Document Title: COPS on Dots Doing What? The Differential Effects of Police Enforcement Actions in Hot Spots

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Document No.: 249880

Date Received: May 2016

Award Number: 2014-IJ-CX-0007

COPS ON DOTS DOING WHAT?
THE DIFFERENTIAL EFFECTS OF POLICE ENFORCEMENT ACTIONS IN HOT SPOTS

A Dissertation
Submitted
to the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree
DOCTOR OF PHILOSOPHY

By
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July, 2015

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ABSTRACT

COPS ON DOTS DOING WHAT?
THE DIFFERENTIAL EFFECTS OF POLICE ENFORCEMENT ACTIONS IN HOT SPOTS
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Doctor of Philosophy
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Although hot spots policing has become one of the most promising policing strategies, the empirical evidence on the effectiveness of hot spots policing does not suggest what police should be doing in crime hot spots. To date, police enforcement actions – pedestrian investigations, traffic enforcement, and arrests – still dominate American policing. Yet empirical studies of these actions have not: focused on micro-geographic areas, employed multiple measures of police enforcement actions, or empirically compared the effectiveness of different enforcement actions. Given these gaps in the literature, a mixed-methods study sought to answer four research questions. (1) Do four police enforcement actions focused on offenders or potential offenders reduce violent crime in hot spots? The four police enforcement actions examined were pedestrian investigations, traffic enforcement events, quality of life arrests, and violent crime arrests. (2) Are any one of these four police enforcement actions more effective than the others? (3) When police commanders allocate resources to crime hot spots, what do police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots?

The first two questions were answered using official data from the Philadelphia Police Department. A purposive sample of 169 high crime street blocks and intersections was drawn and longitudinal data analyses examined the effects of police enforcement actions on monthly violent crime counts from 2009 to 2013 (n = 10,140). Wald Tests were used to test for the differential effectiveness of the four enforcement actions. Qualitative methods answered the

remaining two research questions. Field observations of crime strategy meetings (May, 2014 to August, 2014) and interviews with police commanders (November, 2014 to February, 2015) were conducted.

The quantitative results found total enforcement and pedestrian stop levels in the previous or same month linked to higher expected monthly violent crime counts. The positive effect of pedestrian stops was significantly larger than the effects of traffic enforcement or quality of life arrests. Despite the positive relationship between police enforcement and violent crime, the qualitative results provided insight into what police commanders thought they were doing in crime hot spots. Three themes emerged from the qualitative data: (1) “locking down” crime hot spots, (2) disrupting high risk offenders, and (3) educating potential victims. Police commanders rationalized these beliefs with four explanations of their effectiveness: (1) making offenders “think twice”, (2) denying potential offenders and victims certain places in order to reduce crime opportunities, (3) getting high risk offenders “off the street”, and (4) target hardening.

Drawing on theorizing for how police enforcement actions might actually link to higher levels of crime (Grabosky, 1996) and methodological concerns raised by Taylor (2015), five possible explanations for the observed positive relationships among police enforcement actions and violent crime are provided: (1) an anticipatory effect, (2) over-deterrence, (3) escalation, (4) unintended enticement and self-fulfilling prophecies, and (5) temporal scaling. The anticipatory effect explanation centers on the police correctly anticipating outbreaks of violent crime but violent crime still not being reduced due to (1) dosage, (2) the overuse of enforcement, (3) police legitimacy, (4) temporal displacement or two components the study’s design (5) imprecise measurement and (6) lack of a proper counterfactual. Additionally, police enforcement actions may inadvertently reduce guardianship though over-deterrence, escalate competition among rival offenders, or inform potential offenders of crimes they could or "should" be committing. Finally, the study's temporal scale (i.e., months) may not be fine enough to capture the actual cycling of how increased enforcement actions produce lower violent crime levels. The qualitative data are drawn upon to possibly support these explanations. Additionally, the pros and cons of police commanders' perspectives on the use and effectiveness of enforcement actions are discussed in context of the criminological theory and crime control literatures. Finally, the results are discussed in terms of their implications for crime control theory and policy.

STATEMENT OF FUNDING

This dissertation was supported by the National Institute of Justice's Graduate Research Fellowship Program in the Social and Behavioral Sciences, Award Number 2014-IJ-CX-0007. The National Institute of Justice is part of the Office of Justice Programs and U.S. Department of Justice. The findings, conclusions, and recommendations expressed in this dissertation are the author's and do not necessarily represent those of the National Institute of Justice, Office of Justice Programs, or U.S. Department of Justice.

ACCKNOWLEDGEMENTS

My path to a PhD started at Bowling Green State University. In between our discussions of the Cleveland Indians, Dr. Steve Lab introduced me to environmental criminology and talked me into going to grad school. Thanks, Steve. Dr. Bill King has continuously mentored me since my time at BG. I will always consider Bill a mentor in the academic sense, but more importantly a friend in the grand scheme of life sense. Thanks for everything, Bill.

I will always cherish my time in the Department of Criminal Justice at Temple University. I credit the entire faculty for teaching me, among many things, how to think. Thank you all. Dr. John Goldkamp tremendously impacted my worldview, and I hope that always remains visible in my work. Dr. Kate Auerhahn is a tireless supporter of grad students. Kate, thank you for your relentless support. Being born about 15 minutes apart (spatially not temporally), Dr. George Rengert and I had a natural bond. George's work speaks for itself, but I always felt like I was "doing something right" when he would speak positively about mine. George, among many things, thanks for always encouraging me. Dr. Liz Groff provided tremendous mentorship over the years. Liz always had time for me and her positive attitude kept the stress of graduate school at bay. Thanks you Liz, and I look forward to our future work together. Dr. Jen Wood's guidance and thought provoking comments as a committee member took this dissertation far beyond where it would've ever gone without them. Jen, I thank you for everything, but especially for always being so positive while pushing me to think harder. Dr. Ralph Taylor is one of the smartest criminologists in the world, but he's also a masterful teacher. When I leave Temple, Dr. Taylor will have to figure out what to do with all the extra time he has during his office hours. Dr. Taylor, I probably haven't even realized everything you have taught me, but I

am truly thankful for your patience and mentorship. This dissertation would not have been the same without you. I will do my best to pay it forward.

There's no way to know what graduate school might have looked like without Dr. Jerry Ratcliffe's mentorship, but I know it wouldn't have been as great. Jerry did all the things a student could ever ask for… and then a lot more. Jerry taught me all the "academic stuff", but then also how to balance it with the real-world demands of policing. Jerry provided countless opportunities and taught me about preparation and working hard "behind the scenes", but also stressed the importance of enjoying life outside of work. Jerry taught me that research always has to be rigorous and objective, but mistakes happen and it's OK to have fun while working hard. Of course, the list goes on and on, and Jerry, I'll truly never be able to do justice to explaining what I've learned from you or how much I appreciate what you've done for me, but I look forward to our future work and beers for years to come.

I am honored to have worked on projects with the Philadelphia Police Department during my time at Temple. Commissioner Charles Ramsey's courage to open up the 4th largest police department in the US to empirical scrutiny is beyond admirable. I cannot thank Deputy Commissioners Nola Joyce and Kevin Bethel enough for their support and openness to this project. Tony D'Abruzzo, your assistance and expertise should be recognized, but more importantly I thank you for your friendship. I am also particularly indebted to the 6 police captains who agreed to be interviewed for this study. Sergeant John Ross, you are one of the most admirable people I've ever met and will always be one of the first people I call when I come back to Philly. John, thanks for teaching me about police work and life. I have to stop somewhere, but I am honored and thankful to have met, befriended, and/or learned from so many men and women of the PPD who do one of the hardest jobs in the world.

I also thank the National Institute of Justice for seeing value in this project and awarding me a Graduate Research Fellowship. I hope this study meets the NIJ's expectations and contributes to policy discussions. I also thank Dr. Cynthia Lum for providing such stimulating insight and questions that drastically improved the study, especially the discussion.

Graduate school would not have been the same without Jill Eidson, Jaime Henderson, Ingrid Johnson, Lallen Johnson, Nate Link, Lauren Mayes, Justin Medina, Amber Perenzin, or Caitlin Taylor. Joe O'Rourke, you're not a good dancer, but you are a supportive friend. Mike Vecchio, thanks being a great friend and providing priceless advice (especially about beer selections). Roll along, Mike. It was also a pleasure to enter and finish grad school with my friend, Evan Sorg. Evan always pushed me to do better work, but Evan is also a one-of-a-kind person whose friendship made me a much better person. Thank you, Evan.

Coach Q and Mary, thanks for always believing in me and your selfless kindness. The Osborne's (and Duling's/Burn's), there's too many of you to list, but I am proud to call you family and thankful for your support. Jamie, thanks for always being there and pushing me. It's unfortunate you're not better at FIFA. Skylar and Brandon, thanks for inspiring me. I am proud of and love you guys. Shawn, thanks for stepping up and being proud of me. Mom, thanks for sacrificing so much so that I could have a chance. It's amazing someone can be so strong, yet so caring. I love you. Sarah, my best friend, my boo boo, words can't describe how much your support and sacrifices have done for me over the past 6 years. Your selflessness, optimism, and sense of humor match your beautiful smile; all of which greatly aided in the completion of this dissertation and get me by. I love you so much. Let's go home.

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CHAPTER 1: INTRODUCTION

This study used a mixed-methods design to address four research questions. (1) Do four police enforcement actions focused on offenders or potential offenders reduce violent crime in hot spots? The four enforcement actions that were examined included pedestrian investigations, traffic enforcement events, quality of life arrests, and violent crime arrests. (2) Are any one of these four police enforcement actions more effective than the others? (3) When police commanders allocate resources to crime hot spots, what do police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots?

Chapters 2 and 3 review the literature on police effectiveness and illustrate key gaps in the literature that motivated these questions. The argument put forth is as follows. The police have predominantly relied on enforcement actions for crime control. Deterrence theory and Wilson and Boland's (1978) thesis on legalistic policing provided the theoretical frame for expecting police enforcement actions to be effective for addressing crime. Later, Wilson and Kelling's (1982) Broken Windows Theory and the New York City Police Department's attribution of the New York City crime drop to aggressive policing helped further institutionalize the use of enforcement actions. Evaluations of enforcement actions based on those ideas, however, typically focused on large geographic areas, rarely measured more than one enforcement action, and returned mixed results.

After decades of reform, focusing police resources in crime hot spots is believed to be the most effective policing strategy for crime control (Braga, Papachristos, & Hureau, 2012). Hot spots include "addresses, buildings, block faces, street segments, or clusters of addresses" with disproportionately high levels of crime (Mastrofski, Weisburd, & Braga, 2010, p. 251). Despite calls for police departments to invoke a wide range of policing tactics to address crime hot spots (Eck & Spelman, 1987; Goldstein, 1990), however, the police still predominantly rely on police enforcement actions to address hot spots (Rosenbaum, 2006, 2007). While enforcement actions have played a major role in the tactics evaluated in the hot spots policing literature, the measures and research designs employed in evaluations preclude concluding which *specific* policing tactics are most effective in crime hot spots (Braga, 2001, p. 121; Mastrofski et al., 2010; Telep & Weisburd, 2012; Weisburd & Braga, 2006a). Further, theorizing by scholars suggests police enforcement actions may be ineffective or actually increase crime. Based on these gaps in the reviewed literature, this study's four research questions logically followed.

Chapter 4 details the study's methods. The first two questions regarding the overall and differential effectiveness of police enforcement actions were addressed using official data from the Philadelphia Police Department. A purposive sample of 169 high crime street blocks and intersections was drawn and random effects and generalized estimating equations models examined the effects of enforcement actions on monthly violent crime counts for 2009 to 2013 (n = 10,140). Additionally, Wald Tests compared the effectiveness of the four enforcement actions. Next, field observations of crime strategy meetings (May, 2014 to August, 2014) and interviews with police commanders (November, 2014 to February, 2015) were used to address the two remaining research questions. Answering these questions provided a complementary understanding of how police enforcement actions are perceived and used in practice, but the qualitative data were also used to expand the discussion of the results (Palinkas et al., 2011).

Chapter 5 outlines the study's results in detail. The quantitative analyses found higher levels of total enforcement and pedestrian stops in the previous or same month linked to higher expected monthly violent crime counts in hot spots. Further, the positive effect of pedestrian stops on monthly violent crime counts was significantly larger than the insignificant effects of traffic enforcement and quality of life arrests. Although the quantitative results questioned the effectiveness of police enforcement actions in hot spots, the qualitative analysis revealed police commanders thought they were doing three things in hot spots: (1) "locking down" crime hot spots, (2) disrupting high risk offenders, and (3) educating potential victims. Police commanders rationalized these beliefs based on four explanations of their effectiveness: (1) making offenders "think twice", (2) denying potential offenders and victims certain places in order to reduce crime opportunities, (3) getting high risk offenders "off the street", and (4) target hardening.

Chapter 6 discusses the study's results and limitations. Drawing on theorizing for how police enforcement actions might produce higher crime levels (see Chapter 2) and ideas from Taylor (2015), five explanations are provided for the positive link between enforcement and violent crime. These explanations center on the police: (1) correctly anticipating outbreaks of violent crime yet enforcement actions still linking to higher levels of violence for six possible reasons, (2) inadvertently generating over-deterrence and reducing guardianship, (3) escalating competition and violence among rival offenders, (4) enticing or teaching potential offenders to engage in crime, or (5) the study's temporal scale (i.e., months). Second, the pros and cons of police commanders' perceptions of hot spots policing and the use and effectiveness of police enforcement actions are discussed in light of the criminological theory and crime control literatures. Third, the results' implications for crime control theory are noted. This discussion centers on how the current conceptualizations of crime control theory may be too simple. Fourth, the results' implications for policy are discussed. In short, police commanders use enforcement actions for multiple goals unrelated to crime control, so simply ending their use may not be practical. The recommendations provided for how the use of enforcement actions might be improved in the future center on: (1) improving police departments' analytical capacities to focus quality enforcement actions on the “right places” and “right people”, (2) training officers on the principles of procedural justice and legitimacy, and (3) using enforcement actions as only one component of multi-faceted, evidence-based hot spots policing strategies.

CHAPTER 2: POLICE EFFECTIVENESS

"The basic mission for which the police exist is to prevent crime and disorder."

-- Sir Robert Peel, The Peelian Principles, 1829

This chapter reviews the literature on police effectiveness and makes a number of key points that motivated this study. First, since the development of the standard model of policing, police have predominantly relied on enforcement actions to control crime. Second, scholars have proposed theories explaining why police enforcement actions might reduce crime, but studies of the effectiveness of enforcement actions have employed a range of measures and units of analysis and returned mixed findings. Third, a number of innovative policing strategies for crime control have been proposed, but studies focusing on micro-geographic areas, or crime hot spots, are most promising. Fourth, despite calls for police to use a wide range of tactics in crime hot spots, enforcement actions are the predominant tactics used by police departments (Rosenbaum, 2006, 2007). Fifth, the hot spots policing literature demonstrates that police presence and enforcement actions are effective, but the former often relies on the latter and the literature as a whole fails to identify which enforcement actions are most effective in crime hot spots because the evaluations' measures and/or research designs are limited. Sixth, recent theorizing raises the possibility that police enforcement actions may have unintended effects that actually result in increases in crime over time.

The Standard Model of Policing

Until the early 1900s, police officers performed mostly social-service based functions, such as dealing with drunks, disorderly crowds, or the homeless. Police departments did not have personnel requirements. Police personnel were appointed by political officials when they came into office and usually replaced after each election. Once hired, police officers did not receive any formal training. Corruption, in the form of bribes and kickbacks, was rampant. Crime control was an afterthought (Fogelson, 1977).

In response to this corruption and ineffectiveness, policing entered a state of reform between roughly the 1900s and the 1970s. These reform efforts focused on professionalizing policing. During this era, police departments adopted two-way radios, telephones, and automobiles. These innovations had a profound impact on police operations (Fogelson, 1977; Rosenbaum, 2007; Walker, 1984; Walker & Katz, 2012). Police departments began to operate under the standard model of policing with a focus on: (1) random motor patrol, (2) rapid response to calls for service, (3) intensive enforcement using police presence and enforcement actions, and (4) follow-up investigations (Weisburd & Eck, 2004).

Under the standard model of policing, patrol has become the backbone of policing. In most modern police departments the majority of police personnel are assigned to patrol operations (Bayley, 1994; Bittner, 1990; Maple, 1999; Moskos, 2008; Reiss, 1971). In many jurisdictions, officers are on patrol twenty-four hours a day, seven days a week, fifty-two weeks a year (Bittner, 1990). It is estimated patrol officers spend roughly 20 percent of their shift handling calls for service (Frank, Brandl, & Watkins, 1997), but on busy nights in high crime areas officers may do nothing but answers calls for service (Moskos, 2008). “Even when there aren’t many calls coming in, the *possibility* of receiving a call prevents officers from doing…any activity that may cause an officer to stray too far from the patrol car (Moskos, 2008, p. 108).”

Patrol officers exercise a lot of discretion when deciding how to spend their time outside of calls for service (Black, 1980). Time use studies have found that patrol officers spend roughly a quarter to a third of an eight hour shift conducting routine preventive patrol (i.e., driving around) (Cordner, 1979; Frank et al., 1997; J. R. Greene & Klockars, 1991; Kelling, Pate, Dieckman, & Brown, 1974; Smith, Novak, & Frank, 2001). Black's (1980) qualitative work suggests that police officers may not always be engaged in police work while on patrol. "Police work is, after all, work" and it is almost natural for most people to attempt to get out of work at least some of the time (Reiss, 1971, p. 14). But "patrol divisions generally assume that, when an officer is not in service handling matters assigned to him he is engaged in routine preventive work" (Reiss, 1971, p. 90).

In reality, most patrol officers spend at least some, if not all, of their non-committed time conducting self-initiated police enforcement actions (Black, 1980; Reiss, 1971). Self-initiated police enforcement actions generally involve the police increasing their presence among citizens when they deem a situation to be suspicious (Reiss, 1971; Weisburd & Eck, 2004). In practice, self-initiated police enforcement actions mostly involve stopping, questioning and sometimes frisking suspicious pedestrians, stopping suspicious motorists and/or enforcing traffic laws, and making arrests, mostly for misdemeanor offenses (Black, 1980; Moskos, 2008; Reiss, 1971).

The Nature of Police Enforcement Actions

The police have essentially always engaged in the discretionary practice of stopping and talking to citizens. The landmark *Terry v. Ohio (1968)* ruling provided police officers the legal right to stop, question, and sometimes frisk citizens for weapons when there is reasonable suspicion they have recently committed or are likely to commit a crime in the near future. Police may stop pedestrians after citizens have complained about criminal activity in an area via the city's 911 system, but officers also may use their discretion to stop suspicious citizens without prompting from the public (Bratton & Knobler, 1998; Maple, 1999). In practice, "[k]nowledge of a suspect's prior criminal history, physical movement on the part of a suspect consistent with drug or gun possession, working in a violent or high-drug area, and an officer's level of fear can all be used to articulate reasonable suspicion and justify a police stop…" (Moskos, 2008, p. 30). Studies of how patrol officers spend their time have found that they generally used roughly one to five percent of an eight hour shift broadly investigating suspicious circumstances, including people (Famega, 2009; Smith et al., 2001). Recently, the practice of stop, question, and frisk has received a lot of attention.[1] For example, in New York City where the practice has been credited by some as a major contributor to the city's crime drop, police stops tripled between 2003 and 2010 from 193 per 10,000 residents to 713 per 10,000 residents (Rosenfeld & Fornango, 2014).[2] In Philadelphia, stop, question, and frisk incidents increased from 102,319 to 253,333 incidents between 2005 and 2009 for an increase of 148 percent ("Bailey, et al. v. City of Philadelphia, et al.," 2011).

Traffic enforcement is also a highly discretionary activity (Bittner, 1990; Gottfredson & Gottfredson, 1989; Klockars, 1985). Traffic enforcement consumes roughly five to ten percent of patrol officers' time (Famega, 2009; Frank et al., 1997; Smith et al., 2001), but both informal and formal quotas issued by patrol commanders may influence the actual level of traffic enforcement in an area at any given time (Bittner, 1990; Black, 1980; Reiss, 1971; J. Q. Wilson, 1968). Whitaker (1981), using the Police Services Study data from the Rochester, NY, St. Louis, MO, and Tampa-St. Petersburg, FL metropolitan areas (Ostrom, Parks, & Whitaker, 1978), noted that the officers under study averaged about one traffic stop per shift across the sixty-six neighborhoods studied; however, officers in some neighborhoods averaged more than two

[1] One should be careful concluding that stop, question, frisk is used more frequently now than any other time in law enforcement. Stop, question, and frisk has always been used in law enforcement, and without historical data for a long period there is no way to empirically conclude it is currently used more. Based on the short-term data presented above, however, one can conclude the recorded level of stop, question, and frisk appears to have increased over its recorded level of use at the beginning of the 2000's in these particular cities. Trends in stop, question, and frisk will depend on the city and time frame examined.

[2] More recently stop, question, and frisk has decreased by roughly 60 percent from 2012 to 2013 in NYC after the *Floyd, et al. v. City of New York* decision (Newman, 2013).

traffic stops per shift while officers in other neighborhoods did not generate a single traffic stop during the study. When only the amount of time patrol officers spend engaged with citizens is considered, traffic enforcement is the main driver of police-citizen contact (Bittner, 1990; Hoover, Dowling, & Fenske, 1998; Ostrom et al., 1978).

Arrests are the final discretionary police enforcement action (Bittner, 1990; Gottfredson & Gottfredson, 1989; Klockars, 1985). Most arrests are for misdemeanor offenses. Felony arrests are far less common (Reiss, 1971). "For the most part, officers stumble across felony arrests; officers cannot set out to lock up a violent felon (Moskos, 2008, p. 113)." Officers who know the law well, however, can usually make an arrest for a minor crime on every shift if they choose to (Moskos, 2008). On the other hand, "*the modal tour of duty does not involve an arrest*" (Reiss, 1971, p. 19 emphasis in original). In 1974 roughly 46 percent of Washington, D.C. officers, most of whom were assigned to patrol, failed to produce a single arrest for the year (Forst, Lucianovic, & Cox, 1978 as cited by Whitaker, 1980). Patrol officers in Cincinnati, OH during the mid-1990s spent roughly 6.5 percent of their shift time making arrests (Frank et al., 1997). During the Police Services Study, about five percent of police-citizen encounters resulted in an arrest in the metropolitan areas of Rochester, NY, St. Louis, MO, and Tampa-St. Petersburg, FL (Whitaker, 1981).

Deterrence Theory

Deterrence theory has long underpinned explanations of police effectiveness (Sherman, 1990). In its simplest form, deterrence theory asserts that increasing the certainty, severity and celerity of punishment should dissuade calculating offenders from offending (Beccaria, 1764, translated 1963). Adjusting the certainty, severity, and celerity of punishment can reduce crime through two specific mechanisms: (1) specific deterrence and (2) general deterrence (Zimring &

Hawkins, 1973). First, offenders who receive certain and severe punishments quickly after they are arrested are hypothesized to be deterred from committing more crimes in the future. This is specific deterrence. Second, when other members of society see that the likelihood of being arrested is high and results in severe punishment that is meted out quickly, they will then also be deterred from committing crimes. This is general deterrence. Since police officers are the gatekeepers of the criminal justice processing, they are responsible for the certainty of punishment by detecting and capturing more offenders (Durlauf & Nagin, 2011).

Wilson's Varieties of Police Behavior

In the late 1970s, James Q. Wilson and Barbara Boland (1978) used Wilson's (1968) theory on the *Varieties of Police Behavior* to explain how police departments' use of enforcement actions could link to lower levels of crime via deterrence (Kubrin, Messner, Deane, McGeever, & Stucky, 2010; R. J. Sampson & Cohen, 1988). Wilson's (1968) theory is complex[3], but he generally argued three predominant policing styles exist: (1) watchman style, (2) service style, and (3) legalistic style. Watchman style police departments do not interact with citizens frequently. Service style police departments interact with citizens frequently but use informal means to maintain order. Legalistic style police departments engage with citizens frequently and use formal means (enforcement actions) to maintain order.

Wilson and Boland (1978) then argued the most effective police departments would operate with a legalistic style. Legalistic style police departments generate high numbers of traffic stops and citations and pedestrian investigations. In return, these actions lead to higher levels of arrests. High levels of arrest link to lower levels of crime through deterrence because they communicate to offenders and/or potential offenders that the certainty of punishment is

[3]The theory also discusses how external and organizational factors may influence a police department's organizational strategy and patrol officers' behavior.

high (J. Q. Wilson & Boland, 1978). This theory of aggressive policing was later revised and all police enforcement actions were hypothesized to have a direct effect on crime (R. J. Sampson & Cohen, 1988; J. Q. Wilson & Boland, 1978). In other words, arrests, traffic enforcement, and pedestrian investigations all can act as "certainty communicating devices" and deter crime (Ratcliffe, Taniguchi, Groff, & Wood, 2011).

Police enforcement actions may communicate certainty of punishment through both general and specific deterrence mechanisms. Each police enforcement action communicates to the affected citizen that the police are actively working to detect offenders. If the individual is arrested then the offender knows first-hand that the police are increasing the likelihood of punishment for criminal offenders.[4] If the offender is stopped while driving or walking then the offender knows the police also are actively working. Nonetheless, it is unclear whether all enforcement actions deter offenders equally. For example, arrests for minor offenses may not communicate the same certainty of punishment to an offender as being arrested for a more serious offense. Similarly, being stopped as a pedestrian or in a vehicle may not communicate an increased likelihood of punishment as strongly as an arrest, particularly a felony arrest. This may be especially true if the offender has gotten away with numerous offenses in the past, and views these stops as reflecting officers' failure to catch her (Stafford & Warr, 1993). Nonetheless, if an offender experiences one of these enforcement actions and refrains from offending then she has been specifically deterred.

