0.0053)	-0.1125*** (0.0376)	-0.0015 (0.0124)
Internet	-0.0128** (0.0060)	-0.0642 (0.0539)	-0.0291* (0.0163)
Violent Crime Occurrence	0.0064*** (0.0021)	0.2306*** (0.0217)	0.0379*** (0.0069)
Violent Crime Clearance	-0.0040 (0.0089)	0.2736*** (0.0805)	-0.0026 (0.0240)
Officer per Capita[1)]	0.0131*** (0.0030)	0.0650*** (0.0223)	0.0448*** (0.0095)
Population	0.0149*** (0.0043)	0.2603*** (0.0351)	0.0677*** (0.0116)
Miles	0.0037*** (0.0014)	-0.0298** (0.0142)	0.0016 (0.0042)
MSA Core	0.0175* (0.0104)	0.4958*** (0.0761)	0.2265*** (0.0302)
Education Requirement	-0.0059** (0.0027)	-0.0150 (0.0231)	-0.0126* (0.0074)
White Officer	-0.0416** (0.0168)	-0.0509 (0.1458)	-0.0936* (0.0484)
Female Officer	0.0107 (0.0259)	-0.1202 (0.2434)	0.0145 (0.0746)
Training	0.0004 (0.0058)	0.0610* (0.0333)	0.0424*** (0.0141)
Weapon	0.0007 (0.0012)	0.0341*** (0.0085)	0.0012 (0.0034)
Policy	0.0013 (0.0027)	-0.0162 (0.0249)	-0.0006 (0.0071)
Community	-0.0016 (0.0013)	0.0008 (0.0098)	-0.0119*** (0.0037)
Male	-0.0067 (0.0763)	0.3348 (0.6325)	0.1723 (0.1973)
White	0.0211 (0.0209)	-0.0098 (0.1903)	-0.0666 (0.0655)
Young	-0.1328** (0.0524)	-0.9200* (0.5029)	0.0064 (0.1577)
High School	0.0092 (0.0456)	0.4269 (0.5144)	0.1461 (0.1396)
Income	-0.0005*** (0.0002)	-0.0056*** (0.0019)	-0.0011** (0.0005)
Poverty	0.0753 (0.0498)	0.5578 (0.4568)	-0.0267 (0.1380)
Vacant Homes	-0.0317** (0.0160)	0.0768 (0.1644)	-0.0471 (0.0561)
Inequality	0.1470*** (0.0526)	0.7581 (0.4674)	0.2594 (0.1605)
Moved	-0.0510 (0.0490)	-0.8064* (0.4312)	-0.7377*** (0.1344)
Public Transportation	0.0865 (0.0982)	0.6161 (0.9081)	1.0421*** (0.3122)
Female Workers	0.0211 (0.0430)	0.7931** (0.3803)	-0.1245 (0.1176)
Female Household Head	-0.1258 (0.1013)	0.5935 (1.0081)	-0.4503 (0.3216)
Two Parent Household	0.0573 (0.0743)	0.0524 (0.5648)	0.0746 (0.1675)
Controls	State, MSA, Year	State, MSA, Year	State, MSA, Year
Overall R^2	0.1828	0.6968	0.4339
Wald χ^2	1.5×10^{6}***	2.0×10^{6}***	22648.60***

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 4,915; # of Groups = 3,880; Robust standard errors are in parentheses.

1) The number of full-time sworn police officers with arrest power per 1,000 population

Table A16. Estimation with 2013 Data

Dependent Variable	Log(Officer Killed + 1)	Log(Officer Assaulted + 1)	Log(Offender Killed + 1)
Method	OLS		
	(1)	(2)	(3)
Statistical Analysis	0.0003 (0.0028)	-0.0863** (0.0437)	-0.0284** (0.0132)
Web Site	-0.0016 (0.0036)	-0.1719*** (0.0584)	-0.0582*** (0.0171)
Crime Info	0.0040 (0.0027)	0.0243 (0.0497)	-0.0069 (0.0129)
Crime Reporting	-0.0018* (0.0011)	-0.0086 (0.0214)	0.0071 (0.0052)
Crime Alert	-0.0009 (0.0026)	-0.0350 (0.0466)	-0.0099 (0.0122)
Social Media	0.0005 (0.0010)	0.0363* (0.0212)	0.0158*** (0.0049)
Crime Occurrence	0.0034** (0.0014)	0.1991*** (0.0259)	0.0320*** (0.0065)
Crime Clearance	0.0000 (0.0001)	0.0040*** (0.0011)	0.0001 (0.0003)
Population	0.0006 (0.0019)	0.1520*** (0.0355)	0.0170* (0.0092)
Miles	0.0008 (0.0010)	0.0080 (0.0150)	-0.0004 (0.0045)
MSA Core	-0.0023 (0.0037)	0.3616*** (0.0795)	0.1217*** (0.0178)
Operational Budget	0.0010 (0.0008)	0.0312** (0.0124)	0.0068* (0.0038)
Education Requirement	-0.0017 (0.0018)	0.0064 (0.0325)	0.0030 (0.0085)
White Officer	0.0021 (0.0062)	-0.0826 (0.0974)	-0.0379 (0.0293)
Female Officer	-0.0037 (0.0158)	0.0271 (0.2400)	0.0671 (0.0752)
Weapon	-0.0004 (0.0008)	0.0108 (0.0132)	-0.0050 (0.0038)
Policy	-0.0005 (0.0006)	-0.0215** (0.0098)	-0.0039 (0.0031)
Community	0.0009 (0.0009)	0.0076 (0.0162)	0.0087** (0.0043)
Male	-0.0273 (0.0491)	0.1544 (0.9064)	-0.1096 (0.2337)
White	-0.0061 (0.0111)	-0.1511 (0.1965)	0.0747 (0.0530)
Young	0.0116 (0.0342)	0.7104 (0.6337)	-0.0700 (0.1628)
High School	0.0003 (0.0373)	1.3880** (0.5651)	0.0059 (0.1773)
Income	-0.0001 (0.0001)	-0.0009 (0.0020)	-0.0007 (0.0006)
Poverty	-0.0260 (0.0317)	0.3976 (0.5239)	0.0212 (0.1510)
Vacant Homes	0.0035 (0.0114)	0.1070 (0.1239)	0.0411 (0.0542)
Inequality	-0.0044 (0.0342)	0.5933 (0.5633)	0.2662 (0.1625)
Moved	0.0243 (0.0297)	-0.8068 (0.5050)	-0.3832*** (0.1411)
Public Transportation	-0.0048 (0.0333)	2.0210* (1.0626)	0.5456*** (0.1583)
Female Workers	-0.0092 (0.0285)	0.8907* (0.5028)	-0.0039 (0.1357)
Female Household Head	0.0018 (0.0673)	1.2269 (1.0571)	-0.0959 (0.3203)
Two Parent Household	0.0362 (0.0414)	0.2945 (0.6824)	0.0083 (0.1969)
Controls	State, MSA	State, MSA	State, MSA
R^2	0.3330	0.6778	0.3791
Adjusted R^2	0.1928	0.6101	0.2485
F	2.37***	1089.77***	709.30***
MSE	0.0497	0.8856	0.2364

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; N = 2,499; Robust standard errors are in parentheses.