Similarly, enforcement actions also may communicate to other potential offenders that the certainty of being punished has increased and generally deter potential offenders. The general public may receive the message that the certainty of being detected by the police has

[4] If that offender is incarcerated for a long period of time then some incapacitative effects may also be generated (Zimring & Hawkins, 1973).

increased in two ways. First, since enforcement actions are quite visible, they may directly observe others being stopped or arrested, adjust their perceptions of risk, and refrain from offending. Second, residents may hear about others being stopped or arrested via social networks (Parker & Grasmick, 1979; Stafford & Warr, 1993; Wyant, Taylor, Ratcliffe, & Wood, 2012). For example, after someone is arrested, her family could communicate to neighbors or the arrestee's friends that that she is in jail following an arrest. Again, it is possible that potential offenders do not adjust their perceptions of certainty from seeing or hearing about stops, but do when people in their social network begin to be arrested for serious offenses.

Broken Windows Theory

Broken Windows Theory reframed the importance of using police enforcement actions, particularly disorder crime arrests (misdemeanors), to address crime problems (J. Q. Wilson & Kelling, 1982). Broken Windows Theory outlined a process by which high levels of incivilities lead to high levels of serious crime in "teetering" neighborhoods over time. The process starts when minor incivilities are left unattended. Unattended incivilities then lead residents to infer that neighborhood informal social control is low and residents do not care about the neighborhood. Residents then become concerned about their safety and begin to withdraw from the neighborhood. This withdraw further diminishes neighborhood informal social control. Decreases in informal social control then results in local, minor offenders engaging in disorderly behavior. Over time, more serious offenders from outside the neighborhood take notice of the disorderly behavior and lower levels of informal social control, and then begin to believe they can offend in that neighborhood with impunity. As a result, outside offenders move in to commit more crimes and neighborhood crime levels increase.

Wilson and Kelling (1982) argued that the police are in the best position to maintain order in teetering neighborhoods on the cusp of becoming disorderly. Further, police can ultimately prevent serious crime by taking action against disorder crimes, such as public intoxication, vagrancy, panhandling, and prostitution, among others. Although Broken Windows Theory is only one version of the broader theorizing on incivilities and crime (R. B. Taylor, 2001, pp. 95 - 104) and has never been fully tested, it has had a powerful impact on American policing practices (Bratton, 1998; Sousa & Kelling, 2006). In short, Broken Windows Theory has provided the police further justification to use enforcement actions to address crime (Eck & Maguire, 2000).

The Importance of the New York City Crime Drop for Broken Windows Policing

It is important to recognize the New York City Police Department's (NYPD) role in promoting Broken Windows Theory and the use of police enforcement actions (Kelling & Sousa, 2001; Sousa & Kelling, 2006; Zimring, 2011). Although crime decreased across the US in the 1990s and into the 2000s, New York City (NYC) experienced a crime drop that was far greater than the national drop (Zimring, 2011). Similar to the national drop, there are many explanations for why NYC experienced such a dramatic decrease in crime: (1) changes in population and demographics, (2) changes in drug crime patterns, (3) changes in incarceration practices, and (4) policing (Blumstein & Wallman, 2000; Zimring, 2011). There is still a lot of disagreement, but some scholars have argued that changes in policing seem like the most promising explanation of the "New York Difference" (Bratton, 1998; Maple, 1999; Zimring, 2011).

NYPD Chief William Bratton is credited for developing the policing strategy responsible for the NYC crime drop. Before Bratton became Chief of the NYPD, he served as the New York

Transit Police Department's Chief. The NYC transit system experienced an increase in serious crime prior to Bratton's arrival. In response, Bratton developed an aggressive policing strategy that focused on enforcing disorder crime. Bratton's strategy was greatly influenced by the ideas of Broken Windows Theory and his friendship with George Kelling (Bratton, 1998).

Specifically, Bratton believed that if the Transit Police responded to low level offenses then they could deter and incapacitate criminals (Maple, 1999). For example, arresting a fare evader would deny him or her access to the transit system to commit a more serious crime. Sometimes a search of that offender after an arrest would either return a weapon or determine he was wanted on a warrant, and those additional charges would keep the offender in jail longer (i.e., incapacitation). Once released the offender may not return to the transit system to offend given he now knows the police are not tolerating even the least serious crimes. Other potential offenders may also be deterred from bringing weapons or other criminal tools onto the system or offending after hearing about others who were arrested. Thus, restoring order to the transit system would ultimately result in lower levels of crime (Bratton, 1998, pp. 152-155). Under Bratton, crime decreased on the NYC transit system (Bratton, 1998).

After a brief post as the Boston Police Commissioner, Bratton took over the NYPD and was under intense pressure from then incumbent Mayor Rudy Giuliani to address NYC's high crime rates. Drawing on his experience with the NYC Transit Police, Bratton brought his aggressive enforcement strategy to the NYPD. Due to the NYPD's previous focus on community policing, however, Bratton did not believe the NYPD had an adequate mission statement, organizational structure, or management process for fighting crime. As a result, CompStat was invented (Bratton, 1998).

CompStat started with unsophisticated meetings where patrol commanders would give presentations on crime patterns and trends in their geographic areas of responsibility. As time went on, the meetings became more regular, frequent, and utilized more and more data on crime patterns and trends. Crime maps also began to play a major role in the meetings (Bratton, 1998; Maple, 1999). Eventually the meetings became regular and evolved into police executives and patrol level commanders reviewing crime maps and trends in a systematic fashion. Patrol commanders were either “roasted” for failing to have already addressed or planned to have addressed crime problems or recognized for adequately addressing their precincts’ crime problems prior to the meeting (Bratton, 1998; Maple, 1999).

CompStat ultimately provided the means for executive commanders to ensure mid-level commanders used crime data and maps to focus their policing tactics in their geographic areas of command and hold them accountable if crime problems were not addressed appropriately (Bratton, 1998; Maple, 1999; Silverman, 2006). It is difficult to say for sure what tactics were implemented in high crime areas under the NYPD’s CompStat model (see Kelling & Sousa, 2001). Both Bratton and Jack Maple, the “architect of CompStat”, emphasized the use of innovative tactics tailored specifically to crime problems in their books; however, their descriptions of the NYPD’s policing tactics suggest they relied on: (1) quality-of-life-plus and (2) stop, question and frisk (Bratton, 1998; Maple, 1999).

Maple (1999) described quality-of-life-plus (QLP) as the enforcement of minor level offenses against those believed to be responsible for more serious crime. QLP allows cops to catch serious offenders when they are “off-duty” (Maple, 1999). The idea of QLP is to enforce minor level offenses against those who are believed to be serious offenders. Serious offenders may then admit to other crimes, turn other offenders in for crimes they have committed, or realize the police know about their offending habits. As a result, both the offenders and other offenders may be deterred or incapacitated from offending in the future. Maple (1999) stresses QLP was not designed be a “zero tolerance” tactic. Using a metaphor, Maple (1999) suggested QLP was designed to catch the sharks while avoiding casting a net wide enough to also catch the dolphins. Nonetheless, the Broken Windows / Zero Tolerance rhetoric surrounding the NYPD’s QLP and co-occurring NYC crime drop provides the impetus for police commanders to assume that aggressively enforcing disorder crimes is an effective policing tactic (Sousa & Kelling, 2006).

Stop, question, and frisk (SQF) or pedestrian investigations (also referred to as Terry Stops based on the 1968 case of *Terry v. Ohio*, pedestrian stops, or field investigations) were hypothesized to reduce crime under similar mechanisms (Bratton, 1998). People who have been stopped in the past may be less likely to possess the tools or the willingness to take advantage of an offending opportunity if they perceive they may be stopped again (i.e., specific deterrence). Similarly, people who have not been stopped but perceive an increased likelihood of being stopped due to aggressive policing in an area may also be less likely to plan offenses or possess the motivation or tools to capitalize on opportunities they encounter unexpectedly (i.e., general deterrence) (Rosenfeld & Fornango, 2014).

After the NYPD’s use of CompStat to drive its QLP and SQF tactics coincided with the NYC crime drop, CompStat was widely adopted in American policing (Weisburd, Mastrofski, McNally, Greenspan, & Willis, 2003). By 2000, roughly a third of departments with 100 or more sworn officers reported having adopted a CompStat-like program with roughly another quarter indicating they were planning to adopt it soon (Weisburd et al., 2003). In practice, the components of CompStat vary across departments; however, all departments in the survey were found to rely on enforcement actions such as saturating an area with police, focusing on increasing arrests for targeted or repeat offenders, using checkpoints, and increasing gun seizures among others (Weisburd et al., 2003). Participant observations and interviews of the Minneapolis, MN, Lowell, MA, and Newark, NJ police departments corroborated the survey findings. “In short, district commanders used data to react quickly to crime spikes in hot spots rather than to examine underlying conditions and respond proactively” (Willis, Mastrofski, & Weisburd, 2004, p. 55). Patrol officers were mostly instructed to aggressively enforce laws, identify and track suspicious persons, increase traffic enforcement, and use knock-and-talks in areas that showed increases in criminal activity (Willis et al., 2004). Mid-level commanders relied on police enforcement actions because they felt their experience had taught them that they worked best for reducing crime (Willis et al., 2004). Overall, the widespread adoption of CompStat in American policing, inspired by the NYPD’s use of CompStat to drive its QLP and SQF tactics, helped further institutionalize the use of police enforcement actions by American police departments, albeit with a greater emphasis on using mapping and analysis to drive those tactics in high crime areas (Willis et al., 2004).

The Effectiveness of Police Enforcement Actions

The following section reviews the evidence regarding the effectiveness of police enforcement actions. The review is structured chronologically based on the introduction of the major theoretical frameworks that underpinned the studies (discussed in the last section). The shift in theoretical frames over time is important for understanding the effectiveness of police enforcement actions because it had a direct impact on how police enforcement actions were measured. Early researchers were primarily interested in the deterrent effects of arrest on crime, but Wilson’s (1968) ideas from the *Varieties of Police Behavior* shifted the focus onto the indirect and direct effects of other measures of police enforcement actions. Broken Windows Theory’s subsequent explication and influence in NYC resulted in interest in the effectiveness of arrests for low level, misdemeanor offenses (i.e., disorder crime). Moreover, the association of stop, question, and frisk with the NYC crime drop prompted interest in the effects of SQF on crime (see Rosenfeld & Fornango, 2014; Zimring, 2011).

The Effect of Arrests

The earliest studies were concerned with the direct deterrent effect of arrests on crime levels. Four cross-sectional studies using macro spatial units of analysis found a deterrent effect for arrests. In Florida cities and counties, the percentage of crimes cleared by arrest had an inverse correlation with the total index crime rate in 1971 that was not attenuated after controlling for demographic measures. Examinations of scatter plots suggested the correlation between the clearance rate and the index crime rate was even stronger in cities/counties with clearance rates greater than or equal to 30 percent (i.e., a threshold effect) (Tittle & Rowe, 1974). A subsequent analysis of Florida cities and counties during 1972 replicated the inverse relationship between arrest and crime rates after controlling for police department size, but also found the magnitude of the relationship varied across individual index offenses (Bailey, 1976). A re-analysis of Tittle and Rowe's Florida data along with data for California cities and counties between 1971 and 1973 found an inverse link between arrest and index crime rates, but was unable to replicate the 30 percent clearance rate threshold effect. That failure was attributed to the fact that the Florida data were collected on less populous cities/counties that typically had higher arrest rates (Brown, 1978). Finally, an inverse correlation between clearance rates and property crime rates (burglary, robbery, larceny, and auto-theft) was observed when data for standard metropolitan statistical areas with a population of at least 500,000 were averaged across the years 1970-1973 (Geerken & Gove, 1977).

Cross-sectional designs came under scrutiny due to theorizing that suggested the inverse relationships between arrest and crime rates could alternatively reflect the fact that as crime rates rise the criminal justice system becomes overburdened and unable to maintain high arrest rates (i.e., simultaneity bias). As a result, scholars began to examine the relationship between arrest and crime rates longitudinally (Greenberg, Kessler, & Logan, 1979). These longitudinal studies employed a range of spatial and temporal units and returned a set of mixed findings for the deterrent effect of arrests on crime rates.

Researchers using panel models to study states between 1964 and 1968 (Logan, 1975) and 98 cities with populations of at least 25,000 between 1964 and 1970 (Greenberg et al., 1979) failed to find convincing evidence that arrests impact crime rates even after controlling for demographic and economic composition (Greenberg & Kessler, 1982). However, studies examining time series data in a single city found: (1) arrests lagged one year linked to lower yearly homicide and auto-theft rates in Houston, TX (1960-1976) (Cloniger & Sartorius, 1979), (2) arrest counts lagged one month linked to lower monthly robbery counts in Oklahoma City and Tulsa, OK (1967-1980) (Chamlin, 1988), (3) arrests lagged one month linked to lower robbery and auto-theft counts and arrests lagged one quarter linked to lower quarterly larceny counts in Oklahoma City, OK (1967- 1989) (Chamlin, Grasmick, Bursik, & Cochran, 1992), and (4) arrests counts lagged one day linked to significantly lower daily index crime counts in Orlando, FL (July, 1991-December, 1991) (D'Alessio & Stolzenberg, 1998). Conversely, monthly arrest counts did not significantly impact property crime (robbery, burglary, grand larceny, and auto theft) in seven Pennsylvanian cities (1967-1980), but the author stressed that only a few cities with populations of less than 10,000 residents achieved clearance rates above 40 percent and in these cities there was some evidence that arrests reduced property crime (i.e., a threshold effect) (Chamlin, 1991).

Another series of longitudinal studies examined the link between arrests and crime in geographically smaller police administrative units. First, a study of five police beats averaging roughly a robbery per week from 1986 to 1988 in Oklahoma City, OK failed to find a deterrent effect for arrests when both ARIMA (arrest and robbery counts) and proportional hazards models (effect of a robbery arrest on the time until the next neighborhood robbery) were estimated (Bursik, Grasmick, & Chamlin, 1990). A second study of New York City police precincts from 1989 to 1998 failed to find significant linear relationships between lagged monthly arrests per officer ratios (for homicide, robbery, and aggravated assault arrests) and monthly robbery, burglary, or assault rates, but found significant quadratic relationships for robbery and burglary rates after controlling for structural disadvantage and population mobility. In other words, lagged monthly arrest per officer ratios reduced robbery and burglary rates as they increased but the effect eventually leveled off (Kane, 2006). Finally, a study of Philadelphia police districts for the years 1996 through 2002 found adult arrest rates lagged one quarter were inversely related to later quarterly first time delinquency prevalence, but when the number of lags was increased to 6 or more quarters the relationship between adult arrest rates and later first time delinquency prevalence became positive. These findings suggests arrests may generate short-term crime reduction but have unintended effects over the long term (R. B. Taylor et al., 2009). Although the designs of these studies mean interpreting their findings requires more nuance, a deterrent effect of arrest was shown in two out of three studies using police administrative units.

Finally, a more recent study by Wyant and colleagues (2012) is the only study to date to examine the effect of arrest on any crime type using both micro-spatial and micro-temporal units. Specifically, the authors use a modified Knox test (Johnson et al., 2007; Knox, 1964; Ratcliffe & Rengert, 2008) to examine spatial-temporal interactions between the occurrence of arrests for illegal gun possession and shooting incidents occurring in one street block and two day increments apart in Philadelphia, PA (2004-2007). The results of the study suggest that arrests for illegal gun possession deter shootings roughly a few blocks from the initial arrest, but these deterrent effects are delayed for a couple of days and only lasted for a short time.

The Effect of Legalistic Policing Measures

Wilson's (1968) theory of policing styles influenced scholars to begin examining more sophisticated measures of police enforcement actions. Wilson and Boland (1978) estimated two-stage least squares regression models (2SLS) for a sample of 35 large American cities and found that cities' robbery arrest ratios were a function of the number of citations for moving traffic violations issued per officer, crimes per patrol unit, and the proportion of nonwhite residents. Higher robbery arrest ratios then linked to lower robbery rates (J. Q. Wilson & Boland, 1978).[5] A later study of 171 large American cities during 1980 using a new measure of legalistic policing – the number of disorderly conduct and driving under the influence (DUI) arrests per officer – and 2SLS models demonstrated that the legalistic policing measure had a positive relationship with arrest rates which in return drove down robbery rates, but the legalistic policing measure was also found to have a *direct* inverse effect on robbery rates in a subsequent model (R. J. Sampson & Cohen, 1988). MacDonald (2002) found cross-sectional support for the direct effect of legalistic policing (number of DUI and disorderly conduct arrests per officer) in a sample of 164 cities with populations of at least 100,000 (MacDonald, 2002). Separate cross-sectional models examining robbery rates averaged for 1993 and 1994 and 1997 and 1998 found the legalistic policing measure was the only significant predictor of lower robbery rates

[5] It should be noted that the results of this analysis were criticized after an examination of plots of moving violations (lagged one and two years) versus robbery rates for nine cities from 1948 to 1978 suggested that the two trends varied from city to city and rarely tracked in such a way that would support Wilson and Boland's (1978) findings (see Jacob & Rich, 1981; and then Wilson & Boland, 1982 for a response to these criticisms).

for both periods even after controlling for structure and the adoption of COP in the latter outcome's model. Results for homicide rates mirrored the robbery rate model for the 1993 and 1994 outcome. A pooled cross-sectional time series model with change scores as the outcomes again showed legalistic policing resulted in lower robbery and homicide rates (MacDonald, 2002).

Later researchers attempted to replicate Sampson and Cohen's (1988) study, and then conducted a more rigorous longitudinal test (Kubrin et al., 2010). Using a longitudinal dataset spanning the years 1996 to 2003 for a sample of large US cities (populations of at least 100,000) preliminary cross-sectional 2SLS models failed to find a significant *indirect* effect of legalistic policing (number of arrests for DUI and disorderly conduct per officer) on robbery rates *through* the robbery arrest rate; however, a *direct* inverse effect of legalistic policing on robbery rates was demonstrated even after socio-demographics were held constant. Next, panel models suggested that the legalistic policing measure was endogenous to the robbery rate outcome (i.e., police departments become more active in response to rising crime rates), and once the endogeneity of legalistic policing and arrest rates was accounted for it was shown that increases in legalistic policing linked to significant decreases in robbery rates (Kubrin et al., 2010). In total, when legalistic policing measures were used to operationalize police enforcement actions, scholars were able to consistently demonstrate an inverse relationship with crime at the city level.

The Effect of Broken Windows Policing

After former Police Commissioner William Bratton argued his policing reforms were responsible for NYC's drastic crime drop, some policing scholars examined the effects of disorder crime enforcement in NYC (Bratton, 1998). A within-city analysis analyzing precinct level data for the years 1989 through 1998 found precincts with higher violent crime counts (homicide, rape, felonious assault, robbery) had higher misdemeanor arrest counts in 1989, yet the average yearly misdemeanor count had a significant effect on the negative random slope of time after controlling for the unemployment rate, young male population, and cocaine related hospital admissions (Kelling & Sousa, 2001). Extrapolating from the model's parameter estimates, it was concluded that there was one less violent crime for every 28 additional misdemeanor arrests during the evaluation period. A second city-level study of NYC found that monthly index crime rates (by crime type, excluding arson) between 1974 and 1999 were reduced by higher lagged monthly misdemeanor arrest counts after controlling for the monthly prison population, police force size, health of the economy, young male population, and seasonality (Corman & Mocan, 2005). While the statistical validity of these results have been criticized, together they suggest disorder enforcement can impact crime levels at somewhat geographically larger units of analysis (see Greenberg, 2013; Harcourt & Ludwig, 2006).[6]

The Effect of Pedestrian Stops, Field Investigations, or Stop, Question and Frisk

An early quasi-experiment in San Diego was designed to evaluate whether field investigations, or "contact initiated by a police officer who stops, questions, and sometimes searches a citizen because the officer has reasonable suspicion that the subject may have committed, may be committing, or may be about to commit a crime" – had any impact on crime (Boydstun, 1975, p. 3). After matching three San Diego police beats (within the same District) on

[6] In short, Kelling and Sousa's (2001) model is not specified to assess how changes in misdemeanor arrests tracked with changes in violent crime rates (i.e., a time varying covariate), but rather simply examines how the average yearly number of misdemeanor arrests affects the varying slope of linear time (Harcourt & Ludwig, 2006). Because of their choice to use a linear growth model rather than model misdemeanor arrests as a time-varying covariate, it essentially impossible to rule out that their observed effects are not attributable to regression to the mean, and additional analyses conducted by Harcourt and Ludwig (2006) provide quite tenable support for a regression to the mean explanation. In addition, because Corman and Mocan (2005) employed a time series design, it is nearly impossible to rule out other possible extraneous causes and determine causality from their model (Greenberg, 2013; Harcourt & Ludwig, 2006).

key demographic characteristics, each of the beats were assigned to either the control condition (business as usual policing), the experimental stop program (police officers were specially trained in conducting field investigations in a way that would not negatively impact police-community relations)[7], or an area where field investigations were terminated. Differences in means tests and contingency tables comparing crime in the seven months prior, nine months during, and five months after the initiative, revealed that total suppressible crimes (sex crimes, robbery, assault, burglary, larceny/theft, auto theft, and malicious mischief/disturbances) increased in the beats where field stops were terminated. This suggested field investigations provide some deterrent effect, but provided little guidance on the proper dosage of field investigations (Boydstun, 1975).

The publicity of SQF in regards to the NYC crime drop has renewed interest in the effectiveness of pedestrian investigations for addressing crime; especially since the disproportionate stopping of minorities has become a political and civil rights/legal issue ("Bailey, et al. v. City of Philadelphia, et al.," 2011; Gelman, Fagan, & Kiss, 2007). Rosenfeld and Fornango (2014) conducted the first rigorous evaluation of the NYPD's use of SQF. After employing Arellano-Bond panel models to examine precinct robbery and burglary rates for the years 2003-2010, the authors found that SQF counts (up to two year lags) did not significantly impact yearly robbery or burglary rates after endogeneity and the city's structural composition were held constant (Rosenfeld & Fornango, 2014).

[7] Field investigation (FI) training was provided by a consultant. The training program was designed by the consultant in conjunction with SDPD officers after a series of meetings, videotaped role playing exercises with SDPD officers, and specialized exercise where SDPD officers were placed in situations that resulted in them being the recipients of field investigations in a nearby jurisdiction and debriefed on their experiences. Overall, a ten module training program was delivered to the officers in the experimental field investigation program: (1) videotaped FI simulation exercise, (2) police objectives of FI (law enforcement and keeping the peace), (3) safety aspects of FI, (4) coping with cultural differences in FI, (5) techniques for opening and closing a FI, (6) legal aspects of FI, (7) police environment of FI, (8) field training debriefings where officers discuss how FI impacts officers & citizens, (9) additional experiential field training, and (10) officer evaluations (Boydstun, 1975).

Summary of the Effectiveness of Police Enforcement Actions in Macro Units of Analysis

Empirical support for the effectiveness of police enforcement actions for reducing crime is mixed. Earlier cross-sectional studies found an inverse relationship between arrest and crime using macro-spatial units (Bailey, 1976; Brown, 1978; Geerken & Gove, 1977; Tittle & Rowe, 1974), but longitudinal research mostly failed to find a link between arrest rates and crime levels at the city level (Chamlin, 1991; Chamlin et al., 1992; Greenberg & Kessler, 1982; Greenberg et al., 1979; Logan, 1975). Aside from one exception (Bursik et al., 1990), some studies were able to demonstrate a link between arrests and crime in police administrative units under some scenarios (Kane, 2006; R. B. Taylor et al., 2009; Wyant et al., 2012). Similarly, when researchers started to investigate other measures of enforcement actions, such as DUI and disorderly conduct arrest rates or misdemeanor arrests, police enforcement actions were found to link to lower crime levels at both the city (Corman & Mocan, 2005; Kubrin et al., 2010; MacDonald, 2002; R. J. Sampson & Cohen, 1988; J. Q. Wilson & Boland, 1978) and police administrative unit levels (Kelling & Sousa, 2001). On the other hand, studies of the controversial SQF tactic have returned mixed results at the police administrative unit level (Boydstun, 1975; Rosenfeld & Fornango, 2014). Overall, a range of geographically larger spatial scales and measures of police enforcement actions have been employed, and the effectiveness of these actions remains an open question.

Changes in American Policing

Simultaneous to and possibly as a result of the previously reviewed studies, among others, the standard model of policing began to be criticized (Weisburd & Eck, 2004). By 1994 David Bayley had declared defeat for all modern police departments when he wrote: “The police do not prevent crime. This is one of the best kept secrets of modern life. Experts know it, the police know it, but the public does not know it" (Bayley, 1994, p. 1). Bayley (1994) was reacting to a series of seminal studies that had demonstrated that randomized motor patrol across large police beats (Kelling et al., 1974), rapid response to calls for service (Spelman & Brown, 1984), and generally applied follow-up investigations (Chaiken, Greenwood, & Petersilia, 1976) were all ineffective for reducing crime and/or capturing offenders. Further, the civil unrest of the 1960s and 1970s had eroded the public's confidence in the government and police (Fogelson, 1977; Weisburd & Braga, 2006b; Weisburd & Eck, 2004). As a result, police departments and scholars began focusing on how to fend off the criticisms of the police by developing policing tactics that demonstrated the police were "more effective and more democratic" (Mastrofski, 2006, p. 44). This "crisis in policing" spawned the development of many policing innovations. Community-oriented policing, problem-oriented policing, and hot spots policing became dominant trends in policing (Weisburd & Braga, 2006b; Weisburd & Eck, 2004).

Community-Oriented Policing

While most police departments claim to have adopted community-oriented policing (COP), what police departments actually consider to be COP varies from department to department (Skogan, 2006b; Skogan & Frydl, 2004). Implementations of COP have involved: (1) hosting community meetings, (2) conducting community surveys, (3) creating neighborhood substations, (4) implementing school resource officers, and (5) placing officers on foot patrol to name a few (Skogan, 2006b). Nonetheless, Skogan (2006b) argued that COP is a business process that includes: (1) citizen involvement, (2) problem solving, and (3) decentralization (also see Bayley, 1994). In practice, these principles get implemented differently in different departments, so the amorphous nature of COP makes it difficult to evaluate and determine its effectiveness. Some elements of various COP models may be effective while others show little promise for reducing crime (Mastrofski, 2006; Skogan & Frydl, 2004), but a recent meta-analysis of COP failed to find any crime control benefits (Gill, Weisburd, Telep, Vitter, & Bennett, 2014).

Problem-Oriented Policing

Problem-oriented policing (POP) is easier to define and identify in practice. From a POP perspective, police departments should focus on problems – "two or more incidents similar in one or more ways that is of concern to the police and a problem for the community" (Office of Community Oriented Policing Services, 2009, p. 4) – rather than individual incidents and attempt to adopt holistic solutions that eliminate the problems and prevent future crime and disorder (Goldstein, 1979, 1990). Overall, the nature of POP makes it difficult to evaluate with rigorous scientific methods (Eck, 2003), but there are many case studies (Scott, 2000) and even experimental studies, discussed in detail later, supporting POP's effectiveness (Braga & Bond, 2008; Braga et al., 1999; B. Taylor, Koper, & Woods, 2011). On the other hand, POP is often criticized as being impractical because it is difficult to implement rigorously (Bullock, Erol, & Tilley, 2006; Cordner & Biebel, 2005).[8] To date, the implementation of POP has been deemed "shallow" and suffered from poor problem definition and analysis, lack of creativity when designing responses, and police departments rarely evaluate the success of their POP projects (Braga & Bond, 2008; Bullock et al., 2006; Weisburd & Braga, 2006a).

[8] To guide effective implementation, Eck and Spelman (1987) proposed the SARA Model: (1) Scanning, (2) Analysis, (3) Response, and (4) Assessment. The SARA Model is an applied science model where police actors (1) scan for specific problems, (2) analyze data to understand the problem in-depth, (3) identify a range of responses that target the problem's underlying cause, and (4) assess the success of the responses with the possibility of stating the process over again if the problem has not been reduced (see Clarke & Eck, 2003).

Hot Spots Policing

Most recently, hot spots policing has received major attention in the field of policing (Mastrofski et al., 2010). Hot spots are places – "addresses, buildings, block faces, street segments, or clusters of addresses" (Mastrofski et al., 2010, p. 251) – with disproportionate levels of crime (Chainey & Ratcliffe, 2005, pp. 241-245; Eck & Weisburd, 1995; Sherman, Gartin, & Buerger, 1989). Hot spots policing focuses police resources in crime hot spots (Sherman & Weisburd, 1995). It is possible that as many as nine out of ten police departments are currently using hot spots policing (Police Executive Research Forum, 2008). The National Academy of Science's panel to review police effectiveness concluded that "studies that focused police resources on crime hot spots provide the strongest collective evidence of police effectiveness that is now available" (Skogan & Frydl, 2004, p. 250). Yet which actions are most effective for police to implement in crime hot spots remains an open question (Telep & Weisburd, 2012).

The Existence of Crime Hot Spots

The study of the geography of crime has a long history. Over time scholars have moved down the cone of resolution and shown that crime is concentrated across progressively smaller spatial units of analysis (P. J. Brantingham, Dyreson, & Brantingham, 1976). In the early 19th century, scholars such as Guerry and Quetelet showed that crime varied spatially across large administrative areas in France (Eck & Weisburd, 1995; Groff, 2010; Wortley & Mazerolle, 2008). In the early 20th century, the Chicago School theorists began to show that delinquency was concentrated in certain neighborhoods (Eck & Weisburd, 1995; C. R. Shaw & McKay, 1942). The study of the causes and consequences of community crime rates continues today (Bursik & Grasmick, 1993; Reiss, 1986; R. J. Sampson, 2012; R. J. Sampson, Raudenbush, & Earls, 1997).

In the late 1980s, however, the development of computers and police records management systems allowed researchers to begin to examine even smaller geographies. A seminal study of calls for service in Minneapolis, MN found that roughly 50 percent of calls for service originated from only about three percent of the city's addresses with the authors stressing that most places *within* high crime neighborhoods experienced no crime (Sherman et al., 1989). Similar concentrations of calls for service were found in Boston, MA (Pierce, Spaar, & Briggs, 1988). The discovery of such disproportionate concentrations of crime across a small number of micro spatial units of analysis provided the empirical impetus for researchers' interest in micro-geographies.

Recent longitudinal research has shown that crime concentrates at micro-spatial units for long periods. Research in Seattle, WA across a 14 year period (1989 - 2002) found that the majority of crime incidents are concentrated on a small number of street blocks – the two sides of a street that face one another and are bounded by an intersection at each end.[9] For each of the years in the fourteen year study period roughly four to five percent of street blocks experienced about fifty percent of the year's crime incidents (Weisburd et al., 2004). Furthermore, results from group-based trajectory models found that while some street blocks experienced increasing or decreasing trends over the study period, the majority of street blocks had stable levels of crime over the study period. Thus, not only do a subset of street blocks experience a disproportionate amount of crime, but these crime concentrations persist from year to year (Weisburd et al., 2004). A series of spatial data analyses found that the different

[9] The earlier Seattle studies operationalized street blocks using 100 hundred blocks rather than the physical street network. In Seattle, some street blocks span multiple 100 blocks (e.g., addresses 100-399), and rather than use the actual street network the researchers aggregated incidents to each 100 block (i.e., a street block spanning addresses 100-399 would be treated as three units, 100-199, 200-299, 300-399) (Groff, Weisburd, & Morris, 2009, p. 7; Weisburd, Bushway, Lum, & Yang, 2004, p. 291, footnote 3; Weisburd, Morris, & Groff, 2009, p. 449, footnote 3). Later work in Seattle started to use the actual street geography to bound street segments (Groff, Weisburd, & Yang, 2010; Weisburd, Groff, & Yang, 2012). All of the Seattle studies dropped out crimes geocoded to street corners from the analysis.

trajectory groups identified by Weisburd and colleagues (2009) are spatially independent from one another, thus suggesting the processes generating the different trajectory groups are likely to be operating at a micro-level (Groff et al., 2010).

Using repeated measures multi-level models, a statistical technique that is starkly different than group-based trajectory modeling, research in Boston, MA essentially replicated some of the Seattle findings using data on shootings and robberies (Braga, Hureau, & Papachristos, 2011; Braga, Papachristos, & Hureau, 2010). The examination of shootings between 1980 and 2008 concluded with three major findings: (1) 88.5 percent of street blocks and intersections never experienced a single shooting over the 28 year study period, (2) roughly 6 percent of street blocks and intersections experienced only one shooting during the same period, and (3) just less than five percent of street blocks and intersections experienced more than one shooting and accounted for the majority of gun violence incidents as well as Boston's overall gun violence trend during the study period (Braga et al., 2010). The results for robberies in Boston between 1980 and 2008 were substantively similar (Braga et al., 2011).

Taylor's Counter Argument

It is important to recognize that the concept of crime hot spots has not developed without criticism. Taylor (2010) argues that "hot spots exist in the data world but not the real world" and "[t]o conclude that hot spots are free standing entities existing in the real world is to commit the logical fallacy of reification" (p. 272). It follows that hot spots are typically derived from a number of different spatial units (i.e., addresses, clusters of addresses, street blocks, police administrative units, census administrative areas, or neighborhoods) and arbitrary (yet systematic) decisions have to be made to operationalize hot spots policing deployment areas (see Buerger, Conn, & Petrosino, 1995; Mastrofski et al., 2010). Hence, studies of crime hot spots need to carefully derive spatial units of analysis based on the studies' theoretical (and possibly practical) frames (Weisburd, Bruinsma, & Bernasco, 2009).[10]

Explaining the Existence of Crime Hot Spots

Environmental criminology's opportunity theories provide the theoretical framework for understanding *why* crime concentrates at micro-units of analysis. The environmental criminology framework is comprised of three theories: (1) the rational choice perspective, (2) the routine activity approach[11], and (3) crime pattern theory (Wortley & Mazerolle, 2008). These theories are outlined below.

The rational choice perspective theorizes that in order for a crime event to occur a potential offender must decide the benefits of committing a crime outweigh the potential costs. Offenders make two separate decisions when deciding to commit crimes: (1) involvement decisions and (2) event decisions (Clarke & Cornish, 1985; Cornish & Clarke, 1986). *Involvement decisions* include whether to begin offending (initiation), continue offending (habituation), or desist from offending (desistance decisions). Involvement decisions are made over long time periods, and may be influenced by the many factors outlined by traditional criminologists who study criminality (Cullen, 2011). *Event decisions* involve whether or not one should commit a particular crime event at a given time and place. Event decisions are short-term and regard the

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[10] Taylor (2015), on pages 126 to 129, argued hot spots are a useful concept for policing and short-term crime control, but not theory. Taylor's argument emphasizes thinking about which spatial units are theoretically appropriate for studies of geography and crime.

[11] Routine activity theory originated as a macro-level explanation of crime rates (Felson, 2008; Wortley & Mazerolle, 2008). When aggregate patterns of human activity change, the convergence of motivated offenders and suitable targets lacking adequate guardianship will become more common and aggregate crime rates will increase. Cohen and Felson (1979) used these mechanisms to explain why predatory crime rates increased after World War II even though economic conditions improved. In short, the authors argue that predatory crime rates increased as people—particularly newly employed women—began to spend more time away from home and consumer goods became more widespread and easier to steal (Cohen & Felson, 1979). The three basic elements of a crime event (i.e., motivated offenders, suitable targets, and inadequate guardianship) have since been used to understand crime concentrations in space and time.

preparation, commission, and conclusion of a particular offense at a specific time and place. During the event decision, the offender exercises bounded rationality to determine whether the benefits of capitalizing on a particular offending opportunity at the current time and place outweigh the costs (Clarke & Cornish, 1985). Thus, there is an inherent assumption that offenders have preferences for certain offending situations.

According to routine activity theory, a motivated offender and a suitable target lacking adequate guardianship must converge in time and space in order to initiate the crime event decision making process (Cohen & Felson, 1979). The convergence of these three basic elements of crime depends on the spatial and temporal locations of humans' routine activities (Felson & Boba, 2010). Human activities take place at locations within finite time periods because human activity is constrained by biology, peoples' lack of skills or abilities, and/or laws or regulations imposed by society (Hägerstrand, 1970; Miller, 2005). For example, most people participating in the formal economy likely wake up each day, prepare for work, commute to work, and spend most of the day at their jobs. At the end of the work day, they commute home or finish any evening errands, prepare and eat dinner, and then rest before going to bed. On the weekends they are more likely to engage in recreational activities (Chapin, 1974; Pred, 1981). Humans' daily activities become routinized into daily decision templates where people go about their daily activities without much thought (Horton & Reynolds, 1971). Brantingham and Brantingham (1981) theorized that offenders develop similar crime decision making templates that outline the conditions favorable to offending during event decisions that arise in the course of their routine activities.

The physical layout of a city influences the geography of peoples' non-criminal and criminal decision templates (Horton & Reynolds, 1971). During peoples' daily activities, they travel along pathways – the street network, walkways and alleys, and public transportation lines – to different nodes – places such as homes, work/school sites, or places for leisure activity (P. J. Brantingham & Brantingham, 1991; P. J. Brantingham & P. L. Brantingham, 1993b; P. L. Brantingham & Brantingham, 1981; P. L. Brantingham & P. J. Brantingham, 1993). As people move throughout the city in the course of their routine activities, some places experience more human activity than others (P. J. Brantingham & P. L. Brantingham, 1993a). It is along the pathways and around the nodes with the greatest levels of human activity that the greatest convergences of motivated offenders and suitable targets lacking adequate guardianship occur, and, as a result, concentrations of crime. In other words, certain places facilitate the convergence of motivated offenders and suitable targets that lack adequate guardianship under conditions consistent with offenders' crime templates and event decisions to commit crimes are made (P. J. Brantingham & Brantingham, 1991; P. J. Brantingham & P. L. Brantingham, 1993b; P. L. Brantingham & Brantingham, 1981; Cohen & Felson, 1979).

Opportunity theories of geographic crime patterns have been supported.[12] First, qualitative research on known and/or active offenders demonstrates that they prefer certain types of victims, places, and times for offending. For example, Wright and Decker (1997) interviewed active robbers and found they preferred busy places where people are more likely to be carrying cash. Qualitative work with robbers in Chicago found similar results (St. Jean, 2007). Interviews with burglars also suggest they prefer neighborhoods and targets with particular features (Rengert & Wasilchick, 1989).

Second, empirical studies using discrete choice models provide similar results. Robbers target places that are close to their home, easily accessible, and have high levels of legal and

[12] It should be noted that these theories have been critiqued and contested. For example, Eck (1995) essentially argued that routine activities theory has never been fully tested (see pages 794 – 796).

illegal commercial activity (Bernasco & Block, 2009; Bernasco, Block, & Ruiter, 2013). Commercial robbers exhibit somewhat similar search patterns (Bernasco & Kooistra, 2010). Similarly, burglars seem to prefer neighborhoods that are close to their current or previous homes, more diverse, less likely to have high levels of guardianship, and have more residential units (i.e., targets) (Bernasco, 2006, 2010; Bernasco & Nieuwbeerta, 2005).

Finally, regression models predicting levels of crime (i.e., counts or rates) demonstrate that places with major roads (Bernasco & Block, 2011), high schools (Roman, 2005; Roncek & Faggiani, 1985; Roncek & LoBosco, 1983), bars and taverns (Roncek & Maier, 1991), convenience stores (Schweitzer, Kim, & Maclin, 1999), public transportation stations (Block & Block, 2000; Block & Davis, 1996), check cashing stores (McCord & Ratcliffe, 2007), liquor stores (McCord & Ratcliffe, 2007; Rengert, Ratcliffe, & Chakravorty, 2005), public housing (Haberman, Groff, & Taylor, 2013), and parks (Groff & McCord, 2011), among others link to higher levels of crime.

Opportunity theories provide a theoretical foundation for the existence of crime hotspots, and as a result an indication of leverage points that hot spots policing tactics might target. Specifically, Eck (2003) argues that in order to disrupt hot spots crime prevention tactics could directly focus on offenders, targets, or guardians or indirectly focus on the actors who may be able control any of those three components (R. Sampson, Eck, & Dunham, 2010). On the other hand, there are numerous crime prevention tactics that work through different theoretical mechanisms that may be effective for addressing crime hot spots. Only empirical research with strong measures and designs can parse out which tactics work through which theoretical mechanisms to most effectively address crime hot spots.

Hot Spots Policing in Practice

After it was empirically demonstrated that crime concentrates in hot spots and strong theoretical explanations for crime hot spots were developed, hot spots policing was a natural evolution (Weisburd & Braga, 2006a). Overall, hot spots policing has a rigorous supporting evaluation literature (Lum, Koper, & Telep, 2011); however, exactly what police should be doing in crime hot spots remains an open question (Braga, 2001; Telep & Weisburd, 2012; Weisburd & Braga, 2006a). Researchers have found that (1) increasing police presence (Lawton, Taylor, & Luongo, 2005; Ratcliffe et al., 2011; Sherman & Weisburd, 1995; Telep, Mitchell, & Weisburd, 2012), (2) aggressively using police enforcement actions (sometimes focused on specific offenders) (Groff et al., 2015; Sherman & Rogan, 1995; Weisburd & Green, 1995), and (3) problem-oriented policing (Braga & Bond, 2008; Braga et al., 1999; B. Taylor et al., 2011) can all be effective hot spots policing tactics when compared to the standard model of policing. In practice, despite calls for police to widen the range of tactics they use to address crime problems (Weisburd & Eck, 2004), "[t]he responses are narrow and predictable – surveillance, stop and frisk, question, and arrest – regardless of the nature and causes of the problem" (Rosenbaum, 2006, p. 249; 2007).

A 2008 survey of police executives non-representatively sampled from members of the Police Executive Research Forum generally supports this characterization of hot spots policing tactics (n = 176) (Koper, 2014). Of the 18 hot spots policing tactics asked about in the survey, the top five most common tactics implemented in hot spots were (1) problem solving, (2) targeting known offenders, (3) community policing partnerships, (4) directed patrol, and (5) proactive field contacts. Further, police executives consistently ranked responses involving patrol and enforcement actions among the most effective for addressing homicide/shootings, robbery, assault, gang violence, and drug violence in crime hot spots. It is important to note, however, that these findings have to be considered in the context of the sample's unrepresentativeness and the fact the data do not shed light on the quantity or quality of implementation (Koper, 2014). In sum, while there has been a call for police to use a wide range of actions in crime hot spots, they predominantly rely on police presence and enforcement actions to address crime hot spots (Rosenbaum, 2006).

The Effectiveness of Police Presence in Crime Hot Spots

The Kansas City Preventive Patrol Experiment seriously questioned whether police presence could deter crime in large police beats (Kelling et al., 1974), but Sherman and Weisburd (1995) suspected it could if it was delivered in a *high enough dosage*. Since studies had recently found crime was concentrated spatially (Pierce et al., 1988; Sherman et al., 1989), Sherman and Weisburd (1995) hypothesized police presence should also be concentrated spatially. The Minneapolis Hot Spots Policing Experiment was designed to test that idea in the late 1980s (Sherman & Weisburd, 1995). Analyses of both official calls for service and systematic social observation measures of disorder found a deterrent effect for greater police presence on total calls for service, "soft" crime calls for service, and observed disorder. A second event history modeling analysis of the observational data generated in the Minneapolis Preventive Patrol Experiment demonstrated that police presence of roughly 13 to 15 minutes in the hot spots areas had the greatest effect on the occurrence of disorder in the 20 minutes after the police were present and then leveled off after (Koper, 1995).

In Philadelphia, PA, police presence at drug corners was found to deter crime (Lawton et al., 2005). As part of a special initiative designed by Philadelphia's Mayor, John Street, and the police department, 214 high drug crime locations (a single address, mostly street corners) were identified by the police department and a significant amount of overtime funding was used to keep officers stationed there twenty-four hours a day, seven days a week. Citywide and localized ARIMA models were estimated for three crime incident outcomes: (1) homicides, (2) violent crime (index of homicide, robbery, rape and aggravated assault), and (3) drug crimes (index of the possession, distribution, and manufacturing of all controlled substances). Citywide analyses failed to find any significant deterrence effects, but localized analyses found that the around-the-clock police presence reduced weekly violent crime and drug incidents during the 18 week treatment period when compared to comparison areas.[13]

Police presence delivered by foot patrol officers was also found to deter violent crime in Philadelphia, PA violent crime hot spots (Ratcliffe et al., 2011). The hot spot areas in the Philadelphia Foot Patrol Experiment averaged 1.3 miles of streets, 23.9 street segments, and 14.7 street intersections compared to other studies' use of hot spots operationalized with widths no longer than a linear city block (Koper, 1995; Sherman & Weisburd, 1995; Telep et al., 2012) or a single street corner (Lawton et al., 2005). Foot patrol was found to reduce violent crime (by roughly 23 percent over a three month period), but that effect was limited to hot spots with pre-treatment violence counts in the 60th percentile or greater.[14]

Finally, the Sacramento Police Department sought to directly test Koper's (1995) 15 minute optimal police presence time (Telep et al., 2012). After analyzing calls for service and UCR Part I incidents, 42 approximately one-block long hot spots were identified and block randomization was used to identify 21 treatment and 21 control areas. The control hot spots received "business as usual policing", but the treatment hot spots were visited by police officers for roughly 15 minutes at a time in a random order every two hours. A difference in difference

[13] Comparison areas were created using a one-tenth of a mile buffer area around the centroids of drug crime hot spots identified by a hierarchical nearest neighbor analysis (n = 73).

[14] A follow-on study found the deterrent effects of foot patrol dissipated after the experiment concluded (Sorg, Haberman, Ratcliffe, & Groff, 2013).

analysis comparing the treatment and control areas during the 90-day experimental period to the same 90-day period from the previous year found that both calls for service and UCR Part I incidents were reduced by the increased police presence. Sensitivity analyses, however, found that the reductions were not consistent across all hot spots, and some hot spots experienced increases on the outcome measures relative to their matched control areas (Telep et al., 2012, p. 20).

The Effectiveness of Police Enforcement Actions in Crime Hot Spots

In addition to simply increasing police presence in hot spots, other studies have focused on *purposively* increasing police enforcement actions in hot spots. Weisburd and Green (1995) studied the effect of an aggressive enforcement strategy in Jersey City, NJ drug markets. Drug market hot spot areas were created by linking street segments and intersections with high volumes of arrests and calls for narcotics activity within one block of each other and considered to be part of the same market based on intelligence from narcotics detectives. The majority of the 56 drug hot spot areas were small with seventeen containing one segment or intersection and only two including more than ten segments or intersections. After assigning 20 areas each to the treatment and control groups, the treatment areas received aggressive enforcement – mostly increased arrests – from squads made up of narcotics unit officers. Aggressive enforcement ranged from crackdowns using just the six officers in the narcotics squad to a dozen or more officers from across the department. Some squads also used citations for violations of health and safety codes when businesses were involved. After the initial crackdowns were over, detectives routinely performed surveillance in the drug market hot spots and additional crackdowns were used as needed. An analysis of calls for service for the seven months preceding and succeeding the intervention found both total disorder and the individual categories of suspicious persons, public morals, and persons in need of assistance were significantly reduced with no indications of immediate spatial displacement (Weisburd & Green, 1995).

Sherman & Rogan's (1995) quasi-experimental study in Kansas City, MO also focused on aggressive enforcement by examining the deterrent effect of gun seizures on gun crime. The treatment was implemented in an experimental police beat (eight by ten block area) and compared to another police beat (nearly three times the size of the experimental beat). In short, during 6 hour long overtime shifts (7:00 PM to 1:00 AM), directed motor patrol was used in the high crime police beat to generate high numbers of vehicle and pedestrian stops, traffic citations, and arrests. After employing four different statistical analyses, the nearly 260 percent increase in gun seizures generated through 1,434 traffic and pedestrian stops and 3,186 arrests or traffic citations was found to reduce roughly 83 gun crimes, but the treatment did not impact other types of calls or incidents (Sherman & Rogan, 1995).

Which Police Enforcement Actions Are Most Effective for Addressing Crime Hot Spots?

In contrast to the mixed results from police enforcement actions evaluations of larger spatial units, hot spots policing evaluations have generally found police presence and enforcement actions to be effective. The measures and designs employed in these hot spots policing evaluations, however, limit their ability to provide guidance on what police should actually be doing in crime hot spots (Braga, 2001; Telep & Weisburd, 2012; Weisburd & Braga, 2006a). This point is illustrated with examples below.

Police presence in crime hot spots is complex. For example, when George Kelling visited the treatment areas during the Minneapolis experiment, he noted "some [officers] were reading newspapers or sunning themselves while sitting on the patrol car, while others were engaging citizens in friendly interaction in community-policing style" (Sherman & Weisburd, 1995, p. 634). Lawton and his coauthors (2005) cautioned that because they were unable to measure the officers' activities while in the hot spots, the exact crime reduction mechanisms of the program they evaluated are still unknown (Lawton et al., 2005, p. 495). Ratcliffe and colleagues (2011) noted before they presented their results that they were unable to distinguish between the effects of foot patrol officer presence and activity. During the Philadelphia Foot Patrol Experiment, foot patrol officers increased pedestrian investigations by 90 percent and arrests by nearly 13 percent. Further, the highest crime hot spots that experienced the significant treatment effects were also the hot spots that saw the majority of officer activity (Ratcliffe et al., 2011). Moreover, the Sacramento Experiment concluded the effectiveness of the treatment varied across hot spots, but the authors were unable to determine if that variation was due to some hot spots having been policed differently or perhaps some other unmeasured factors, such as a treatment-environment interaction (Telep et al., 2012, p. 25).

Initiatives designed to specifically increase enforcement in crime hot spots have also been complex. For example, during the Kansas City Gun Project, directed motor patrol was used in a high crime police beat to generate high numbers of vehicle and pedestrian stops, traffic citations, arrests, and gun seizures. One police action was generated every forty minutes during the six hour overtime shifts (7:00 PM to 1:00 AM) (Sherman & Rogan, 1995). During the Jersey City Drug Markets Experiment, crackdowns involving directed patrol and arrests for drug law violations as well as some non-enforcement tactics, such as code enforcement, were implemented (Weisburd & Green, 1995).

One exception to the failure of evaluations to employ direct measures of the complex range of actions taken in crime hot spots is an evaluation conducted in St. Louis, MO (Rosenfeld, Deckard, & Blackburn, 2014). In collaboration with their research partners, the St. Louis Metropolitan Police Department tested the effects of strict directed patrol (n = 8) versus directed patrol with a focus on self-initiated officer activity (i.e., arrests, pedestrian checks, traffic stops, foot patrols, and problem solving) (n = 8) versus the standard model of policing (n = 16) across 32 hot spots in eight police districts. A difference in difference analysis found that directed patrol with a focus on self-initiated officer activity reduced total nondomestic firearm violence. Further, when predictors of total directed patrols and the individual self-initiated officer activities were entered into the model with the treatment group dummies, the treatment effect was mediated and only arrests and traffic enforcement were found to statistically reduce nondomestic firearm assault. The authors concluded the original treatments effects were driven by these individual actions via deterrence because they increased the certainty of apprehension. Nonetheless, notwithstanding the study's other limitations, the authors did not provide a statistical comparison of the effects of the different self-initiated officer activities.

The previous discussion is not a criticism of the researchers, but rather typical of how evaluation research evolves. Early evaluations typically determine if an effect exists at all and later work then seeks to understand any observed effects in more depth (Shadish, Cook, & Campbell, 2002). For example, the pioneering Minneapolis hot spots policing evaluation was designed to determine if delivering a high dosage of police presence in crime hot spots could impact crime at all (see Sherman & Weisburd, 1995, pp. 625 - 630) after the Kansas City Preventive Patrol Experiment had seriously questioned the effectiveness of police presence (Kelling et al., 1974). Nonetheless, following the lead of Rosenfeld and colleagues (2014) and Goldkamp's (2010) advice, the next steps in hot spots policing evaluation are at minimum to: (1) clearly explicate the theoretical reasons for expecting specific hot spots policing tactics to reduce crime, (2) directly measure the dosage of each tactic implemented with valid and reliable measures, and (3) conduct statistical tests that empirically compare the effectiveness of the tactics implemented. Given, the police's continued reliance on police enforcement actions (Koper, 2014; Rosenbaum, 2006), researchers should prioritize evaluations of those actions.

The Possible Unintended Consequences of Police Enforcement Actions

Well-intended crime control strategies can have unintended effects (Grabosky, 1996). Until this point, police enforcement actions have been considered for their crime control potential, but there are plausible hypotheses for how police enforcement actions may unintentionally increase crime. Five hypotheses for how police enforcement actions might increase crime are outlined below.

First, police enforcement actions may undermine citizens' perceptions of procedural justice and police legitimacy, thereby linking to less compliance with the law and higher crime levels over time. In sum, citizens who perceive the police as legitimate – or as an institution that should be respected and obeyed – are less likely to offend (Sunshine & Tyler, 2003; Tyler, 2004). Citizens' perceptions of police legitimacy are strongly determined by their perceptions of procedural justice. Citizens' perceptions of procedural justice are predicated on whether the police allow citizens to have a voice during decision making, act neutral, treat people with dignity and respect, and appear trustworthy when coming into contact with them. Even one poor experience with police can diminish citizens' perceptions of the police (Skogan, 2006a). Hot spots policing has not been found to detrimentally impact citizens' perceptions of procedural justice/legitimacy (Hinkle & Weisburd, 2008; Ratcliffe, Groff, Sorg, & Haberman, in press; J. W. Shaw, 1995; Weisburd, Hinkle, Famega, & Ready, 2011), but aggressively using enforcement actions has been shown to negatively impact citizens' perceptions of the police in interviews with young minorities living in high crime areas (Brunson, 2007; Brunson & Miller, 2006; Gau &

Brunson, 2010) and possibly increase individual offending rates or crime rates over the long-term (R. B. Taylor et al., 2009). Since minorities are disproportionately the recipients of police enforcement actions (Fagan & Davies, 2000; J. A. Greene, 1999), it leaves further room for citizens to perceive police enforcement actions as procedurally unjust and diminish police legitimacy. However, no direct measures of aggregate level legitimacy have been linked to higher aggregate crime levels (Walker, 2015).

Second, police enforcement actions could escalate the potential for violent situations to occur (Grabosky, 1996) by facilitating turf battles or retaliatory violence (Anderson, 1999). For example, police enforcement actions may successfully remove offenders, such as narcotics dealers, from a hot spot. Next, different offenders may attempt to take over that location. When the original group eventually returns, a turf battle between the two groups may occur. An analysis of shootings in Philadelphia revealed spatio-temporal patterns that were consistent with a retaliatory violence hypothesis (Ratcliffe & Rengert, 2008). Additionally, there are case studies to support this dynamic (Dean, Gottschalk, & Fahsing, 2010, p. 115; Dunn, 2014). Finally, it has been demonstrated that drug corners in Camden, NJ with more than one distribution group experience more crime than unrivaled corners (Taniguchi, Ratcliffe, & Taylor, 2011).

Third, police enforcement actions may increase violent crime through unintentional enticement or self-fulfilling prophecies (Grabosky, 1996). Unintentional enticement would occur if police enforcement actions motivate potential offenders who would not have otherwise offended to begin offending. For example, police enforcement actions focused on a gang who are presumed to have the potential to retaliate for a recent shooting may encourage them to do so in order to maintain their reputation (Anderson, 1999). Alternatively, potential robbers may become motivated robbers if they are the recipients of police enforcement actions and they internalize the perception that they are effective offenders or learn about good robbery opportunities in the areas they normally hang out in from the police (Grabosky, 1996).

Fourth, police enforcement actions could result in over-deterrence which discourages citizens from legitimately using a hot spot (Grabosky, 1996). As legitimate users of the area decrease, guardianship levels in the area would also decrease (Jacobs, 1961). As discussed in the theory on why hot spots exist, guardianship is important for reducing offending opportunities (Cohen & Felson, 1979; Reynald, 2009), so offenders may capitalize on offending opportunities in hot spots when the police and/or legitimate users are not present.

Fifth, displacement is always concern with targeted crime policies (Grabosky, 1996; Reppetto, 1976). Displacement can occur in a number of forms, but not all are necessarily plausible in response to police enforcement actions (Reppetto, 1976).[15] Spatial displacement may occur if targeted police enforcement actions in hot spots result in offenders moving to other locations to offend. Spatial displacement has rarely been found in place-based policing evaluations, and crime usually declines in nearby locations (Bowers, Johnson, Guerette, Summers, & Poynton, 2011; Weisburd et al., 2006). Temporal displacement may occur if offenders change the times of offending to account for police presence and enforcement actions. Moskos (2008) suggests offenders altered their offending patterns around police shift changes to avoid detection. Offenders may also change their offending tactics. For example, gang members may switch from on foot shootings to drive-by shootings to avoid recently deployed foot patrols. Offenders may also change the type of offense they commit. If police increase their enforcement actions against robbers, then those robbers could hypothetically become burglars. Finally, offenders discouraged or incapacitated by police enforcement actions

[15] Target displacement is not considered here.

may be replaced by new offenders. For example, if the local drug dealers are arrested after a recent spate of shootings, then their younger siblings may take over their turf and continue to operate the market and its associated violence.

Summary

This chapter reviewed the literature on police effectiveness and made a number of key points that underlie the importance of this study. The chapter started by illustrating the importance of police enforcement actions in American policing. From the development of the standard model of policing through the rise of hot spots policing, police enforcement actions have been the primary tactic the police have used to address crime. This chapter then reviewed the prominent theories that explain how police enforcement actions might reduce crime. Next, the effectiveness of police enforcement actions was discussed. While evaluations of police enforcement actions returned mixed results using a wide range of measures in geographically large units of analysis, hot spots policing evaluations showed consistent crime reduction effects. Nonetheless, evaluations of police enforcement actions has failed to identify which police enforcement actions are most effective in crime hot spots due to issues of measurement and/or research design. This point is important because one of the biggest gaps in the hot spots policing evaluation literature is the fact that it is not yet able to direct police commanders on which actions are most effective in crime hot spots. Finally, the chapter recognized theorizing that has raised the possibility that police enforcement actions may actually increase crime over time.

CHAPTER 3: CONSIDERING A WIDER RANGE OF TACTICS

As noted before, while policing reformers were suggesting police should narrow their focus to high crime areas, they were also calling for police to widen the range of tactics they used to address crime (e.g., community-oriented policing and problem-oriented policing) (Weisburd & Eck, 2004). This chapter reviews hot spots policing evaluations of a wider range of tactics implemented in crime hot spots. These tactics are not the focus of this study, but the results of the current research may have implications for this wider range of hot spots policing tactics for two reasons. First, police enforcement tactics have commonly been a major component of the implementation of responses that were intended to use non-enforcement tactics. Second, evaluations of non-enforcement tactics have been more likely to evaluate multiple hot spots policing tactics in order to address the lack of evidence on which hot spots policing tactics are most effective; however, the measures and analytic plans used in these studies preclude making such determinations. Thus, this dissertation's methods and analytical plan may help assuage these limitations in the future.

The Effectiveness of Problem-Oriented Policing in Crime Hot Spots

The first experimental evaluation of POP took place in Jersey City, NJ (Braga et al., 1999). The POP treatments implemented in twelve treatment violent crime hot spots (versus twelve control violent crime hot spots that received the standard model of policing) mostly consisted of aggressive order-maintenance policing (i.e., foot and motor patrols, dispersing loiterers, enforcing public drinking and narcotics laws, and conducting field investigations) and efforts to improve the physical conditions of the treatment areas (i.e., non-enforcement interventions). General linear models for eleven calls for service and crime incident outcomes measured during the 6 months after implementation, controlling for six month pretreatment scores and randomization blocking group, suggested the POP treatment reduced: (1) the total number of incidents and calls for service, (2) street fight calls for service, (3) robbery incidents (but not calls), (4) property crime calls and incidents, and (5) narcotics calls (but not arrests). After eliminating one of the treatment areas due to unreliable data, nonparametric sign tests also revealed that POP alleviated two physical and social disorder systematic social observation measures in ten of the eleven treatment areas. (Braga et al., 1999, p. 569).

The Limitations of Problem-Oriented Policing Hot Spots Policing Evaluations

Braga and colleagues (1999) noted "the difficulties inherent in evaluating problem-oriented policing programs that utilize a broad mix of tactics prevent us from specifying the specific interventions responsible for these gains in crime control" (p. 569). In total, 28 different tactics were implemented across the 12 treatment hot spots that saw reductions in violent crime calls for service. The POP treatment predominantly consisted of crackdowns focused on increasing aggressive enforcement rather than situational crime prevention-based tactics that POP proponents often stress (Clarke & Eck, 2003; Goldstein, 1979, 1990). In fact, all twelve hot spots experienced aggressive order-maintenance policing, nine areas experienced drug enforcement, five experienced parking enforcement, three experienced intensive robbery investigations, and one experienced directed patrol. The remaining 23 responses were more consistent with a situational crime prevention approach, but each response was rarely implemented in more than three hot spot areas. These tactics ranged from cleaning up storefronts, litter in vacant lots, and graffiti to improving lighting or razing abandoned buildings. Therefore, when discussing how the effects of the POP hot spots policing initiative might have been generated, the authors suggested increased police presence and other order-maintenance/enforcement tactics may have generated deterrence, changes to the physical environment may have removed opportunities and incapacitated offenders, or reductions in disorder may have changed offenders' favorable perceptions of the hot spots and generated additional deterrence/incapacitation. Overall, the multi-faceted treatment means that the observed crime reduction effects cannot be linked to any particular tactic(s) or theoretical mechanisms (Braga et al., 1999, p. 554).

Multi-Tactic Hot Spots Policing Evaluations

In response to the growing recognition that the hot spots policing evaluation literature is limited in its ability to determine which tactics police should implement in crime hot spots, three hot spots policing studies evaluated multiple hot spots policing tactics in a single study. In partnership with the Lowell, MA Police Department, Braga and Bond (2008) designed an experiment to evaluate the effectiveness of problem-oriented policing for addressing disorder crime hot spots. Disorder crime hot spots were identified by analyzing 2004 emergency calls for service and intelligence from patrol officers. A total of 34 areas covering roughly 2.7 percent of the city's 14.5 square miles were assigned to the treatment and control groups through random block assignment. Within a POP framework, crime data and community input were analyzed for the treatment areas, and police commanders came up with specific tactics to address their assigned hot spots. CompStat-esque meetings were used to monitor implementation (Braga & Bond, 2013). Per Braga and Bond's (2008) description, all seventeen treatment areas received aggressive order-maintenance policing (i.e., foot and motor patrols, enforcement of loitering, public drinking, and narcotics laws, and field investigations) and a number of situational interventions (*RANGE* = 2 - 4) with twelve treatments areas also receiving some social-service interventions. A series of generalized linear models revealed that the treatment areas experienced reductions in total calls for service as well as reductions in the individual categories of robbery, nondomestic assault, and burglary. Reductions were also observed for physical and social disorder systematic social observation measures.

In an effort to address the limitations of Braga and colleagues (1999) previously discussed study, data on the individual tactics implemented within each treatment hot spot were regressed on a total calls for service outcome using a mediation analysis framework. The analysis decomposed the treatment effect into three mediators: (1) the number of misdemeanor arrests executed, (2) the number of situational measures implemented, and (3) the number of social service actions undertaken. The mediation analysis revealed that the situational interventions significantly linked to lower calls for service with the aggressive order maintenance policing generating statistically significant reductions at the *p* of .10 and the social-service interventions failing to produce statistically significant reductions in total calls for service (Braga & Bond, 2008). The overall treatment effect did not reach statistical significance and suggested total mediation was achieved (MacKinnon & Dwyer, 1993).

A second experiment used randomization to compare directed patrol and POP to business as usual policing in Jacksonville, FL violent crime hot spots (B. Taylor et al., 2011). The researchers used spatial analyses to identify 83 hot spots that had high levels of violence between January, 2006 and May, 2008 and at least one violent street crime between January, 2008 and May, 2008. The 83 hot spots were randomly assigned to the directed patrol (n=21), POP (n=22), and the control condition (n=40) in blocks. The hot spots averaged about .02 square miles. Both the directed patrol and POP areas experienced statistically significant increases in officer-initiated activity during the 90-day treatment period (199 and 50 percent respectively) and the directed patrol areas experienced an 85 percent increase in field stops compared to the 33 percent increase in the POP areas (relative to the control areas). The POP areas also received a range of additional tactics based on problem analyses using the SARA model (Clarke & Eck, 2003; Eck & Spelman, 1987). The authors note the study's limited statistical power has to be considered when interpreting the results. Nonetheless, analyses of calls for service and crime incidents failed to find any statistically significant effects for directed patrol relative to the control areas during the 90-day intervention or post-intervention periods (albeit the results were in the hypothesized negative direction), but the POP treatment statistically significantly reduced violent street crime by roughly 33 percent relative to the control areas during the 90-day post-treatment period (B. Taylor et al., 2011).

Third, Groff and her colleagues (2015) sought to understand how foot patrol, problem-oriented policing, and an offender-focused policing tactic[16] might impact violent crime hot spots in Philadelphia, PA. The researchers used spatial statistics to identify violent street crime hot spots (homicides, armed robberies, and aggravated assaults). Executive police commanders then applied their experiential knowledge to the statistical hot spot analysis to identify eighty-one violent crime hot spots. The hot spots averaged a geographic area of 0.04 square miles. Police commanders' assessments of which areas would be most amenable to each treatment condition were used to create three qualitative strata of twenty-seven areas for each treatment modality, and randomization occurred within each of the three strata (20 treatment areas versus 7 control areas per strata). Repeated measures multi-level models of bi-weekly violent crime counts using a contrast coding scheme found that the offender-focused treatment tactic significantly reduced violent street crime felonies and an all violent crime outcome relative to the 7 offender-focused control areas (Groff et al., 2015).

[16] Offender-focused policing consisted of using intelligence analysis to identify and target repeat violent offenders through field investigations, arrest, or other means.

The Limitations of Multi-Tactic Hot Spots Policing Evaluations

Unfortunately, these studies have limitations that preclude concluding which tactics were most effective. Braga and Bond's (2008) hot spots policing evaluation using mediation analysis is the only study to date to develop direct measures of the tactics being evaluated; however, their conclusion that situational tactics are most effective is not based on a convincing statistical analysis. Braga and Bond (2008) describe the order-maintenance policing approach implemented as "making repeat foot and radio car patrols, dispersing groups of loiterers, making arrests for public drinking, arresting drug sellers, and performing "stop and frisks" of suspicious persons" (p. 585), yet the tactic is measured using only the number of misdemeanor arrests executed during the initiative. This operationalization makes two assumptions: (1) the different components of the order-maintenance tactic had equal effects on the outcome and (2) misdemeanor arrest counts capture all facets of the order-maintenance construct (i.e., construct validity via content validity) without measurement error (see Furr & Bacharach, 2013, Chapter 8). These somewhat intertwined assumptions are crucial because the mediation analysis employed will yield biased (attenuated) estimates when variables are measured with error (Baron & Kenny, 1986; Judd & Kenny, 1981; MacKinnon & Dwyer, 1993). Given Clarke's (1980, 2008) multi-faceted definition of situational crime prevention,[17] the operationalization of situational tactics makes the construct validity of the situational tactics measure somewhat questionable (see Furr & Bacharach, 2013 Chapter 8). Other operationalizations of the tactics implemented in the study may have produced different results and conclusions.

[17] Clarke (1980) outlines five major dimensions of situational crime prevention: (1) increase the effort, (2) increase the risks, (3) reduce rewards, (4) reduce provocations, and (5) remove excuses. Further, these five dimensions can be sub-divided (e.g., increasing the effort might involve hardening targets, controlling access to locations, screening exits, deflecting offenders, or controlling tool/weapons). Tactics derived from one dimensions of situational crime prevention may work through different theoretical mechanisms than tactics based on a different dimension (see Clarke, 1980; 2008 for examples).

In addition, since Braga and Bond's (2008) conclusions are based on comparing the statistical significance of the three mediator effects, other components of Braga and Bond's (2008) study undermine the strength of their conclusions. First, while the treatment and control conditions were randomly assigned, the tailoring of individual tactics to hot spots may have introduced a selection effect (i.e., treatment-hot spot interaction) that has not been accounted for in the mediation analysis (Baron & Kenny, 1986; Hope, 2005; MacKinnon & Dwyer, 1993). Second, the study's limited statistical power (n = 34) reduces the confidence readers can have in the study's significance tests. The authors also do not provide standard errors for their mediation model, so it is impossible to derive confidence intervals for the mediators' parameters. Even with high statistical power, statistical significance alone does not equate to statistical or practical importance, especially for treatment effects (Nuzzo, 2014). It may be possible that the mediators' effects have wide confidence intervals that overlap and/or the differences in the magnitudes of the true effects of the different tactics may not be that large. These previous points are particularly important since the magnitudes of the treatment effects were not compared empirically. Taken together, these problems with Braga and Bond's (2008) analysis call into question the study's statistical conclusion validity (Shadish et al., 2002).

Taylor and colleagues' (2011) study of hot spots policing in Jacksonville, FL suffers from the same limitations previously noted in the hot spots police evaluation literature. Although the study found that POP reduced violent crime over the long term (B. Taylor et al., 2011), it is again hard to tell which tactics implemented by POP officers actually drove the empirical findings. Jacksonville POP officers implemented 283 different tactics across 22 POP sites. Taylor and colleagues (2011, p. 158) described the POP treatment as follows:

> The most common were situational crime prevention measures, such as repairing fences, installing or improving lighting, and erecting road barriers.

> Officers commonly worked with business owners and rental property managers regarding security measures, business practices, and other forms of prevention and collaboration. Other activities fell into the realms of community organizing (e.g., conducting community surveys and other forms of citizen outreach), social services (e.g., improving recreational opportunities for youth), code enforcement, aesthetic community improvements (e.g., removing graffiti or cleaning up a park), and nuisance abatement. Enforcement and investigation were also used in some locations, though JSO [Jacksonville Sheriff's Office] project managers generally encouraged officers to rely more on prevention and deeper measures whenever possible.

Even though the authors appear to have some detailed knowledge of the actions taken during the initiative, they simply use dummy variables (treatment versus control) to capture the effects of the broader experimental policing tactics. Therefore, it is virtually impossible to determine which tactics implemented under the guise of POP contributed to the significant reduction in violence during the 90-day post-treatment period and are important for policy (Goldkamp, 2010).

Further, Taylor and colleagues' (2011) analysis only compares the effectiveness of the directed patrol and POP treatments to the business as usual control areas; thus, only demonstrating that POP statistically significantly reduced violence while directed patrol did not *when compared to the control areas*. In other words, the analysis does not directly compare directed patrol to POP. Given the authors' concern about interpreting the statistical significance of their parameter estimates due the study's limited statistical power and the problems with statistical significance testing noted previously (Nuzzo, 2014), simply stating that the POP effect was statistically significant while the directed patrol effect was not is insufficient for determining which tactic is more effective. Thus, the authors' study as designed and analyzed does not determine if the POP tactic, as a general construct, is "better" than directed patrol and provides no empirical determination of which components of the POP treatment are important for policy/practice.

Finally, the Philadelphia Policing Tactics Experiment did not find POP (or foot patrol) reduced violent crime and favored the offender-focused tactic that concentrated police resources on high risk offenders in violent crime hot spots (Groff et al., 2015). Explanations for differences in the results of this study and the previously described studies could include differences in the implementation or dosage, organizational culture, or local context of the different police departments and locations studied. Nonetheless, this study suffers from the same limitations as the previous two studies that sought to understand more than one hot spots policing tactic in a single study. The study's construct validity is limited because it fails to fully explicate and analyze the range of tactics that occurred within each of the larger tactical classifications. The study's statistical conclusion validity is limited because it does not conduct an analysis that directly compares the effectiveness of the three broad hot spots policing tactics that were implemented.

Summary

This chapter focused on hot spots policing evaluations that examined a wider range of hot spots policing tactics. Those tactics, such as problem solving or offender-focused policing, are not the focus of this study. However, the review of those evaluations made two important points. First, police enforcement actions played a pivotal role in the responses implemented in those evaluations; therefore, gaining a deeper understanding of their effectiveness should also help future implementations of all hot spots policing tactics. Second, most of those studies sought to address the field's lack of understanding regarding which tactics are most effective for hot spots policing, but due to the measures and research designs used in those evaluations it is not possible to draw any firm conclusions about which actions are most effective.

CHAPTER 4: RESEARCH QUESTIONS, DATA, & METHODS

This chapter describes in detail the research questions that were addressed in this study as well as the mixed-methods research design and analysis plans used to address those questions.

Research Questions

This study seeks to understand the effectiveness of police enforcement actions in violent crime hot spots. The police effectiveness literature review made a number of key points that underlie this study. First, since the development of the standard model of policing, the police have predominantly relied on police enforcement actions to address crime problems. The reliance on police enforcement actions has persisted even in light of the major policing reforms that suggested the police should use non-enforcement tactics to address crime problems over the last few decades. In fact two police reforms, CompStat and hot spots policing, have helped to further institutionalize the use of police enforcement, albeit these reforms have further shifted the police's focus and use of enforcement actions to micro high crime places.

Early evaluations of police enforcement actions returned mixed effectiveness, but examined a range of police enforcement actions measures, rarely examined more than one action, and focused on geographically large units of analysis. Evaluations of police enforcement actions in crime hot spots have shown them to be effective, but have not measured the direct effects of police enforcement actions (see Rosenfeld et al., 2014 for an exception) and failed to employ analytical plans that could determine which hot spots policing tactics were most effective.

Based on these gaps in the literature, the first two research questions addressed by this study were: (1) Do four police enforcement actions focused on offenders or potential offenders reduce violent crime in hot spots? The four police enforcement actions examined were pedestrian stops, traffic enforcement events, quality of life arrests (misdemeanor) arrests, and violent crime arrests. (2) Are any one of these four police enforcement actions more effective than the others? Note the study did not focus on the wider range of tactics discussed in Chapter 3, but may have implications for evaluations of those tactics in the future. As detailed in this chapter, these questions were addressed using a quasi-experimental longitudinal analysis of official crime data.

While the primary focus of this study was to gain an empirical understanding of the effects of police enforcement actions in crime hot spots based on well-established theoretical frames, two additional questions were answered using qualitative methods. (3) When police commanders allocate resources to crime hot spots, what do police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots? Answering these two research questions with qualitative methods served the functions of 'complementarity' and 'expansion' as defined by Morse (1991) and Palinkas (2011). First, answering these questions served the complementary function of understanding how police enforcement actions are understood and rationalized in practice by police commanders implementing hot spots policing strategies (Morse, 1991; Palinkas et al., 2011). Second, the qualitative data analysis revealed insights for understanding the quantitative findings, thus serving an expansion function (Morse, 1991; Palinkas et al., 2011). In sum, this study was designed as a mixed-methods study examining the effectiveness of police enforcement actions in crime hot spots quantitatively, while using qualitative methods to understand the implementation of those actions in practice and the quantitative results in more depth.

Study Site

The Philadelphia Police Department (Philadelphia, Pennsylvania) was the focus of the present study. The City of Philadelphia is located in the northeastern region of the U.S. Travelling by car along U.S. Interstate 95, Philadelphia is located approximately two hours south of New York City and two hours north of Washington, D.C. Based on the 2010 U.S. Census, Philadelphia's roughly 1.5 million residents make it the fifth largest city in the U.S. Philadelphians are predominantly African American and white (roughly 43 and 41 percent, respectively) with approximately 12 percent identifying as Hispanic/Latino. Further, roughly 12 percent of Philadelphia's population self-reported being born outside the U.S. (US Census Bureau, 2010). In 2011, roughly 26 percent of residents reported living in poverty. Philadelphia's median income was $34,207, compared to the national median income of $50,502 (US Census Bureau, 2011). Unfortunately, Philadelphia has consistently ranked as one of the most violent large American cities during the past decade (Zimring, 2011).

The Philadelphia Police Department's (PPD) approximately 6600 sworn officers and 800 civilian employees make it the fourth largest police department in the U.S. The PPD divides the 140 square miles of Philadelphia into two regions: Regional Operations Command North (ROC North) and Regional Operations Command South (ROC South). Each ROC is overseen by a Chief Inspector. The ROCs are further sub-divided into six police divisions (Northwest, Northeast, East, Central, Southwest, and South) which are commanded by an Inspector. The PPD's six police divisions are divided into 21 districts. Captains are the commanding officers for districts. Districts are further subdivided into Police Service Areas (PSA). Each PSA is commanded by a PSA Lieutenant. The PPD operates three main shifts: (1) 8:00 AM to 4:00 PM, (2) 4:00 PM to 12:00 AM, and (3) 12:00 AM to 8:00 AM. Typically, at least one Sergeant supervises each shift in each

District. PPD patrol officers are assigned to a specific PSA. This organizational structure facilitates geographic accountability in the department.[18]

The PPD is an ideal organization for studying hot spots policing. In 2005 and 2006, the City of Philadelphia averaged more than a homicide a day and was considered the most dangerous large city in America (Nutter, 2007). Philadelphia experienced 377 and 407 homicides in 2005 and 2006, respectively (Federal Bureau of Investigation, 2005, 2006). Both locals and outsiders began to dubiously refer to Philadelphia as “Killadelphia” or the “City of Bodily Harm” rather than the “City of Brotherly Love and Sisterly Affection”. As a result, leading up to the 2007 mayoral election, incumbent Michael A. Nutter, now serving his second term, campaigned on bringing down violent crime. In 2007, Mayor Nutter released his “Safety Now” plan that declared a crime emergency in Philadelphia. Mayor Nutter’s Safety Now plan focused on the police department. Mayor Nutter pledged to make sure the PPD was focusing on violent crime hot spots. Among other tactics, the Safety Now plan specifically called for an increase in “stop-and-frisk procedures to confiscate illegal guns” (2007, p. 2) as well as a focus on repeat offenders, fugitives, and probation/parole violators. In order to support the PPD in this mission, the Safety Now plan promised “to hire the best person in the City, region, or anywhere in the country as Police Commissioner” (p.12) and pledged to find resources to hire additional police officers (p.11).

Police Commissioner Charles Ramsey was ultimately appointed the first week of January, 2008. By the end of the month, Commissioner Ramsey presented Mayor Nutter with the PPD’s Crime Fighting Strategy. The 2008 PPD Crime Fighting Strategy set specific goals focused on reducing violent crime (particularly homicides and shootings), increasing gun

[18] There are also specialized units (such as Highway Patrol and K-9 units) that are available to be assigned to different parts of the city by command staff at PPD Headquarters.

seizures, and increasing the homicide clearance rate (Ramsey, 2008, p. 4). In order to meet the PPD's violence goals, Commissioner Ramsey outlined the PPD's operational strategy. The strategy starts with "uniform patrol as the core…" and states that "[a]s crime trends and patterns shift so will our deployment in order to aggressively attack *concentrated pockets of crime*" (Ramsey, 2008, p. 8, emphasis added). Commissioner Ramsey's 2008 Crime Fighting Strategy is anchored by a number of components: (1) the geographic concentration of violent crime, (2) establishing geographic accountability for commanders, (3) strategically deploying patrol and special unit officers to conduct aggressive enforcement (including but not limited to: stop-and-frisk, arrests for illegal gun possession, and arrest warrant enforcement) in crime hot spots, (4) preventing retaliatory violence, (5) quality of life enforcement, (6) aggressive traffic enforcement, (7) collaborations with city residents, (8) collaboration with other city agencies to improve living conditions (e.g., removing abandoned cars, boarding up abandoned homes, removing graffiti, and improving street lighting), (9) collaboration with other law enforcement agencies, and (10) constant evaluation of the PPD's crime prevention efforts.

During the summers of 2009 and 2010, the PPD, in collaboration with Temple University researchers, conducted two hot spots policing experiments: (1) the Philadelphia Foot Patrol Experiment (Ratcliffe et al., 2011) and (2) the Philadelphia Policing Tactics Experiment (Groff et al., 2015). In 2011, Commissioner Ramsey updated the PPD's strategic plan and maintained that "[the PPD's] strategies and tactics are guided by data, information, intelligence and evidence-based practices" (Nutter & Ramsey, 2011, p. 5). The crux of the PPD's crime fighting strategy continues to be focusing uniform police personnel in high crime areas (Nutter & Ramsey, 2011); however, PSA Lieutenants have been assigned to use crime and intelligence analysis to develop PSA crime fighting plans (Nutter & Ramsey, 2011). The PPD also released an online mapping tool that allows personnel to view crime hot spots in nearly real time. The PPD has also partnered with Temple University researchers to train commanders and patrol officers in crime analysis and crime science. Overall, the PPD's organizational strategy is moving towards a neighborhood policing model that responds to calls for service, and maintains a high uniform visibility, while engaging in hot spots policing, zero-tolerance policing, COP, and POP when and where appropriate (Nutter & Ramsey, 2011).

Quantitative Methodology

The quantitative component of this dissertation addressed research questions one and two: (1) Do four police enforcement tactics focused on offenders or potential offenders reduce violent crime in hot spots? (2) Are any one of these four police enforcement actions more effective than the others?

Data Sources

Two data sources were used for the quantitative component of this dissertation: (1) the Philadelphia Police Department's INCT (incident) database and (2) the Philadelphia Police Department's arrest database. INCT is an event-level database that captures all founded crime events and official police actions. INCT is less inclusive than a calls-for-service database where more than one 911 call may be entered for each crime event. INCT reflects only events where an officer deemed a crime actually occurred. Thus, INCT reflects officer discretion; however, crimes are still recorded in INCT even if an arrest has not been made. Similarly, two police enforcement actions (e.g., traffic enforcement or pedestrian investigations) also appear in INCT. It is recognized that officers may fail to report some activity (Reiss, 1971) or report activity that did not occur to improve performance evaluations (Eterno & Silverman, 2010, 2012). Records in INCT include the following variables: (1) an event unique identifier, (2) date of occurrence, (3) event location, and (4) event type (i.e., crime or activity type). INCT was geocoded by the PPD at approximately a 98 percent hit-rate.

This dissertation also used the Philadelphia Police Department's arrest database. The arrest database contains a record for each arrest made by a PPD officer. Records in the arrest database can be linked to INCT using a unique identifier. When more than one person is arrested for a crime event or a person is charged with more than one crime, there are multiple records in the arrest database for that event or accused person. It is important to point out that a record in the arrest database does not mean that the District Attorney's Office filed formal charges. Formal charges are not filed after an arrest for many reasons (Gottfredson & Gottfredson, 1989). Records in the arrest database include the following variables: (1) an event unique identifier, (2) date of occurrence, (3) arrest location, (4) arrest charge. The PPD's arrest data were geocoded by the author at an approximately 96 percent hit-rate.

The limitations of using official crime and police activity measures are well-known (Wolfgang, 1963). Official crime measures undercount true crime levels because many victims fail to report crimes to the police (Gottfredson & Gottfredson, 1989). The police enforcement actions measures may undercount true activity levels if officers fail to report their actions (Reiss, 1971) or over-count police activity if officers fabricate actions in order to receive better performance evaluations (Eterno & Silverman, 2010, 2012). However, it is unlikely that it would be feasible to conduct a study to answer the present research questions with alternative data sources.

Study Period

The quantitative component of this study spanned from January 1, 2009 to December 31, 2013. Commissioner Ramsey was sworn in January 7, 2008 and spent time learning about

Philadelphia, the PPD, and planning the implementation of his hot spots policing strategy, so starting the study January 1, 2009 provided a year grace period for the PPD to have fully implemented Commissioner Ramsey's hot spots policing strategy. Also, using a longer period in longitudinal statistical modeling, discussed in more detail below, allows the analyst to better model temporal variation and account for possible confounding temporal effects (i.e., seasonality and/or long-term trends) (Raudenbush & Xiao-Feng, 2001).

Spatial Units of Analysis

According to Weisburd et al. (2009), the spatial unit of analysis for a study should be determined by theory. The assumption underlying the transmission of certainty of punishment from the general and specific deterrence mechanisms outlined in Chapter 2 is that deterrence has a geographic extent (i.e., ecological deterrence) (Cousineau, 1973; Kane, 2006; Nagin, 1998). In other words, when police increase activity in areas, they communicate specifically to the recipients of that activity and generally to the public that the certainty of being punished has increased in an area. Of course, if police activity does not occur or appears as an empty threat it may communicate to potential offenders that the area is a good place to offend (Stafford & Warr, 1993). The spatial extent of ecological deterrence is an open empirical question (Cousineau, 1973; Wyant et al., 2012), but researchers have suggested homogenous units that align with the geographic extent of peoples' social networks are consistent with how the mechanisms of deterrence are transmitted and are therefore the most theoretically relevant (Bursik et al., 1990; Chamlin et al., 1992; Kane, 2006; Wyant et al., 2012).

Since this study explored hot spots policing, the unit of analysis for the proposed dissertation is the micro-level violent crime hot spot. Crime hot spots are difficult to define (Buerger et al., 1995; R. B. Taylor, 2010), but have generally been thought of "addresses, buildings, block faces, street segments, or clusters of addresses" (Mastrofski et al., 2010, p.251) with disproportionate crime levels (Chainey & Ratcliffe, 2005, p. 241-245; Eck & Weisburd, 1995; Sherman et al., 1989). In the hot spots policing literature, hot spots have ranged in size from street corners (Lawton et al., 2005) to areas roughly the size of multiple American football fields (Groff et al., 2015) to high crime police beats (Sherman & Rogan, 1995). This dissertation used the Philadelphia street blocks and intersections with the high levels of violent crime as hot spots. Street blocks include both sides of the street that face each other and bounded by an intersection at each end (R. B. Taylor, 1997). Intersections are the points at which two or more streets intersect. Based on zoning laws and urban planning, many intersections in Philadelphia include properties that are angled to face the intersection and are often zoned for commercial land use.

Both street blocks and intersections are theoretically relevant for studying the geography of crime and the deterrent effect of police enforcement actions because they can serve as behavior settings under some circumstances (R. B. Taylor, 1997). Behavior settings are "small-scale social systems whose components include people and inanimate objects" (Wicker, 1987, p. 614). The social system is bounded by time and space with the various components of the system interacting in particular fashions in order to carry out the setting's defined functions (Wicker, 1987, p. 614).

Taylor (1997) specifically argued that many street blocks have key features that may allow them to operate as behavior settings. First, people who use particular street blocks get to know one another during their routine activities. As regular recurring patterns of human activity are developed, different roles and norms are established for behavior on the street block. Furthermore, the physical makeup and boundaries of the street block are important for understanding the human behavior taking place on a street block. For example, the presence of a convenience store that sells alcohol with outside seating may facilitate public drinking that may not occur on the next street block over. Finally, street blocks can evolve over time as land use and occupants change. Based on these principles of behavior settings and environmental criminology, street blocks are important for understanding spatial crime patterns (also see Weisburd et al., 2012).

Street intersections are also important behavior settings for urban life. Street intersections have long been recognized as important places within urban neighborhoods (Liebow, 1967). Street intersections can be staging areas – "hangouts where a wide mix of people gather for various reasons" – in urban neighborhoods (Anderson, 1999, p. 77). As people gather at street intersections, they become familiar with each other. Similar to street blocks, street intersections also develop recurring patterns of behavior. For example, residents may gather on a street corner in the evening hours to socialize or street corners may become all day hangouts for unemployed or retired folks. The presence of non-residential land uses, such as bars, commonly located at intersections due to city zoning laws can facilitate recurring activity patterns at street intersections (for example see Anderson, 1978). Of course, the recurring human activity that occurs at street corners may also be facilitated by illicit markets (drug dealing, prostitution, etc.) that are commonly located at street intersections (Jankowski, 1991, pp. 128 - 129; 185; Moskos, 2008; Simon & Byrne, 1997; Taniguchi et al., 2011). Nonetheless, the physical location of these types of places at street corners gives them their physical demarcation, helps determine the types of recurring activity that might occur at the street intersection, and in return leads to the development of roles and norms for actors within the street intersection behavior setting. Street intersections may also evolve over time as land use changes, property owners remove attractive features of the corner (i.e., benches, trash cans, etc.), buildings are demolished, or other changes to the area are made. Therefore, high crime street blocks and intersections serve as micro units of analysis that coincide with how the general and specific deterrence mechanisms of police enforcement actions may be transmitted through social interaction to potential offenders.

Drawing from Weisburd et al. (2012), in addition to being theoretically important, street blocks and intersections provide additional advantages. The use of a micro-level unit of analysis provides the benefit of capturing the spatial heterogeneity of crime patterns that is obscured with larger spatial units (Groff et al., 2009; Weisburd, Morris, et al., 2009). Street blocks and intersections are also heuristically useful. City dwellers commonly use street blocks and intersections in their everyday life. For example, someone might give directions to their house at 1266 McKean Street by telling the visitor to first go to 12th and McKean. In cities with grid systems most residents would then know that the address of 1266 McKean is on the block of McKean between 12th and 13th Streets. Street blocks and intersections are also commonly used as reference points in policing. For example, a PPD police officer working in West Philadelphia's 19th District might identify the district's hot spots as "Five-Two and Market" for the intersection of 52nd and Market Streets and "the unit block of Salford" for the (notorious) 100 block of Salford Street. Finally, due to the imprecision of geocoding, police incident point data are not always accurate at the address level (Chainey & Ratcliffe, 2005). Aggregating geocoded event level data to street blocks and intersections is within the precision of current geocoding practices, and provides a unit of analysis small enough to accurately reflect the spatial variation in crime patterns but large enough to alleviate concerns over inaccurate geocoding (Weisburd et al., 2012).

Sampling

A purposive sampling procedure was used to study the highest violent crime street blocks and intersections in Philadelphia. The sampling frame for the dissertation was all street blocks and intersections in Philadelphia (n = 59,227). Street blocks and/or intersections with five or more violent crimes (homicides, aggravated (felony) assaults, and robberies) during 2008 were then sampled (n = 169).[19] Even though Philadelphia experiences violent crime levels that are higher than comparably sized cities (see Zimring, 2011), violent crime hot spots are still quite rare. The 169 hot spots experienced approximately 10 percent of violent crime in 2008, but only represented about 0.29 percent of street blocks and intersections in Philadelphia. The five violent crimes threshold ensured only street blocks and intersections with levels of violent crime high enough to be deemed worthy of the PPD's scare resources in the past were included in the study (Groff et al., 2015; Ratcliffe et al., 2011). The five violent crime threshold also reduced the number of observations with zero counts on the dependent variable which can help improve statistical power and the precision of statistical estimates (Twisk, 2003).[20]

Temporal Units of Analysis

Monthly periods were used as the temporal units in this dissertation. The period from January 1, 2009 to December 31, 2013 provided 60 monthly observations. Police departments are notorious for focusing on short-term crime problems (Eck & Maguire, 2000; Goldstein, 1979, 1990; Ratcliffe, 2008; Tilley, 2003). Police departments' responsivity to politicians and the media often means they are pressured to deal with "the problem of the day" (Crank, 2003; Crank & Langworthy, 1992; Haberman, Groff, Ratcliffe, & Sorg, 2013; J. Q. Wilson, 1968). CompStat also

[19] Originally 170 hot spots were identified, but one street block was excluded because it housed one of Philadelphia's jails where a high level of violent crime incidents was recorded.
[20] Sensitivity analyses of the impact of the five 2008 violent threshold for identifying hot spots on the substantive results are shown in Appendix D.

focuses police commanders on short-term crime problems as they work to ensure they can demonstrate they have a current crime fighting strategy for dealing with recent crime patterns (Bratton, 1998; Maple, 1999; McDonald, 2002). In Philadelphia, crime strategy meetings (the PPD's version of CompStat) are held approximately monthly. Thus, monthly periods provided a temporal unit that coincided with the temporal focus of Philadelphia police commanders. Using shorter temporal units (i.e., one week periods, one day periods, etc.) *in conjunction with* a micro spatial unit of analysis would drastically inflate the number of zero count observations and reduce variation in the dependent variable, possibly lowering statistical power and/or reducing the precisions of the statistical estimates (Twisk, 2003). A total of 10,140 hot spot monthly observations were available for analysis (169 hot spots by 60 months).

Dependent Variable

The dependent variable examined in this dissertation was monthly violent crime counts in each hot spot. The focus on violent crime is primarily driven by politics. Because Mayor Nutter campaigned on addressing violent crime in Philadelphia, specifically gun violence, he directed Commissioner Ramsey to focus on reducing violent crime, specifically gun violence (Nutter, 2007; Ramsey, 2008). For example, in Commissioner Ramsey's five year strategic plan released 24 days after being sworn-in (January 7, 2008 – January, 30, 2008), the Commissioner opens with a letter to Mayor Nutter in which the second sentence declares: "This strategy is designed to reach *your* goal of reducing homicides by thirty to fifty percent over the next three to five years" (Ramsey, 2008 emphasis added). Similarly, seven of the eight performance goals stated in the five year strategic plan for the PPD are focused on reducing violence (Ramsey, 2008).

As shown in Table 1, violent crime included (1) homicide, (2) aggravated assault, and (3) street robbery because these crimes are the primary focus of the PPD. Between January 1, 2009 and December 31, 2013, there were 1,426 homicides, 26,192 aggravated assaults, and 29,114 street robberies for a total of 56,372 violent crimes recorded and geocoded in the data provided by the PPD. Univariate statistics for all model variables can be found in Table 2. The monthly violent crime count dependent variable ranges from 0 to 7 with a mean of 0.241 and a standard deviation (SD) of 0.592. Roughly 82 percent (8,293 out of 10,140) of monthly hot spot violent crime observations were zero counts.[21] A histogram of the dependent variable is displayed in Figure 1.

Independent Variables

This study examined the impact of total police enforcement as well as the individual effects of four different enforcement actions on violent crime. The independent variables were operationalized as both raw counts and hot spot mean centered counts. Group mean centered predictors have substantively different interpretations (Kreft, De Leeuw, & Aiken, 1995; Paccagnella, 2006). Centering the predictors on each hot spot mean changes the interpretation of the effect to a within hot spot effect. Now a one-unit increase in a hot spot mean centered predictor represents an observation where the level of enforcement exceeds the average enforcement level by one action in that particular hot spot. As a result, the hot spot mean centered predictors provided an estimate of the impact of the enforcement actions relative the average level of enforcement actions *within* each hot spot. The within-hot spot effects also eliminate differences across hot spot that may confound the effects of the police enforcement actions. Overall, the hot spot mean centered effect implies that the enforcement actions are hot spot specific and depend on their elevation above what is “average” in a particular hot spot while not being confounded by across hot spot differences.

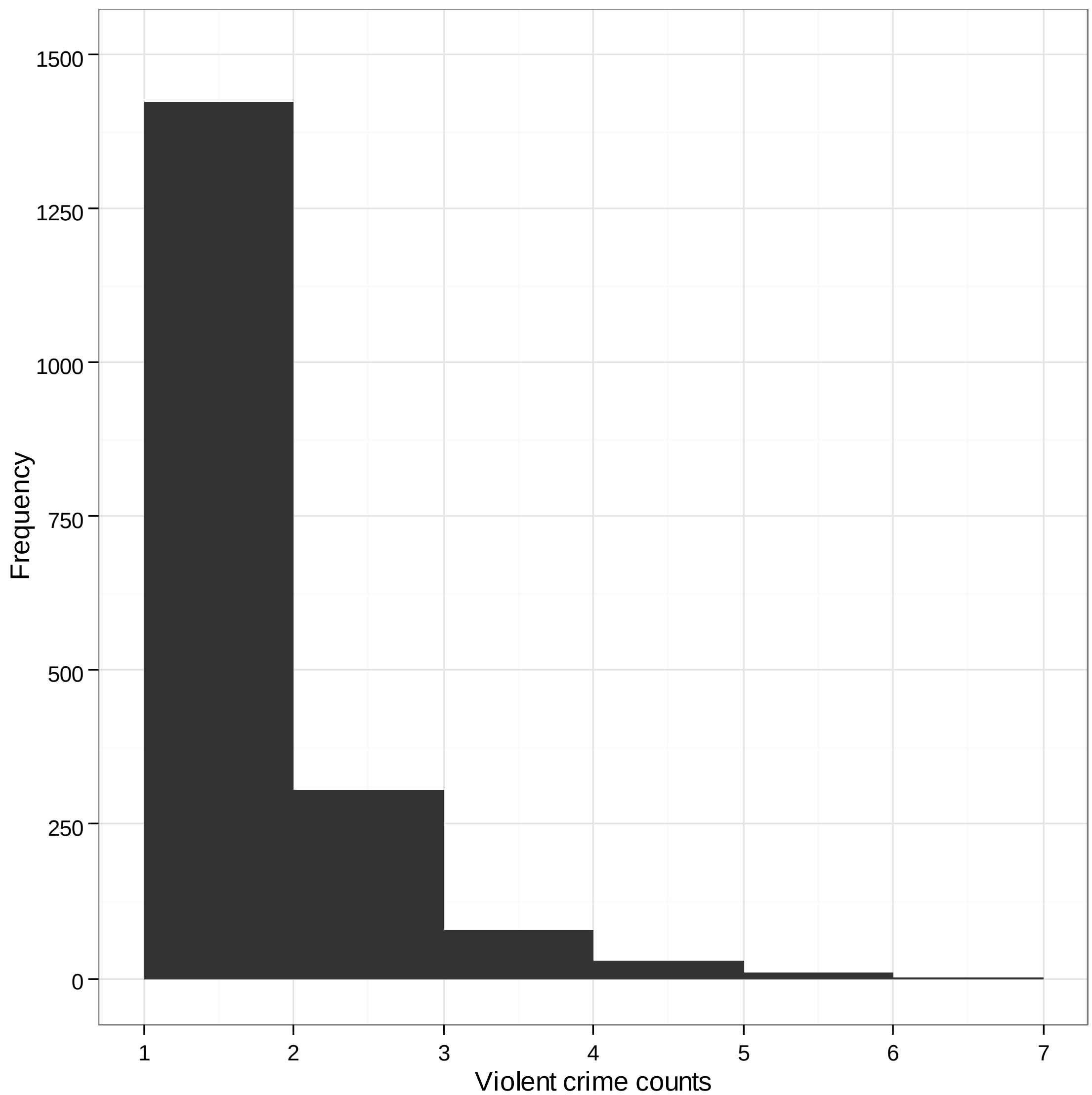
[21] Sensitivity analyses of the operationalization of the dependent variable are shown in Appendix E. A personal violence dependent variable (homicides and aggravated assaults) and a street robbery only dependent variable were analyzed.

Table 1. UCR classification codes for all variables

Variables	UCR classification codes
Violent crime	
Homicide	111 – 116
Aggravated assault	411 – 416
Street robbery	300 - 308
Pedestrian stops	2701
Traffic stops	2702, 2800 series
Quality of life arrests	
Prostitution	1600 series
Narcotics distribution & possession	1800 series
Illegal gambling	1900 series
Liquor law violation	2200 series
Public drunkenness	2300 series
Disorderly conduct	2400 series
Vagrancy & loitering	2500 series
Curfew violations	2680 – 2685
Felony Arrests	
Homicide	100 series
Aggravated assault	400 series
Robbery	300 series
Illegal firearm possession	1500 series

Notes: Model dependent and independent variables are in bold. The items that make up those variables are not bolded and listed below each variable when applicable.

Figure 1. Histogram of all violent crime dependent variable



Notes: Observations are street block and intersection monthly violent crime counts (n = 10,140). Zero monthly violent crime counts are excluded for visualization purposes (82 percent, n = 8,293). The frequencies by count are: 0 (n = 8,293), 1 (n = 1,423), 2 (n = 306), 3 (n = 78), 4 (n = 28), 5 (n = 9), 6 (n = 2), and 7 (n = 1).

Pedestrian stops. A pedestrian stop involves the temporary detainment, questioning, and possibly frisk or search of a person for weapons within Philadelphia city limits. Pedestrian stops are recorded in the INCT database. It is department policy that all pedestrian stops are recorded regardless of the outcome. When a police officer initiates a pedestrian stop, he or she then informs a dispatcher, and a record of the stop is made in the INCT database. Each pedestrian stop is given a unique identifier (termed, DC Number). Officers are required to file a report for each pedestrian stop they make after the conclusion of the event. Between January 1, 2009 and December 31, 2013, a total of 1,086,184 pedestrian stops were recorded and geocoded in the data provided by the PPD. Pedestrian stops per year ranged from a low of 201,814 in 2011 to a high of 231,639 in 2009 for an average of about 217,237 per year. Monthly pedestrian stop counts for the study hot spots ranged from 0 to 118 with the average hot spot experiencing 5.046 pedestrian stops per month (SD = 9.073). Hot spot mean centered police enforcement actions predictors were also used in the analysis. The monthly hot spot mean centered pedestrian stop independent variable ranged from -35.333 to 89.967 with a mean of 0 and standard deviations of 6.808.

Traffic stops. The PPD INCT database also contains a record for each traffic stop. Traffic stops are recorded in the same manner as pedestrian stops. A traffic stop is recorded whenever an officer stops a vehicle regardless of whether or not an officer issues a citation/ticket or makes an arrest. Between January 1, 2009 and December 31, 2013, a total of 1,197,600 traffic stops were conducted by the PPD. Traffic stops per year ranged from a low of 229,314 in 2012 to a high of 250,984 in 2010 for an average of about 239,520 per year. Monthly traffic stop counts for the study hot spots ranged from 0 to 158 with a mean of 6.475 and a standard deviation of 11.504. The monthly hot spot mean centered traffic stop counts ranged from -68.200 to 88.800 with a mean of 0 and a standard deviation of 6.662.

Quality of life arrests. Quality of life arrests are misdemeanor offenses that involve significant officer discretion (Gottfredson & Gottfredson, 1989; Moskos, 2008; Reiss, 1971). The monthly quality of life arrests summative index included: (1) prostitution, (2) narcotics distribution and possession, (3) gambling offenses, (4) liquor law violations, (5) public drunkenness, (6) disorderly conduct, (7) vagrancy / loitering, and (8) curfew violations (see Table 1). The citywide average annual number of quality of life arrests across the study period was 28,219 reaching a maximum of 30,426 in 2010 with the lowest count of 24,970 being recorded in 2013. The average hot spot experienced 0.389 quality of life arrests per month with the least number of monthly quality of life arrests equaling 0 and the greatest totaling 41 (SD = 1.529). The hot spot mean centered quality of life predictor ranged from -10.833 to 32.117 with a mean of 0 and a standard deviation of 1.054.

Felony arrests. The monthly violent crime felony arrests summative index included: (1) homicides, (2) aggravated assaults, (3) robberies, and (4) Violations of the Uniform Firearms Acts (VUFAs) (i.e., illegal firearm possession arrests) (see Table 1). Arrests for these more serious felony offenses are typically considered to involve less officer discretion (Gottfredson & Gottfredson, 1989; Moskos, 2008; Reiss, 1971). Violent crime arrests are somewhat less common with the citywide average annual number of violent crime arrests totaling about 7,285 and ranging from 6,604 in 2013 to 7,909 in 2009. Hot spots in the study hosted anywhere from 0 to 12 felony violent crime arrests per month with the monthly hot spot average equaling 0.071 (SD = 0.387). For the hot spot mean centered felony arrest predictor the mean equaled 0 (SD = 0.347) with a range from -1.867 to 10.133.

Total enforcement. A summative index of total monthly hot spot police enforcement actions was derived by adding the monthly counts of traffic enforcement, pedestrian stop, quality of life arrest, and felony arrest counts together. The total monthly hot spot police enforcement actions index ranged from 0 to 187 with a mean of 11.981 and a SD of 18.668. The monthly hot spot mean centered total police enforcement actions measure ranged from -98.367 to 117.671 with a mean of 0 and a standard deviation of 11.630.

Control Variables

Temporal variation. To control for seasonality and long term temporal trends a series of time indicator variables were used (Twisk, 2003). The first set of indicator variables specified the month of observation in order to control for seasonality (11 dummies for February through December with January serving as the referent). The second set of indicator variables specified the year of observation in order to control for period effects (four dummies for 2010 through 2013 with 2009 serving as the referent). Univariate statistics are shown in Table 2. Since the study employed a balanced design, the univariate statistics for each month and year dummy variables are numerically identical for each variable and only one row of statistics are shown in Table 2.

Hot spots policing experiments. All analyses included time variant dummy variables to control for the violence reduction effects of the Philadelphia Foot Patrol Experiment (Ratcliffe et al., 2011) and/or the Philadelphia Policing Tactics Experiment (Groff et al., 2015). A total of 49 of the 169 hot spots overlapped with the 60 treatment areas from the Philadelphia Foot Patrol Experiment (hereafter PFPE). The PFPE was implemented in two phases. Phase one was implemented from March 31, 2009 to August 31, 2009 (n = 24). Phase two was implemented from July 07, 2009 to September 29, 2009 (n = 36) (Ratcliffe et al., 2011; Sorg et al., 2013). Any hot spot from the current study that overlapped with one of the PFPE deployment areas was coded as “1” on the time-varying PFPE dummy during the months the overlapping foot patrol was operational and “0” during all other periods. Hot spots that did not overlap with the PFPE deployment areas were always coded “0” on the PFPE dummy.

The Philadelphia Policing Tactics Experiment (hereafter PPTE) evaluated the impact of three separate hot spots policing interventions, so three time-varying indicators were used to control for hot spots that overlapped with the foot patrol, problem-solving, or offender-focused areas during the implementation periods of those treatments. Further, the implementation schedule in the PPTE varied across and within treatments, so each PPTE dummy is coded “1” for 41 hot spots that overlapped with a PPTE treatment area only during the months when that particular area experienced the specific treatment and “0” during all other months. The remaining hot spots that did not overlap with any of the PPTE deployment areas were always coded “0”. Descriptive statistics for the PFPE and PPTE dummies are shown in Table 2.

The hot spots policing experiment dummy variables did not contrast the treatments with the original control areas from the experiments. Therefore, those variables did not capture experimental effects. Rather, the variables captured policing in addition to police enforcement actions that are the focus here. Therefore, these effects should not be compared with the results of those studies.

Hot spot length. To control for the varying geographic sizes of the street blocks and intersections a variable measuring street block or intersection length in feet was used as a control variable. Because intersections are a point, they were assigned a constant radius of ten feet. Buffering ten feet around each intersection point allowed for the allocation of crime events recorded at the first address of each block to be assigned to an intersection. Hot spot length ranged from 10 to 3,776.739 feet with a mean of 143.345 feet (SD = 409.483)[22].

Quantitative Analysis Plan

Statistical Techniques. Repeated observations of a dependent variable from the same unit over time are not independent. First, observations from the same hot spot may share variance arising from hot spot specific, time-invariant random processes. Second, repeated observations from the same hot spot closer in time may co-vary more closely than observations farther away in time because they share more time-variant processes, thus creating temporal autocorrelation (Rabe-Hesketh & Skrondal, 2012a, p. 244). Such dependencies violate the statistical assumption of independence of observations and result in incorrect standard errors in statistical models that make that assumption. Incorrect standard errors result in incorrect hypothesis/significance tests (Rabe-Hesketh & Skrondal, 2012a, pp. 128 - 129). Therefore, two statistical techniques appropriate for the data structure here were used.

[22] The average length of all street blocks in Philadelphia was about 700 feet, but that figure includes busy, major thoroughfares that tend to be longer. Residential blocks are closer to average of about 400 feet (Ratcliffe & Rengert, 2008). Only four street blocks in the sample were longer than 1,000 feet. The remaining units were less than 875 feet. The four units longer than 1,000 feet were three stretches of major thoroughfares that mostly consisted of commercial and industrial land use as well as a major tourist attraction along the Delaware River and a residential block that hosted two large apartment complexes and bus lines.

Table 2. Univariate statistics

Variables	N	Min	Max	Mean	Median	S.D.
Dependent variables						
Total violent crime count	10140	0.000	7.000	0.241	0.000	0.592
Time variant independent variables						
Total enforcement	10140	0.000	187.000	11.981	5.000	18.668
HS mean centered total enforcement	10140	-98.367	117.617	0.000	-0.733	11.630
Pedestrian stops count	10140	0.000	118.000	5.046	2.000	9.073
Traffic stops count	10140	0.000	158.000	6.475	3.000	11.504
Quality of life arrests count	10140	0.000	41.000	0.389	0.000	1.529
Felony arrests count	10140	0.000	12.000	0.071	0.000	0.387
HS mean centered pedestrian stops	10140	-35.333	89.967	0.000	-0.600	6.808
HS mean centered traffic stops	10140	-68.200	88.800	0.000	-0.233	6.662
HS mean centered quality of life arrests	10140	-10.833	32.117	0.000	-0.083	1.054
HS mean centered felony arrests	10140	-1.867	10.133	0.000	-0.033	0.347
Lagged time variant independent variables						
Total enforcement	9971	0.000	187.000	12.042	5.000	18.692
HS mean centered total enforcement	9971	-98.367	117.617	0.061	-0.717	11.603
Pedestrian stop count	9971	0.000	118.000	5.081	2.000	9.117
Traffic stop count	9971	0.000	158.000	6.498	3.000	11.488
Misdemeanor arrest count	9971	0.000	41.000	0.391	0.000	1.539
Felony arrest count	9971	0.000	12.000	0.072	0.000	0.390
HS mean centered pedestrian stops	9971	-35.333	89.967	0.035	-0.567	6.824
HS mean centered traffic stops	9971	-68.200	88.800	0.023	-0.233	6.624
HS mean centered quality of life arrests	9971	-10.833	32.117	0.002	-0.083	1.058
HS mean centered felony arrests	9971	-1.867	10.133	0.001	-0.033	0.349

Notes: Spatial units are street blocks and intersections (n = 169). Temporal units are months (n = 60). Observations are street block and intersection monthly observations (n = 10,140). The lag period is one month. [a]The study has a balanced design, so the univariate statistics for each month and year dummy variables are numerically identical for each variable and only one row of statistics are shown.

Abbreviations: HS = Hot spot PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment, Min = Minimum, Max = Maximum, S.D. = Standard deviation

Table 2. Univariate statistics (cont.)

Variables	N	Min	Max	Mean	Median	S.D.
Time variant control variables						
Month[a]	10140	0.000	1.000	0.083	0.000	0.276
Year[a]	10140	0.000	1.000	0.200	0.000	0.400
PFPE Treatment	10140	0.000	1.000	0.020	0.000	0.141
PPTE Foot Patrol Treatment	10140	0.000	1.000	0.008	0.000	0.091
PPTE Offender Focused Treatment	10140	0.000	1.000	0.007	0.000	0.086
PPTE Problem Solving Treatment	10140	0.000	1.000	0.004	0.000	0.065
Time invariant control variables						
HS length	169	10.000	3776.739	143.345	10.000	409.483

Notes: Spatial units are street blocks and intersections (n = 169). Temporal units are months (n = 60). Observations are street block and intersection monthly observations (n = 10,140). The lag period is one month [a]The study has a balanced design, so the univariate statistics for each month and year dummy variables are numerically identical for each variable and only one row of statistics are shown.

Abbreviations: HS = Hot spot PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment, Min = Minimum, Max = Maximum, S.D. = Standard deviation

First, generalized multilevel models (aka called mixed-effects, random effects, or hierarchical models) were employed. Multilevel models recognize nested data structures and partition the dependent variable's variance into within-hot spot (level-one) and between-hot spot (level-two) variance. Dependence among observations from the same unit is accounted for through multiple random intercepts – one for each hot spot. Error variances and covariances also are adjusted. Predictors are either time-varying and linked to within hot spot outcome variance or spatially varying and linked to between hot spot outcome variance (Rabe-Hesketh & Skrondal, 2012a; Raudenbush & Bryk, 2002). The level-one coefficients that this study is interested in from the multi-level models are subject specific effects and describe how an increase in the predictor impacts a hot spot's level of violence after controlling for differences across hot spots through the random intercept.

Generalized estimating equations (GEE) were also used. GEE models are marginal models (aka population average models) and estimate the impact of predictors on a non-normal dependent variable while taking into account the dependence among observations from the same unit using quasi-likelihood methods (Hardin & Hilbe, 2013; Liang & Zeger, 1986). In GEE, the analyst specifies the residual correlation structure prior to estimation. This correlation structure is commonly referred to as the "working correlation structure". Numerous correlation structures are available to the analyst (Hardin & Hilbe, 2013, Chapter 3). After the analyst chooses the working correlation structure, a generalized linear model assuming an independent error structure is estimated using the link function corresponding with the specified outcome probability distribution (e.g., log-link for the negative binomial distribution). Next, the correlation structure of the residuals is estimated based on the model's standardized residuals and a priori working correlation structure. Based on the updated residual correlation structure / (co)variance matrix, the model parameters are also updated. The previous two steps then iterate until the model converges (also see Deane, Armstrong, & Felson, 2005, pp. 960 - 961). GEE models are said to be robust to misspecification of the residual correlation matrix because that matrix ultimately is estimated from the data. Nonetheless, choosing the correct matrix up front helps estimate more precise parameters (Ghisletta & Spini, 2004). The coefficients from the GEE models are interpreted as the change in the dependent variable per a one-unit increase in the predictor for the average hot spot, thus ignoring differences across hot spots (Zuur, Leno, Walker, Saveliev, & Smith, 2009, Chapter 12).

Model Specification. All models were specified with a negative binomial probability distribution (Long & Freese, 2006; Rabe-Hesketh & Skrondal, 2012b; Raudenbush & Bryk, 2002). To address research question one, hot spot monthly violent crime counts were predicted with the hot spot monthly total enforcement actions predictor after controlling for the month indicators, year indicators, the PFPE treatment dummy, PPTE treatment dummies, and hot spot length. Models were estimated with both the raw count and hot spot mean centered total enforcement actions predictors. Recall, the hot spot mean centered predictors only explain within hot spot temporal variation in the dependent variable and ignore across hot spot differences.

Deterrence theory does not specify the temporal scale in which the crime control benefits of police enforcement actions occur (R. B. Taylor, 2015, Chapters 6 & 7). The deterrent effects of police enforcement actions may be contemporaneous or require time for offenders to become aware of the police activity and internalize the concept that offending is no longer a viable option (Cousineau, 1973). Deterrent effects of police enforcement actions, or at least arrests, have been observed for periods as short as a day (D'Alessio & Stolzenberg, 1998) to as long as a year (Kubrin et al., 2010). Therefore, the previous models were run after temporally lagging the monthly total enforcement actions independent variables by one month. Lagging the independent variables implied that the effects of earlier total police enforcement required roughly a month to take hold. In contrast, the models using the unlagged total police enforcement actions predictors implied the deterrence effects were contemporaneous in the same month. Temporal ordering with lagged predictors assists with causality and reduces the likelihood of non-recursive dynamics contaminating the results.[23]

To address research question two, the hot spot monthly violent crime count was modeled with separate monthly counts of (1) pedestrian stops, (2) traffic enforcement, (3) quality of life arrests, (4) violent crime arrests and all of the control variables. The model was repeated using hot spot mean centered predictors. Both models were then repeated using temporally lagged predictors (i.e., one month). Further, Wald Tests tested if the four police enforcement actions had significantly different effects.[24] A statistically significant Wald test would indicate the police enforcement actions were differentially effective.[25] The Wald tests were computed for both the contemporaneous and temporally lagged effects models.

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[23] Variance inflation scores were checked using single-level models with robust standard errors for all of the variable combinations estimated. Across all models estimated for any combination of variables the maximum variance inflation score was less than 2.25.

[24] Hypothesis testing with the Wald test can be performed using only coefficient and standard error estimates from an estimated model (Engle, 1984; Nezlek, 2001; Nezlek & Zyzniewski, 1998). The null hypothesis tested with the Wald test is that the individual police enforcement actions parameters are equal. The actual null hypothesis tested for this application of the Wald test is that the differences among coefficients is equal to zero which is mathematically equivalent to testing whether or not the coefficients are equal to each other (Gelman & Hill, 2007, p. 20; Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2011).

[25] With four parameter estimates, a total of six comparisons of law enforcement-oriented actions pairs are needed. Thus, Barnett and colleagues (Barnett, Marshall, Raudenbush, & Brennan, 1993) recommend performing an omnibus test that performs all comparisons in one test in order to avoid a Type I error associated with conducting multiple hypothesis tests (also see Barnett, Brennan, Raudenbush, & Marshall, 1994). If an overall statistically significant difference is found across the six comparisons then post-hoc comparisons can be performed to determine which effects are statistically significantly different in magnitude (Raudenbush et al., 2011, p. 54).

The above series of models were estimated three times in Stata 13 (StataCorp, 2013). First, the series of models was estimated as negative binomial random effects models using Stata's *menbreg* command. Robust standard errors were obtained using the *vce(robust)* option. Next, negative binomial generalized estimating equation (GEE) models were estimated using Stata's *xtgee* command. The GEE models were estimated twice using both a first-order autoregressive (hereafter AR1) and second-order autoregressive (hereafter AR2) error structure. Finally, Stata's *test* command was used to compute all of the equality of coefficient Wald tests for all three series of models.

Qualitative Methodology

The qualitative component of this dissertation addressed complementary research questions three and four. (3) When police commanders allocate resources to crime hot spots, what do police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots? Answering these complementary questions was vital for understanding how police enforcement actions are implemented and perceived by police commanders in practice (Palinkas et al., 2011). Two sources of data were used for the qualitative component of the dissertation: (1) field observations of PPD crime strategy meetings and (2) interviews with PPD commanders.

Field Observations: Data Collection

Non-participant field observations were conducted during the PPD's regular crime strategy meetings. Non-participant field observations involve observing real life situations in order to develop a deep understanding of a particular phenomenon (Padgett, 2008).[26] PPD

[26] As a non-employee of the PPD, participant observations were not possible, but this should not diminish the quality of the data given the nature of the research. Key informant interviews were also be used to attempt to account for the inability to participate.

crime strategy meetings involve police executive and district level commanders engaging in discussions that draw on crime and intelligence analysis in order to determine operational strategy and resource deployments. Therefore, observing the interactions that took place during the crime strategy meetings provided meaningful insight into how policing is actually implemented in Philadelphia relative to a more abstract description of how policing might be intended to be implemented (Rosaline, 2008).

Spradley's (1980) general guidelines for conducting field observations were followed during data collection (see pages 53 – 84). Observations focused on Spradley's (1980, p. 78) nine dimensions of social situations: (1) *space*: the physical place, (2) *actor*: the people involved, (3) *activity*: the set of related acts people do, (4) *object*: the physical things present, (5) *act*: single actions people do, (6) *event*: a set of related activities that people carry out, (7) *time*: the sequencing that takes place over time, (8) *goal*: the things people are trying to accomplish, and (9) *feeling*: the emotions felt and expressed. Based on the research questions posed, specific areas of emphasis during the field observations included: (1) the general focus of each crime strategy meeting, (2) the types of crime problems discussed, (3) how those problems were identified, (4) the types of responses commanders stated they used to address those problems, and (5) the interactions among different crime strategy actors during the process of developing responses to crime hot spots.

Field notes were recorded on these dimensions during all field observations. Because participants in these meetings carried notebooks and frequently took notes, it is not believed that note taking drew attention to the researcher, disrupted the meetings, or resulted in reactivity (Padgett, 2008). As soon as possible after each observation (usually within 24 hours), all condensed field notes were be typed up and expanded upon to ensure accurate depictions of the crime strategy meetings (Fife, 2005; Spradley, 1979).

Field Observations: Sampling

A purposive sampling approach was used for the field observations. Since violent crime typically increases during the summer in Philadelphia, summer crime strategy meetings were focused on in order to better ensure that violent crime problems would be the focus of the meetings. The author attended every crime strategy meeting possible during the summer of 2014. Field observations began May, 2014 and concluded August, 2014. In total, eight meetings were attended (three in May, two in June, two in July, and one in August). Crime strategy meetings generally lasted one and a half hours for a total of approximately twelve hours of observation.

All PPD crime strategy meetings followed the same format. Though scheduled to start at 10:00 AM, participants typically showed up approximately 15 to 30 minutes early. Meetings started promptly when the executive commanders would arrive, at which time everyone in the room stood up to show respect for the chain of command. Once the executive commanders directed everyone to sit (within a matter seconds), the meetings would begin. The meetings were organized by divisions and the order of presentations was predetermined. The division chief inspectors would start the meetings by giving an overview of the crime trends in his or her division. Typically the chief inspectors would note which Part I crimes were trending upwards and downwards compared to the same time last year, the previous month, and/or the previous two or four weeks. Next, each district captain would stand at the podium at the front of the room and discuss the crime problems in his or her district. A crime analyst would operate a crime map that was displayed on an overhead projector. The map could display any crime type as well as the pedestrian stops, traffic enforcement, and arrests made by both district and special unit personnel. The meetings typically focused on homicides, shootings/aggravated assaults, robberies, burglaries (residential and commercial), theft of automobiles, and theft from automobiles. After attending eight meetings, it became clear the crime strategy discussions among the executive commanders and captains were quite routinized. The redundancy of themes in the crime strategy meetings – as well as the interview data collected (described in the next session) – demonstrated that saturation had been achieved and that observation of additional meetings would not necessarily provide more insight into answering research questions three and four.

Interviews: Data Collection

Semi-structured interviews were also conducted by the author with PPD commanders responsible for implementing hot spots policing. Interviews provide the researcher with data on the interviewees' understanding of, experiences with, and attitudes towards a phenomenon, process, or practice (Flick, 2007, p. 79). Given the focus on police commanders' perceptions in research questions three and four, qualitative interview data were imperative because "[p]urely behavioral studies of police cannot explore cognitive aspects of police work" (Mastrofski & Parks, 1990, p. 477). The use of an interview guide ensured consistency across all conducted interviews (Flick, 2007). As is common during semi-structured interviews, however, the interviewer deviated from the guide at times in order to elicit greater detail through the use of probes as well as to build rapport with the interviewee by maintaining a more conversational interview structure. The interview guide can be found in Appendix C.

All interviews were audio recorded. The interviews lasted between 20 and 45 minutes depending on the level of detail the interviewees provided in their answers. After the interviews, audio recordings were transcribed and then destroyed once the transcripts' accuracy was verified. All personally identifying information was removed during transcription and subjects were assigned pseudonyms in order to ensure confidentiality to the interviewees.[27]

Interviews: Sampling

The main purpose of the qualitative interview sampling plan was to purposively target people who had the relevant experience necessary to answer the study's research questions. Researchers are limited to subjects who are knowledgeable about the research topic, capable of clearly answering interview questions, and willing to spend the necessary time with the researcher (Flick, 2007). Recognizing this, purposive sampling was used. The six district captains (out of a possible 21) with the greatest number of hot spots in his or her district were interviewed. All captains sampled agreed to participate in the interviews. This approach ensured that the captains would have the relevant experience necessary to provide insight into research questions three and four. Analysis of the six interviews revealed similar responses across all commanders thereby suggesting that saturation had been achieved for the study's focal areas.

Qualitative Analysis Plan

The focus of the qualitative analysis was to identify patterns and themes that emerged specific to how hot spots policing tactics are conceptualized and implemented in practice as well as how police commanders use and perceive the use of police enforcement actions in violent crime hot spots. In order to examine these foci, the field observation field notes and interview transcripts were imported into *Atlas.ti. Atlas.ti* is a software program that helps organize, systematically code, and visualize qualitative data in order to identify and refine emergent

[27] Complete anonymity could not be ensured because the subjects signed an informed consent form per IRB guidelines.

patterns and themes. With the aid of *Atlas.ti*, data were coded and analyzed in multiple cycles (Saldaña, 2009, pp. 45 - 46).

Descriptive coding was applied first. “Descriptive coding assigns basic labels to data to provide an inventory of their topics” (Saldaña, 2009, p. 66). The goal of descriptive coding is to label each passage with codes that simply describe its contents. Descriptive coding is useful for outlining the breadth of topics covered in the data (Saldaña, 2009). Based on the purposes of this research project, eleven descriptive codes were applied to the data. Seven codes were used to describe data based on the crime type that was being discussed during the crime strategy meetings: (1) *homicide/shootings*, (2) *street robbery*, (3) *commercial robbery*, (4) *residential burglary*, (5) *commercial burglary*, (6) *theft from motor vehicles*, and (7) *theft of motor vehicles*. While these codes were needed to describe the crime strategy observation data, the focus of this study is violent crime and, therefore, police commanders were asked to focus on violent crime during the interviews. Two codes were applied to identify data discussing crime reduction and prevention actions: (8) *police enforcement actions* and (9) *other crime fighting actions*. The *police enforcement actions* code was applied to any passage that discussed the use of police presence, arrest, pedestrian investigations, or traffic enforcement to disrupt crime problems. The *other crime fighting actions* code was applied to passages discussing any other actions implemented to address crime problems. Finally, because the qualitative component of this study was designed with a particular interest in two research questions, two codes were created to capture data that corresponded to those research questions: (10) *research question three* and (11) *research question four*. The code *research question three* captured data where police commanders’ implemented tactics or perceptions of what they were doing in crime hot spots was discussed during a crime strategy meeting or interview. The code *research question four* was applied to any data where police commanders provided rationales for what they were doing in crime hot spots. Particular attention was paid to passages where police commanders detailed why the tactics they reported using were perceived to be effective.

The second round of coding focused on developing further insight from the codes that were already developed. A number of refined codes inductively emerged. A distinction between the quantity of activity and the quality of activity began to emerge. A versus code, (12) *quantity vs. quality*, was then created to capture that dynamic. Versus coding is commonly used in studies examining policies when there is a clear conflict in ideas, beliefs, or perspectives among study subjects (Saldaña, 2009, p. 94). The *quantity vs. quality* code was applied to all data points discussing: (A) “how much” police enforcement actions were being generated, (B) police enforcement actions described as “effective”, applied to “right places” or “right people”, or leading to arrests, and (C) passages explicitly detailing the conflict.[28]

Next, all data coded as *research question three* were further analyzed for subthemes. In order to keep police commanders’ beliefs on what they thought they were doing in their own words *in vivo* codes were developed and indexed. *In* vivo codes involve using the verbatim wording of qualitative data (Saldaña, 2009, p. 74).[29] Initially, three codes emerged: (13A) *locking down,* (14A) *off the street*, and (15A) *target hardening*. It is important to point out that these codes were further refined later. However, originally *locking down crime places* was applied to data discussing increasing police presence and enforcement actions in high crime areas based on field observation data where commanders commonly used the term. The code *off the street* was similarly developed and applied to all passages that focused on incarcerating offenders to stop the occurrence of crime, again based on police commanders’ terminology observed during the crime strategy meetings. Finally, *target hardening* was identified when Captain L used the

[28] The focus on quality activity including enforcement actions that resulted in arrest emerged somewhat later in the coding process than the themes of focusing on the “right places” and the “right people”.
[29] Spradley (1979, pp. 73 - 76) referred to *in vivo* codes as *native terms.*

term during his interview. The code was then applied to all data where police commanders discussed using education to encourage potential crime victims to protect themselves from victimization.

In order to develop a deeper understanding of the data coded *research question four*, a similar approach was used to develop additional codes for the data. During analysis, it was determined that the aforementioned codes developed for research question three needed to be further refined. Ultimately three additional codes emerged in reference to research question three: (13B) *locking down*, (14B) *disrupting high risk offenders*, (15B) *education*. The code *locking down* was developed and applied as described above. *Disrupting high risk offenders* emerged from the data originally coded *off the street* after it was realized that some passages described getting offenders off the street as an end and other passages suggested police commanders focused on getting offenders off the street because it achieved an end, which was *disrupting high risk offenders*. Similarly, the code *education* emerged from the conclusion that police commanders believed that they were educating potential victims in order to increase individual engagement in target hardening.

Analysis and refinement of these codes contributed to the subsequent development of codes used to inspect and more thoroughly answer research question four. Specifically, five additional codes emerged: (16) *think twice,* (17) *denying the place*, (18) *off the street*, (19) *just keep going*, and (20) *target hardening.* The code *think twice* emerged from interview narratives; specifically the presumption that when they sent their officers to an area, the captains believed this act would send a message to potential offenders that they should reconsider offending in that location. First identified by Captain M, *denying the place* involved the conclusion that using police enforcement actions to remove people from an area was expressly believed to reduce opportunities for crime. The codes *off the street* and *just keep going* were interrelated codes. *Off the street* was defined and applied as described above, and involved the assertion that getting offenders off the street through arrest was related to police commanders' belief that offenders will continue to offend unless they were incapacitated. This code also led to the creation and application of *just keep going*. Finally, *target hardening,* described and defined above, emerged as the rationalization for police commanders' emphasis on educating community members about crime problems and prevention techniques.

The third and final derivations of codes were developed through the inductive coding and analysis process. As it was apparent that police commanders frequently used enforcement actions for other possible benefits as well, the code (21) *other benefits* applied to passages that noted other benefits of enforcement actions that did not include crime control. *Other benefits* was further refined into: (22) *the community*, (23) *intelligence,* and (24) *public safety.* These codes captured instances where commanders expressed how police enforcement actions can be used to improve police-community relations, gather intelligence, and improve the safety of citizens outside of crime control, respectively. Finally, (25) *limitations* was developed and applied at the end of the coding process to all data points where the commanders described ways in which their approaches to addressing crime problems had failed.

These inductively identified codes were applied to the qualitative data throughout the analysis process, including numerous passes through the data. Each time a new set of codes was applied, each field observation and interview narrative was coded. During the analysis process, one code was considered at a time in order ensure the coding was systematic and robust. After it was believed the data were coded completely, *Atlas.*ti was used to generate a series of reports by exporting data points for each code. Reports were also created for each of the research question three and four subcodes. A lengthy inspection of the exported reports revealed the codes adequately characterized the qualitative data. The results of the analysis are discussed in the second half of Chapter 5.

CHAPTER 5: RESULTS

Chapter 4 outlined a mixed-methods study to answer four research questions. The quantitative component was designed to answer two research questions. (1) Do four police enforcement actions focused on offenders or potential offenders reduce violent crime in hot spots? (2) Are any one of the four police enforcement actions more effective than the others? The qualitative component was designed to address two more complementary research questions. (3) When police commanders allocate resources in crime hot spots, what do they police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots? The results of those analyses follow.

Quantitative Results

The results from the random effects models are followed by the results from the GEE models. Incident rate ratios (IRR) are presented for ease of interpretation. Based on the log-link function used in negative binomial models, IRR are obtained by exponentiating the coefficients. The IRRs can then be converted into percent changes in the dependent variable per one-unit increase in a predictor by subtracting one from the IRR and multiplying the difference by 100. If the product is negative then it can be interpreted as a percentage decrease in the expected count of the dependent variable per one-unit increase in the predictor. If the product is positive then it can be interpreted as a percentage increase in the expected count of the dependent variable per one-unit increase in the predictor (Long & Freese, 2006, p. 360). Because hypotheses about one outcome and eight sets of independent variables (8 separate models) across three different statistical techniques (24 models total) are tested, there is an inflated chance of making a Type I error. Different methods are used to adjust *p*-values in order to account for multiple testing (Aickin & Gensler, 1996), but given the large number of hypotheses tested the most conservative option was employed: only effects with $p < 0.001$ are considered statistically significant.

Random Effects Models

Prior to running the full random effects models discussed below, null random effects models were estimated to confirm significant variance across hot spots existed and estimating the full random effects models was appropriate (Raudenbush & Bryk, 2002, Chapter 2).[30]

Total police enforcement counts. The random effects model results with the monthly total police enforcement actions independent variable predicting the monthly violent crime outcome net of the control variables are shown in Table 3. Model A (Table 3) demonstrates that the contemporaneous effect of total police enforcement actions was found to be positively and statistically significantly associated with the monthly violent crime outcome at the 0.001 alpha level net of the control variables. Each additional one-unit increase in the monthly total police enforcement actions index linked to a 1.05 percentage increase in the expected count of monthly violent crime net of the control variables (IRR = 1.0105, $p < .001$).

Model B (Table 3) shows the effect of monthly total police enforcement actions from the previous month on monthly all violent crime counts in the focal month. Net of the controls in the model, an increase of one police enforcement action in the previous month resulted in a 0.87 percent increase in monthly expected violent crime counts in the focal month even after all other variables in the model were held constant (IRR = 1.0087, $p < .001$).

[30] In the null model, the level-two variance component equaled 0.8315 with a standard error of 0.1074 (95% confidence interval = 0.6455 to 1.0712).

Table 3. All violent crime and total police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.7176	0.1184	0.1795	0.1216	0.2650	-1.5714	0.1354	0.2078	0.1331	0.3244
Total enforcement	0.0104***	0.0019	1.0105	1.0040	1.0170	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0086***	0.0020	1.0087	1.0020	1.0154
Month – February	-0.2142	0.1027	0.8072	0.5757	1.1317	-0.3521	0.1132	0.7032	0.4845	1.0207
Month – March	-0.0553	0.1076	0.9462	0.6640	1.3483	-0.1588	0.1182	0.8532	0.5783	1.2586
Month – April	0.0644	0.1152	1.0665	0.7301	1.5579	-0.0602	0.1193	0.9416	0.6358	1.3943
Month – May	0.1936	0.1017	1.2137	0.8686	1.6958	0.0658	0.1140	1.0680	0.7338	1.5543
Month – June	0.0102	0.1033	1.0103	0.7192	1.4191	-0.1119	0.1138	0.8941	0.6148	1.3003
Month – July	0.2451	0.1039	1.2778	0.9077	1.7987	0.1085	0.1132	1.1146	0.7679	1.6179
Month – August	0.2705	0.1073	1.3106	0.9208	1.8655	0.1190	0.1186	1.1263	0.7623	1.6641
Month – September	0.2560	0.1039	1.2918	0.9176	1.8186	0.0882	0.1185	1.0922	0.7396	1.6129
Month – October	0.2245	0.1048	1.2517	0.8866	1.7672	0.0887	0.1191	1.0927	0.7385	1.6169
Month – November	-0.0640	0.1173	0.9380	0.6376	1.3800	-0.2114	0.1273	0.8094	0.5324	1.2308
Month – December	-0.8033***	0.1487	0.4478	0.2745	0.7306	-1.0482***	0.1619	0.3506	0.2058	0.5972
Year – 2010	0.0405	0.0671	1.0414	0.8350	1.2988	0.0657	0.0698	1.0679	0.8488	1.3434
Year – 2011	-0.0940	0.0650	0.9103	0.7350	1.1274	-0.0894	0.0685	0.9145	0.7299	1.1457
Year – 2012	-0.7641***	0.0994	0.4657	0.3358	0.6460	-0.7775***	0.1024	0.4596	0.3281	0.6437
Year – 2013	-0.8404***	0.1067	0.4315	0.3038	0.6130	-0.8398***	0.1109	0.4318	0.2997	0.6221

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 3. All violent crime and total police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
PFPE Foot patrol	-0.2212	0.1508	0.8016	0.4880	1.3166	-0.1568	0.1428	0.8549	0.5344	1.3676
PPTE Foot patrol	0.0734	0.1668	1.0761	0.6217	1.8628	0.0851	0.1699	1.0888	0.6225	1.9047
PPTE Offender-focused	0.2655	0.2369	1.3041	0.5980	2.8438	0.2644	0.2443	1.3027	0.5830	2.9107
PPTE Problem solving	-0.0319	0.1896	0.9686	0.5190	1.8079	-0.0423	0.1902	0.9585	0.5126	1.7926
Unit length	-0.0001	0.0001	0.9999	0.9995	1.0003	-0.0001	0.0001	0.9999	0.9995	1.0003
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.6071	0.0946	-----	0.4473	0.8239	0.6479	0.1011	-----	0.4771	0.8798
lnalpha	-1.4526	0.2926	-----	-2.0261	-0.8791	-1.4479	0.2870	-----	-2.0104	-0.8854

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Hot spot mean centered total police enforcement counts. After controlling for the other variables in the model, each additional police enforcement action above a hot spot's average level of monthly total enforcement linked to a 0.74 percent higher expected monthly violent crime count (Table 4, Model A , IRR = 1.0074, $p < .001$). Each additional police enforcement action in the previous month above a hot spot's average level of police enforcement linked to a 0.57 percent increase in the expected monthly violent crime count in the following month after controlling for the other variables in the model (Table 4, Model B, IRR = 1.0057, $p < .001$).

Individual police enforcement actions counts. Only contemporaneous pedestrian stops linked significantly to higher violence after controlling for the other variables in the model (Table 5, Model A). Each additional pedestrian stop linked to a 1.36 percent increase in expected monthly violent crime counts (IRR = 1.0136, $p < .001$). Likewise, pedestrian stops lagged one month also linked to higher violence (Table 5, Model B). Each pedestrian stop in the previous month linked to a 1.36 percentage increase in the expected monthly violent crime count in the focal month (IRR = 1.0136, $p < .001$).

Individual police enforcement actions hot spot mean centered counts. With each additional pedestrian stop above the hot spot's monthly average, the expected monthly violent crime count was 1.14 percent higher during that same month (Table 6, Model A, IRR = 1.0114, $p < .001$). Also, each additional pedestrian stop above the hot spot average in the previous month linked to an increase of 1.17 percent in the expected monthly violent crime count in the focal month (Table 6, Model B, IRR = 1.0117, $p < .001$).

Table 4. All violent crime and hot spot mean centered total police enforcement actions random effects models

	Model A					**Model B**				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.5839	0.1180	0.2052	0.1391	0.3026	-1.5031	0.1403	0.2224	0.1402	0.3530
MC total enforcement	0.0074***	0.0018	1.0074	1.0014	1.0135	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0057	0.0019	1.0057	0.9994	1.0120
Month – February	-0.2156	0.1021	0.8061	0.5761	1.1279	-0.3032	0.1135	0.7384	0.5083	1.0726
Month – March	-0.0490	0.1073	0.9522	0.6690	1.3552	-0.1127	0.1187	0.8934	0.6045	1.3202
Month – April	0.0668	0.1142	1.0691	0.7342	1.5567	-0.0112	0.1193	0.9889	0.6679	1.4641
Month – May	0.1971	0.1012	1.2178	0.8729	1.6990	0.1168	0.1148	1.1239	0.7704	1.6396
Month – June	0.0151	0.1023	1.0152	0.7250	1.4217	-0.0610	0.1146	0.9408	0.6452	1.3717
Month – July	0.2463	0.1036	1.2793	0.9099	1.7989	0.1596	0.1136	1.1730	0.8071	1.7048
Month – August	0.2649	0.1070	1.3033	0.9167	1.8531	0.1671	0.1205	1.1819	0.7950	1.7571
Month – September	0.2434	0.1036	1.2756	0.9072	1.7935	0.1340	0.1193	1.1434	0.7720	1.6933
Month – October	0.2132	0.1040	1.2376	0.8789	1.7426	0.1251	0.1198	1.1332	0.7640	1.6809
Month – November	-0.0788	0.1168	0.9242	0.6294	1.3572	-0.1755	0.1280	0.8390	0.5507	1.2784
Month – December	-0.8475***	0.1489	0.4285	0.2625	0.6993	-1.0159***	0.1626	0.3621	0.2120	0.6182
Year – 2010	0.0430	0.0662	1.0439	0.8396	1.2980	0.0618	0.0693	1.0637	0.8468	1.3363
Year – 2011	-0.0996	0.0635	0.9052	0.7346	1.1154	-0.0962	0.0675	0.9083	0.7275	1.1340
Year – 2012	-0.7984***	0.0988	0.4500	0.3252	0.6229	-0.8128***	0.1023	0.4436	0.3168	0.6212
Year – 2013	-0.8709***	0.1071	0.4186	0.2943	0.5954	-0.8760***	0.1117	0.4164	0.2883	0.6015

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 4. All violent crime and hot spot mean centered total police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
PFPE Foot patrol	-0.1589	0.1489	0.8531	0.5227	1.3925	-0.0997	0.1413	0.9051	0.5685	1.4409
PPTE Foot patrol	0.0806	0.1644	1.0840	0.6311	1.8617	0.0932	0.1660	1.0977	0.6357	1.8955
PPTE Offender-focused	0.2658	0.2356	1.3045	0.6008	2.8323	0.2654	0.2426	1.3039	0.5868	2.8973
PPTE Problem solving	-0.0352	0.1873	0.9654	0.5213	1.7877	-0.0391	0.1890	0.9616	0.5163	1.7912
Unit length	-0.0002	0.0001	0.9998	0.9994	1.0003	-0.0002	0.0001	0.9998	0.9994	1.0003
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.8076	0.1059	-----	0.6245	1.0443	0.8233	0.1097	-----	0.6341	1.0690
lnalpha	-1.5205	0.3001	-----	-2.1087	-0.9323	-1.4900	0.2908	-----	-2.0599	-0.9201

Notes: ***p < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 5. All violent crime and individual police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.7026	0.1199	0.1822	0.1228	0.2703	-1.5702	0.1364	0.2080	0.1328	0.3258
Pedestrian stops	0.0135***	0.0027	1.0136	1.0046	1.0227	-----	-----	-----	-----	-----
Traffic stops	0.0067	0.0031	1.0067	0.9964	1.0172	-----	-----	-----	-----	-----
QOL arrests	0.0215	0.0102	1.0217	0.9879	1.0566	-----	-----	-----	-----	-----
Felony arrests	0.0124	0.0449	1.0125	0.8733	1.1739	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0135***	0.0024	1.0136	1.0057	1.0216
Traffic stops lag	-----	-----	-----	-----	-----	0.0048	0.0031	1.0048	0.9945	1.0152
QOL arrests lag	-----	-----	-----	-----	-----	-0.0224	0.0124	0.9779	0.9388	1.0185
Felony arrest lags	-----	-----	-----	-----	-----	-0.0007	0.0334	0.9993	0.8952	1.1156
Month – February	-0.2098	0.1025	0.8108	0.5786	1.1360	-0.3390	0.1135	0.7125	0.4905	1.0351
Month – March	-0.0558	0.1077	0.9458	0.6636	1.3479	-0.1482	0.1191	0.8622	0.5826	1.2760
Month – April	0.0603	0.1166	1.0622	0.7237	1.5589	-0.0406	0.1194	0.9602	0.6483	1.4221
Month – May	0.1913	0.1019	1.2108	0.8658	1.6934	0.0746	0.1143	1.0775	0.7398	1.5693
Month – June	0.0043	0.1046	1.0043	0.7119	1.4169	-0.1069	0.1139	0.8986	0.6178	1.3071
Month – July	0.2350	0.1057	1.2650	0.8932	1.7914	0.1139	0.1126	1.1206	0.7736	1.6232
Month – August	0.2635	0.1087	1.3015	0.9101	1.8611	0.1216	0.1186	1.1293	0.7645	1.6683
Month – September	0.2470	0.1056	1.2802	0.9045	1.8119	0.0846	0.1189	1.0883	0.7360	1.6093
Month – October	0.2191	0.1054	1.2450	0.8802	1.7610	0.0847	0.1197	1.0884	0.7342	1.6137
Month – November	-0.0679	0.1179	0.9343	0.6339	1.3772	-0.2078	0.1274	0.8124	0.5342	1.2356
Month – December	-0.8102***	0.1493	0.4448	0.2722	0.7268	-1.0396***	0.1619	0.3536	0.2075	0.6025

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 5. All violent crime and individual police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0326	0.0665	1.0332	0.8301	1.2858	0.0626	0.0701	1.0647	0.8455	1.3407
Year – 2011	-0.0975	0.0647	0.9071	0.7332	1.1223	-0.0765	0.0680	0.9264	0.7405	1.1589
Year – 2012	-0.7715***	0.0992	0.4623	0.3336	0.6408	-0.7592***	0.1027	0.4680	0.3338	0.6563
Year – 2013	-0.8512***	0.1041	0.4269	0.3031	0.6014	-0.8386***	0.1098	0.4323	0.3012	0.6204
PFPE Foot patrol	-0.2752	0.1588	0.7594	0.4504	1.2805	-0.2018	0.1443	0.8173	0.5083	1.3141
PPTE Foot patrol	0.0558	0.1710	1.0574	0.6023	1.8565	0.0900	0.1755	1.0942	0.6142	1.9493
PPTE Offender-focused	0.2629	0.2355	1.3007	0.5994	2.8227	0.2657	0.2422	1.3043	0.5879	2.8941
PPTE Problem solving	-0.0323	0.1885	0.9682	0.5207	1.8006	-0.0460	0.1883	0.9550	0.5139	1.7747
Unit length	-0.0001	0.0001	0.9999	0.9995	1.0003	-0.0001	0.0001	0.9999	0.9995	1.0003
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.6134	0.0961	-----	0.4512	0.8340	0.6590	0.1032	-----	0.4849	0.8957
lnalpha	-1.4567	0.2949	-----	-2.0346	-0.8787	-1.4618	0.2870	-----	-2.0243	-0.8993

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 6. All violent crime and hot spot mean centered individual police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.5696	0.1191	0.2081	0.1407	0.3080	-1.5176	0.1407	0.2192	0.1380	0.3483
MC pedestrian stops	0.0113***	0.0026	1.0114	1.0029	1.0200	-----	-----	-----	-----	-----
MC traffic stops	0.0026	0.0032	1.0026	0.9921	1.0133	-----	-----	-----	-----	-----
MC QOL arrests	0.0188	0.0098	1.0189	0.9867	1.0523	-----	-----	-----	-----	-----
MC felony arrests	0.0103	0.0449	1.0103	0.8715	1.1712	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0116***	0.0023	1.0117	1.0041	1.0193
MC traffic stops lag	-----	-----	-----	-----	-----	0.0006	0.0029	1.0006	0.9911	1.0102
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0297	0.0124	0.9708	0.9319	1.0113
MC felony arrests lag	-----	-----	-----	-----	-----	-0.0048	0.0357	0.9952	0.8849	1.1192
Month – February	-0.2109	0.1021	0.8098	0.5788	1.1332	-0.2843	0.1135	0.7526	0.5180	1.0934
Month – March	-0.0493	0.1076	0.9519	0.6681	1.3562	-0.0963	0.1200	0.9082	0.6119	1.3479
Month – April	0.0617	0.1157	1.0637	0.7268	1.5566	0.0151	0.1191	1.0153	0.6861	1.5023
Month – May	0.1938	0.1014	1.2138	0.8694	1.6947	0.1310	0.1151	1.1400	0.7806	1.6648
Month – June	0.0073	0.1036	1.0073	0.7164	1.4165	-0.0511	0.1151	0.9501	0.6507	1.3874
Month – July	0.2337	0.1054	1.2632	0.8929	1.7870	0.1693	0.1130	1.1845	0.8168	1.7178
Month – August	0.2552	0.1084	1.2908	0.9034	1.8443	0.1736	0.1204	1.1896	0.8003	1.7681
Month – September	0.2307	0.1052	1.2595	0.8909	1.7806	0.1327	0.1196	1.1419	0.7703	1.6928
Month – October	0.2053	0.1045	1.2279	0.8705	1.7320	0.1225	0.1202	1.1304	0.7610	1.6790
Month – November	-0.0846	0.1173	0.9189	0.6246	1.3519	-0.1687	0.1280	0.8448	0.5544	1.2874
Month – December	-0.8588***	0.1496	0.4237	0.2589	0.6931	-1.0033***	0.1627	0.3667	0.2147	0.6263

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 6. All violent crime and hot spot mean centered individual police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0334	0.0655	1.0339	0.8334	1.2827	0.0573	0.0696	1.0590	0.8423	1.3315
Year – 2011	-0.1033	0.0634	0.9018	0.7321	1.1109	-0.0823	0.0672	0.9210	0.7383	1.1488
Year – 2012	-0.8074***	0.0989	0.4460	0.3222	0.6175	-0.7930***	0.1029	0.4525	0.3225	0.6349
Year – 2013	-0.8850***	0.1043	0.4127	0.2928	0.5818	-0.8774***	0.1105	0.4159	0.2891	0.5982
PFPE Foot patrol	-0.2242	0.1561	0.7992	0.4781	1.3359	-0.1531	0.1428	0.8581	0.5364	1.3726
PPTE Foot patrol	0.0621	0.1690	1.0640	0.6102	1.8554	0.0979	0.1725	1.1028	0.6252	1.9453
PPTE Offender-focused	0.2622	0.2334	1.2997	0.6030	2.8015	0.2676	0.2395	1.3068	0.5941	2.8742
PPTE Problem solving	-0.0353	0.1858	0.9653	0.5238	1.7787	-0.0422	0.1868	0.9586	0.5184	1.7728
Unit length	-0.0002	0.0001	0.9998	0.9994	1.0003	-0.0002	0.0001	0.9998	0.9994	1.0003
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.8083	0.1058	-----	0.6254	1.0446	0.8196	0.1094	-----	0.6310	1.0646
lnalpha	-1.5271	0.3038	-----	-2.1226	-0.9316	-1.5055	0.2911	-----	-2.0761	-0.9349

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Random Effects Models Equality of Coefficients Wald Tests

Wald tests indicated statistically significant differences among the coefficients of the individual police enforcement actions (Table 7).

Individual police enforcement actions counts. The top half of Table 7 shows the results of the equality of coefficients tests using the raw count predictors. The omnibus test indicated no differential contemporaneous impacts (Table 7, χ^2 = 3.94, *df* = 3, n.s.). On the other hand, when comparing the sizes of the four police enforcement actions coefficients lagged one month on monthly violent crime counts from the random effects model, the omnibus test revealed statistically significant differences for the four temporally lagged raw count predictors (Table 7, χ^2 = 15.72, *df* = 3, $p < 0.001$). The temporally lagged pedestrian stops impact was significantly larger than the effect of lagged traffic stops on the monthly violent crime count outcome (Table 7, χ^2 = 5.08, *df* = 1, $p < 0.05$). The pedestrian stops impact also exceeded the impact of lagged quality of life arrests (Table 7, χ^2 = 7.61, *df* = 1, $p < 0.01$). Finally, the impact of the lagged monthly quality of life arrests was significantly smaller than the impacts of lagged monthly traffic stops even though neither effect was significantly different than zero (Table 7, χ^2 = 4.41, *df* = 1, $p < 0.05$).

Individual police enforcement actions hot spot mean centered counts. The omnibus tests suggested differential effects only for the lagged model (Table 7, χ^2 = 22.84, *df* = 3, $p < 0.001$). Centered pedestrian stops had a larger impact than centered traffic stops (Table 7, χ^2 = 8.36, *df* = 1, $p < 0.01$). Further, centered pedestrian stops also had a larger impact than the centered quality of life arrests (Table 7, χ^2 = 10.22, *df* = 1, $p < 0.001$). The lagged hot spot mean centered misdemeanor arrest effect was also found to be statistically significantly smaller than the effect of lagged monthly hot spot mean centered traffic stops predictor on monthly violent crime counts (Table 7, $\chi^2 = 5.59$, $df = 1$, $p < 0.05$).

Summary of Random Effects Models Results

There were three major findings for the random effects models. First, except for the lagged model with hot spot mean centered predictors, the total enforcement predictors linked to higher levels of violence. Second, pedestrian stops also consistently linked to higher levels of violent crime. Third, the effects of pedestrian stops were consistently larger than the effects of traffic enforcement and quality of life arrests in the lagged models; however, the impact of lagged traffic enforcement exceeded the impact of lagged quality of life arrests.

Generalized Estimating Equations Models

The GEE models were estimated with both first-order and second-order autoregressive error structures. By definition, GEE models estimate population-average effects.[31]

Total police enforcement actions counts. In the AR1 model, each police enforcement action in the focal month increased the expected monthly violent crime count by 2.33 percent (Table 8, IRR = 1.0233, $p < .001$). Nearly identical results were found in the AR2 model (Table 9, IRR = 1.0226, $p < .001$). In the lagged AR1 model, each police enforcement action in the previous month resulted in a 2.22 percent increase in the focal month's expected violent crime count (Table 8, IRR = 1.0222, $p < .001$). Again, nearly identical results were observed in the AR2 model (Table 9, IRR = 1.0213, $p < .001$).

[31] The effect of a predictor in a marginal model is interpreted as the change in the dependent variable per one-unit increase in the predictor for the average unit. Differences across units are averaged out (Zuur, Leno, Walker, Saveliev, & Smith, 2009, Chapter 12).

Hot spot mean centered total police enforcement actions counts. In the AR1 mean centered contemporaneous model, each police enforcement action above the hot spot monthly mean linked to a 1.38 percent increase in the expected monthly violent crime count (Table 10, IRR = 1.0138, $p < .001$). A similar effect was observed in the AR2 model (Table 11, IRR = 1.0118, $p < .001$). Similar significant links appeared in the temporally lagged and centered AR1 (Table 10, IRR = 1.0099, $p < .001$) and AR2 (Table 11, IRR = 1.0077, $p < .001$) models.

Individual police enforcement actions counts. In the contemporaneous GEE AR1, pedestrian stops and traffic enforcement linked to significantly higher levels of violence. Each additional pedestrian stop linked to a 3.1 percent increase in expected monthly violent crime counts (Table 12, IRR = 1.0310, $p < .001$). Each additional car stop resulted in 1.81 percent higher expected monthly violent crime counts (Table 12, IRR = 1.0181, $p < .001$). The results for pedestrian stops (Table 13, IRR = 1.0292, $p < .001$) and traffic enforcement (Table 13, IRR = 1.0182, $p < .001$) were similar in the GEE AR2 model.

The temporally lagged models showed similar results. In the AR1 model, each additional pedestrian stop in the previous month linked to a 3.04 percent higher expected monthly violent crime count during the focal month (Table 12, IRR = 1.0304, $p < .001$). Expected monthly violent crime counts were 1.79 percent higher for each additional traffic stop that occurred in the previous month (Table 12, IRR = 1.0179, $p < .001$). In the AR2 models, the impacts of temporally lagged pedestrian stops (Table 13, IRR = 1.0289, $p < .001$) and traffic stops (Table 13, IRR = 1.0174, $p < .001$) were similar.

Table 7. All violent crime random effects models equality of coefficient Wald tests

	Contemporaneous Model	Lagged Model
	χ^2 (*df*)	**χ^2 (*df*)**
Table 5: Individual count predictors model		
Omnibus test	3.94(3)	15.72(3)***
Pedestrian stops vs. Traffic stops	-----	5.08(1)*
Pedestrian stops vs. Misdemeanor arrests	-----	7.61(1)**
Pedestrian stops vs. Felony arrests	-----	n.s.
Traffic stops vs. Misdemeanor arrests	-----	4.41(1)*
Traffic stops vs. Felony arrests	-----	n.s.
Misdemeanor arrests vs. Felony arrests	-----	n.s.
Table 6: Individual hot spot mean centered predictors model		
Omnibus test	4.88(3)	22.84(3)***
Pedestrian stops vs. Traffic stops	-----	8.36(1)**
Pedestrian stops vs. Misdemeanor arrests	-----	10.22(1)***
Pedestrian stops vs. Felony arrests	-----	n.s.
Traffic stops vs. Misdemeanor arrests	-----	5.59(1)*
Traffic stops vs. Felony arrests	-----	n.s.
Misdemeanor arrests vs. Felony arrests	-----	n.s.

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table 8. All violent crime and total police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.6616	0.0981	0.1898	0.1375	0.2621	-1.3886	0.1147	0.2494	0.1710	0.3638
Total enforcement	0.0231***	0.0009	1.0233	1.0202	1.0264	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0220***	0.0009	1.0222	1.0191	1.0254
Month – February	-0.2078	0.1144	0.8124	0.5575	1.1839	-0.5129***	0.1253	0.5988	0.3964	0.9044
Month – March	-0.0863	0.1169	0.9173	0.6243	1.3478	-0.3181	0.1265	0.7275	0.4797	1.1033
Month – April	0.0603	0.1150	1.0622	0.7274	1.5509	-0.2106	0.1244	0.8101	0.5381	1.2198
Month – May	0.1563	0.1131	1.1692	0.8058	1.6965	-0.1131	0.1227	0.8931	0.5964	1.3373
Month – June	-0.0320	0.1171	0.9685	0.6588	1.4238	-0.3021	0.1264	0.7393	0.4878	1.1205
Month – July	0.2175	0.1125	1.2429	0.8584	1.7997	-0.0674	0.1221	0.9349	0.6256	1.3971
Month – August	0.2544	0.1122	1.2897	0.8915	1.8658	-0.0609	0.1219	0.9409	0.6300	1.4052
Month – September	0.2610	0.1121	1.2983	0.8977	1.8775	-0.0792	0.1221	0.9238	0.6181	1.3807
Month – October	0.2290	0.1126	1.2573	0.8681	1.8212	-0.0414	0.1218	0.9594	0.6425	1.4326
Month – November	-0.0330	0.1182	0.9675	0.6557	1.4277	-0.3375	0.1273	0.7135	0.4693	1.0849
Month – December	-0.6826***	0.1412	0.5053	0.3175	0.8041	-1.1569***	0.1478	0.3145	0.1933	0.5115
Year – 2010	0.0385	0.0768	1.0392	0.8073	1.3378	0.0962	0.0789	1.1010	0.8493	1.4274
Year – 2011	-0.0648	0.0779	0.9372	0.7254	1.2109	-0.0440	0.0803	0.9569	0.7348	1.2463
Year – 2012	-0.6598***	0.0929	0.5169	0.3808	0.7017	-0.6580***	0.0950	0.5179	0.3789	0.7078
Year – 2013	-0.7236***	0.0946	0.4850	0.3553	0.6621	-0.6933***	0.0966	0.4999	0.3638	0.6870
PFPE Foot patrol	-0.2956	0.1533	0.7441	0.4493	1.2322	-0.2245	0.1541	0.7989	0.4812	1.3264
PPTE Foot patrol	0.2737	0.2086	1.3149	0.6620	2.6117	0.2816	0.2068	1.3253	0.6712	2.6169
PPTE Offender-focused	0.1234	0.2744	1.1313	0.4586	2.7907	0.0986	0.2732	1.1036	0.4492	2.7115
PPTE Problem solving	0.1118	0.3711	1.1182	0.3298	3.7914	0.0853	0.3682	1.0890	0.3242	3.6578
Unit length	-0.0001	0.0001	0.9999	0.9997	1.0002	-0.0001	0.0001	0.9999	0.9997	1.0002

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 9. All violent crime and total police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.6483	0.0998	0.1924	0.1385	0.2672	-1.3797	0.1163	0.2516	0.1716	0.3689
Total enforcement	0.0224***	0.0010	1.0226	1.0194	1.0259	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0211***	0.0010	1.0213	1.0180	1.0247
Month – February	-0.1991	0.1143	0.8195	0.5626	1.1935	-0.4919***	0.1250	0.6114	0.4052	0.9225
Month – March	-0.0820	0.1130	0.9213	0.6353	1.3360	-0.3095	0.1229	0.7338	0.4898	1.0994
Month – April	0.0635	0.1142	1.0656	0.7317	1.5518	-0.1999	0.1237	0.8188	0.5450	1.2300
Month – May	0.1595	0.1128	1.1729	0.8093	1.6999	-0.1011	0.1224	0.9038	0.6042	1.3519
Month – June	-0.0293	0.1170	0.9712	0.6607	1.4274	-0.2894	0.1263	0.7487	0.4941	1.1344
Month – July	0.2215	0.1125	1.2479	0.8619	1.8067	-0.0541	0.1220	0.9473	0.6340	1.4155
Month – August	0.2588	0.1122	1.2954	0.8956	1.8737	-0.0470	0.1218	0.9541	0.6391	1.4244
Month – September	0.2642	0.1118	1.3023	0.9014	1.8816	-0.0679	0.1217	0.9344	0.6259	1.3947
Month – October	0.2315	0.1120	1.2605	0.8720	1.8220	-0.0322	0.1211	0.9683	0.6501	1.4423
Month – November	-0.0334	0.1150	0.9672	0.6624	1.4121	-0.3321	0.1234	0.7175	0.4781	1.0767
Month – December	-0.6877***	0.1411	0.5027	0.3159	0.7999	-1.1529***	0.1482	0.3157	0.1939	0.5141
Year – 2010	0.0422	0.0801	1.0431	0.8015	1.3574	0.1004	0.0824	1.1056	0.8431	1.4499
Year – 2011	-0.0743	0.0821	0.9284	0.7087	1.2162	-0.0520	0.0847	0.9493	0.7183	1.2546
Year – 2012	-0.6690***	0.0979	0.5122	0.3711	0.7070	-0.6663***	0.1003	0.5136	0.3693	0.7144
Year – 2013	-0.7238***	0.0996	0.4849	0.3494	0.6728	-0.6968***	0.1020	0.4982	0.3562	0.6968
PFPE Foot patrol	-0.3010	0.1572	0.7401	0.4412	1.2412	-0.2226	0.1577	0.8004	0.4763	1.3449
PPTE Foot patrol	0.2432	0.2143	1.2753	0.6301	2.5812	0.2543	0.2125	1.2896	0.6409	2.5951
PPTE Offender-focused	0.1062	0.2868	1.1121	0.4328	2.8574	0.0796	0.2860	1.0828	0.4225	2.7751
PPTE Problem solving	0.1046	0.3819	1.1103	0.3160	3.9006	0.0832	0.3785	1.0867	0.3128	3.7756
Unit length	-0.0001	0.0001	0.9999	0.9996	1.0002	-0.0001	0.0001	0.9999	0.9996	1.0002

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 10. All violent crime and hot spot mean centered total police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.2378	0.0958	0.2900	0.2116	0.3975	-1.1305	0.1140	0.3229	0.2218	0.4699
MC total enforcement	0.0137***	0.0021	1.0138	1.0069	1.0207	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0098***	0.0021	1.0099	1.0028	1.0169
Month – February	-0.2080	0.1068	0.8122	0.5716	1.1542	-0.3233	0.1186	0.7237	0.4898	1.0693
Month – March	-0.0730	0.1124	0.9296	0.6421	1.3458	-0.1475	0.1230	0.8629	0.5757	1.2934
Month – April	0.0289	0.1120	1.0293	0.7119	1.4881	-0.0645	0.1226	0.9375	0.6264	1.4032
Month – May	0.1455	0.1099	1.1566	0.8056	1.6605	0.0547	0.1207	1.0563	0.7101	1.5711
Month – June	-0.0386	0.1138	0.9621	0.6615	1.3993	-0.1294	0.1243	0.8786	0.5837	1.3224
Month – July	0.2026	0.1093	1.2246	0.8546	1.7549	0.0996	0.1200	1.1047	0.7443	1.6397
Month – August	0.2250	0.1093	1.2523	0.8741	1.7940	0.1032	0.1200	1.1088	0.7472	1.6454
Month – September	0.2228	0.1092	1.2496	0.8723	1.7901	0.0840	0.1200	1.0877	0.7328	1.6144
Month – October	0.1985	0.1094	1.2196	0.8508	1.7482	0.0943	0.1195	1.0989	0.7416	1.6286
Month – November	-0.0868	0.1146	0.9169	0.6289	1.3368	-0.2129	0.1240	0.8082	0.5374	1.2155
Month – December	-0.8165***	0.1347	0.4420	0.2838	0.6884	-1.0394***	0.1401	0.3537	0.2230	0.5608

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 10. All violent crime and hot spot mean centered total police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1072	0.0792	1.1132	0.8579	1.4445	0.1381	0.0818	1.1481	0.8771	1.5029
Year – 2011	-0.0380	0.0811	0.9627	0.7371	1.2574	-0.0283	0.0839	0.9721	0.7376	1.2811
Year – 2012	-0.7242***	0.0986	0.4847	0.3504	0.6704	-0.7479***	0.1009	0.4734	0.3396	0.6597
Year – 2013	-0.7726***	0.0999	0.4618	0.3325	0.6415	-0.7875***	0.1026	0.4550	0.3246	0.6376
PFPE Foot patrol	0.0324	0.1577	1.0329	0.6146	1.7357	0.1283	0.1570	1.1369	0.6782	1.9058
PPTE Foot patrol	0.2879	0.2119	1.3336	0.6641	2.6782	0.3105	0.2103	1.3641	0.6828	2.7255
PPTE Offender-focused	-0.0885	0.2882	0.9153	0.3545	2.3630	-0.1038	0.2883	0.9014	0.3490	2.3279
PPTE Problem solving	-0.0740	0.3834	0.9286	0.2630	3.2794	-0.0752	0.3813	0.9276	0.2645	3.2526
Unit length	-0.0003	0.0001	0.9997	0.9995	1.0000	-0.0003	0.0001	0.9997	0.9994	1.0000

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 11. All violent crime and hot spot mean centered total police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.2198	0.0989	0.2953	0.2133	0.4088	-1.1281	0.1171	0.3236	0.2202	0.4758
MC total enforcement	0.0118***	0.0022	1.0118	1.0046	1.0191	-----	-----	-----	----	----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0077***	0.0022	1.0077	1.0004	1.0151
Month – February	-0.1917	0.1065	0.8256	0.5815	1.1721	-0.2824	0.1182	0.7540	0.5110	1.1125
Month – March	-0.0631	0.1046	0.9388	0.6654	1.3246	-0.1237	0.1160	0.8837	0.6034	1.2942
Month – April	0.0401	0.1095	1.0409	0.7260	1.4923	-0.0359	0.1204	0.9647	0.6491	1.4338
Month – May	0.1562	0.1083	1.1691	0.8187	1.6694	0.0832	0.1193	1.0868	0.7339	1.6093
Month – June	-0.0295	0.1131	0.9710	0.6692	1.4088	-0.1009	0.1237	0.9040	0.6017	1.3581
Month – July	0.2156	0.1088	1.2406	0.8673	1.7744	0.1333	0.1195	1.1426	0.7710	1.6932
Month – August	0.2368	0.1086	1.2672	0.8863	1.8116	0.1361	0.1194	1.1458	0.7736	1.6972
Month – September	0.2288	0.1079	1.2571	0.8814	1.7929	0.1103	0.1186	1.1166	0.7558	1.6496
Month – October	0.2030	0.1074	1.2250	0.8603	1.7444	0.1136	0.1173	1.1203	0.7615	1.6482
Month – November	-0.0878	0.1081	0.9159	0.6417	1.3074	-0.1971	0.1165	0.8211	0.5597	1.2046
Month – December	-0.8296***	0.1347	0.4362	0.2801	0.6794	-1.0269***	0.1407	0.3581	0.2254	0.5690

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 11. All violent crime and hot spot mean centered total police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Year – 2010	0.1043	0.0852	1.1099	0.8387	1.4689	0.1327	0.0880	1.1419	0.8549	1.5253
Year – 2011	-0.0733	0.0895	0.9293	0.6922	1.2476	-0.0642	0.0926	0.9379	0.6916	1.2718
Year – 2012	-0.7561***	0.1086	0.4695	0.3285	0.6711	-0.7795***	0.1111	0.4587	0.3182	0.6612
Year – 2013	-0.7885***	0.1098	0.4545	0.3167	0.6524	-0.8103***	0.1130	0.4447	0.3066	0.6451
PFPE Foot patrol	-0.0143	0.1635	0.9858	0.5756	1.6883	0.0815	0.1623	1.0849	0.6360	1.8507
PPTE Foot patrol	0.2105	0.2208	1.2343	0.5969	2.5525	0.2275	0.2198	1.2555	0.6092	2.5874
PPTE Offender-focused	-0.0922	0.3078	0.9120	0.3313	2.5107	-0.1054	0.3080	0.8999	0.3267	2.4793
PPTE Problem solving	-0.0444	0.3949	0.9566	0.2609	3.5079	-0.0411	0.3925	0.9597	0.2638	3.4915
Unit length	-0.0003	0.0001	0.9997	0.9994	1.0001	-0.0003	0.0001	0.9997	0.9994	1.0001

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 12. All violent crime and individual police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.6597	0.0981	0.1902	0.1377	0.2626	-1.3922	0.1147	0.2485	0.1704	0.3625
Pedestrian stops	0.0306***	0.0024	1.0310	1.0229	1.0392	-----	-----	-----	-----	-----
Traffic stops	0.0179***	0.0017	1.0181	1.0123	1.0240	-----	-----	-----	-----	-----
QOL arrests	0.0138	0.0134	1.0139	0.9702	1.0596	-----	-----	-----	-----	-----
Felony arrests	0.0083	0.0526	1.0084	0.8480	1.1991	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0300***	0.0024	1.0304	1.0224	1.0386
Traffic stops lag	-----	-----	-----	-----	-----	0.0177***	0.0018	1.0179	1.0120	1.0238
QOL arrests lag	-----	-----	-----	-----	-----	-0.0146	0.0148	0.9855	0.9388	1.0346
Felony arrest lags	-----	-----	-----	-----	-----	-0.0136	0.0576	0.9865	0.8162	1.1923
Month – February	-0.2035	0.1148	0.8159	0.5592	1.1902	-0.5121***	0.1256	0.5993	0.3964	0.9059
Month – March	-0.0840	0.1171	0.9194	0.6253	1.3518	-0.3160	0.1267	0.7291	0.4806	1.1061
Month – April	0.0594	0.1152	1.0612	0.7264	1.5503	-0.2027	0.1245	0.8165	0.5421	1.2298
Month – May	0.1503	0.1133	1.1622	0.8005	1.6872	-0.1140	0.1228	0.8923	0.5957	1.3364
Month – June	-0.0411	0.1173	0.9597	0.6524	1.4118	-0.3080	0.1265	0.7349	0.4846	1.1144
Month – July	0.2092	0.1127	1.2326	0.8508	1.7858	-0.0706	0.1222	0.9318	0.6234	1.3929
Month – August	0.2481	0.1123	1.2816	0.8856	1.8548	-0.0678	0.1220	0.9344	0.6255	1.3960
Month – September	0.248*	0.1123	1.2824	0.8862	1.8559	-0.0980	0.1224	0.9066	0.6060	1.3563
Month – October	0.2242	0.1127	1.2514	0.8636	1.8131	-0.0549	0.1220	0.9466	0.6336	1.4143
Month – November	-0.0319	0.1183	0.9686	0.6562	1.4296	-0.3409	0.1274	0.7111	0.4676	1.0815
Month – December	-0.6770***	0.1414	0.5082	0.3191	0.8092	-1.1535***	0.1480	0.3155	0.1939	0.5136

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 12. All violent crime and individual police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0308	0.0767	1.0313	0.8014	1.3272	0.0960	0.0788	1.1008	0.8494	1.4266
Year – 2011	-0.0603	0.0778	0.9415	0.7288	1.2163	-0.0313	0.0803	0.9692	0.7441	1.2624
Year – 2012	-0.6445***	0.0928	0.5247	0.3866	0.7121	-0.6307***	0.0950	0.5322	0.3894	0.7275
Year – 2013	-0.7232***	0.0945	0.4852	0.3556	0.6621	-0.6857***	0.0966	0.5037	0.3666	0.6922
PFPE Foot patrol	-0.4300	0.1597	0.6505	0.3847	1.1001	-0.3270	0.1584	0.7211	0.4282	1.2143
PPTE Foot patrol	0.2290	0.2103	1.2573	0.6295	2.5114	0.2834	0.2070	1.3277	0.6718	2.6238
PPTE Offender-focused	0.1243	0.2737	1.1323	0.4601	2.7865	0.0999	0.2723	1.1050	0.4511	2.7069
PPTE Problem solving	0.1077	0.3706	1.1137	0.3290	3.7699	0.0743	0.3681	1.0771	0.3208	3.6163
Unit length	-0.0001	0.0001	0.9999	0.9997	1.0002	-0.0001	0.0001	0.9999	0.9997	1.0002

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 13. All violent crime and individual police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.6472	0.0997	0.1926	0.1387	0.2674	-1.3849	0.1163	0.2503	0.1708	0.3670
Pedestrian stops	0.0287***	0.0025	1.0292	1.0208	1.0376	-----	-----	-----	-----	-----
Traffic stops	0.0180***	0.0018	1.0182	1.0121	1.0243	-----	-----	-----	-----	-----
QOL arrests	0.0154	0.0136	1.0155	0.9709	1.0622	-----	-----	-----	-----	-----
Felony arrests	0.0111	0.0523	1.0112	0.8514	1.2010	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0285***	0.0025	1.0289	1.0205	1.0374
Traffic stops lag	-----	-----	-----	-----	-----	0.0173***	0.0019	1.0174	1.0112	1.0237
QOL arrests lag	-----	-----	-----	-----	-----	-0.0170	0.0153	0.9831	0.9348	1.0339
Felony arrest lags	-----	-----	-----	-----	-----	-0.0034	0.0573	0.9966	0.8253	1.2035
Month – February	-0.1961	0.1146	0.8220	0.5638	1.1984	-0.4911***	0.1252	0.6119	0.4053	0.9240
Month – March	-0.0805	0.1133	0.9226	0.6355	1.3396	-0.3075	0.1231	0.7353	0.4904	1.1025
Month – April	0.0622	0.1144	1.0642	0.7303	1.5509	-0.1923	0.1238	0.8250	0.5489	1.2400
Month – May	0.1540	0.1130	1.1665	0.8044	1.6916	-0.1015	0.1225	0.9035	0.6038	1.3518
Month – June	-0.0376	0.1172	0.9631	0.6549	1.4165	-0.2947	0.1264	0.7447	0.4913	1.1289
Month – July	0.2138	0.1126	1.2384	0.8548	1.7940	-0.0573	0.1221	0.9443	0.6318	1.4113
Month – August	0.2529	0.1123	1.2878	0.8900	1.8634	-0.0533	0.1219	0.9481	0.6348	1.4159
Month – September	0.2533	0.1120	1.2883	0.8910	1.8627	-0.0851	0.1221	0.9185	0.6146	1.3724
Month – October	0.2270	0.1121	1.2548	0.8677	1.8147	-0.0445	0.1213	0.9565	0.6417	1.4257
Month – November	-0.0323	0.1152	0.9682	0.6626	1.4146	-0.3350	0.1235	0.7153	0.4764	1.0741
Month – December	-0.6829***	0.1413	0.5052	0.3173	0.8042	-1.1490***	0.1483	0.3170	0.1945	0.5164

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 13. All violent crime and individual police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0360	0.0799	1.0366	0.7971	1.3482	0.1013	0.0822	1.1066	0.8443	1.4505
Year – 2011	-0.0692	0.0819	0.9332	0.7128	1.2217	-0.0382	0.0847	0.9626	0.7284	1.2720
Year – 2012	-0.6559***	0.0977	0.5190	0.3763	0.7159	-0.6390***	0.1002	0.5278	0.3795	0.7341
Year – 2013	-0.7227***	0.0992	0.4855	0.3502	0.6729	-0.6877***	0.1018	0.5027	0.3596	0.7028
PFPE Foot patrol	-0.4113	0.1631	0.6628	0.3876	1.1334	-0.3075	0.1615	0.7353	0.4322	1.2508
PPTE Foot patrol	0.2077	0.2156	1.2308	0.6055	2.5018	0.2623	0.2125	1.2999	0.6459	2.6160
PPTE Offender-focused	0.1067	0.2858	1.1126	0.4345	2.8492	0.0799	0.2849	1.0832	0.4242	2.7661
PPTE Problem solving	0.1019	0.3810	1.1073	0.3161	3.8788	0.0733	0.3781	1.0760	0.3101	3.7340
Unit length	-0.0001	0.0001	0.9999	0.9996	1.0002	-0.0001	0.0001	0.9999	0.9996	1.0002

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Individual police enforcement actions hot spot mean centered counts. In both the AR1 and AR2 models respectively, the average hot spot experienced a 1.83 percent (Table 14, IRR = 1.083, $p < .001$) or a 1.44 percent (Table 15, IRR = 1.0144, $p < .001$) increase in the expected monthly violent crime count for each additional pedestrian stop that occurred above the average. When the four hot spot mean centered police enforcement actions were lagged one month, each additional pedestrian stop above the hot spots mean linked to later expected violent counts that were 1.71 percent greater (Table 14, IRR = 1.0171, $p < .001$) in the AR1 model and 1.46 percent greater in the AR2 model (Table 15, IRR = 1.0146, $p < .001$).

Generalized Estimating Equations Models Equality of Coefficients Wald Tests

Individual police enforcement actions counts. The omnibus test revealed statistically significant differences in the magnitudes of the individual police enforcement actions count predictors in both the AR1 (Table 16, $\chi^2 = 12.22$, $df = 3$, $p < .01$) and AR2 (Table 17, $\chi^2 = 8.21$, $df = 3$, $p < .05$) contemporaneous models. In the contemporaneous models, the effect of pedestrian stops was greater than the impact of traffic enforcement in the AR1 (Table 16, $\chi^2 = 12.09$, $df = 1$, $p < .05$) and AR2 (Table 17, $\chi^2 = 8.12$, $df = 1$, $p < .05$) models.

The omnibus tests for the lagged individuals police enforcement actions models were also significant for the AR1 (Table 16, $\chi^2 = 16.96$, $df = 3$, $p < .001$) and AR2 (Table 17, $\chi^2 = 14.18$, $df = 3$, $p < 0.01$) models. In the AR1 lagged model, the effect of pedestrian stops was greater than the effect of traffic stops (Table 16, $\chi^2 = 11.39$, $df = 1$, $p < 0.001$) as well as quality of life arrests (Table 16, $\chi^2 = 8.09$, $df = 1$, $p < 0.05$). The effect of traffic stops was also greater than the effect of quality of life arrests (Table 16, $\chi^2 = 4.86$, $df = 1$, $p < 0.05$). The results from the GEE AR2 lagged model are substantively equivalent (Table 17).

Individual police enforcement actions hot spot mean centered counts. The omnibus tests revealed no differences for the contemporaneous effects of the mean centered predictors in both the AR1 (Table 16, $\chi^2 = 3.05$, $df = 3$, n.s.) and AR2 (Table 17, $\chi^2 = 1.31$, $df = 3$, n.s.) models. In the lagged models, the omnibus tests revealed differences in the effects of the mean centered predictors in both the AR1 (Table 16, $\chi^2 = 12.03$, $df = 3$, $p < .01$) and AR2 (Table 17, $\chi^2 = 10.20$, $df = 3$, $p < .05$.) models. In the AR1 lagged model, the effect of pedestrian stops was greater than the effect of traffic enforcement (Table 16, $\chi^2 = 3.98$, $df = 1$, $p < 0.05$) and quality of life arrests (Table 16, $\chi^2 = 8.53$, $df = 1$, $p < 0.01$). The impact of traffic enforcement was also greater than the effect of quality of life arrests (Table 16, $\chi^2 = 5.99$, $df = 1$, $p < 0.05$). The only difference in the AR2 models was that the impact of pedestrian stops was not greater than the effect of traffic enforcement like it was in the GEE AR1 model (Table 17).

Summary of Quantitative Results

Two consistent relationships held in both the lagged and contemporaneous models across all three statistical techniques. Table 18 displays a summary of the results for the statistical models. The IRR's have been converted into the percentage change in the expected monthly violent crime count per standard deviation increase in the predictor (see Table 2). Only statistically significant effects have numerical values.

First, the total enforcement predictors linked to significantly higher levels of violence across all of the models. The only exception was the random effects lagged model with hot spot mean centered predictors. A standard deviation increase in total enforcement in the focal month increased expected violent crime counts in the focal month anywhere from about 20 to 40 percent (Table 18). A standard deviation increase in total enforcement in the previous month increased expected violent crime counts in the focal month anywhere from about 16 to 40 percent (Table 18). A standard deviation increase in contemporaneous (and mostly lagged) total enforcement above a hot spot's average level increased monthly expected violent crime counts by about 8 to 16 percent (Table 18).

Second, pedestrian stops also consistently linked to higher levels of violent crime across all models. Expected monthly violent crime counts were increased by approximately 12 to 28 percent for each additional standard deviation unit increase in pedestrian stops in the same month. The substantive effects were similar for the lagged effects of pedestrian stops (Table 18). Again, the mean centered effects were also patterned similarly. Increasing pedestrian stops above the hot spot mean by one standard deviation in the focal month increased expected monthly violent crime counts anywhere from about 8 to 12 percent. The lagged effects of mean centered pedestrian stops were substantively similar. Note when operationalized as raw counts, the traffic enforcement predictors linked to significantly higher monthly violent crime counts in both the contemporaneous and lagged GEE AR1 and AR2 models, but these results did not hold in the more stringent mean centered models where the effects are independent of across hot spot differences.

Differences across coefficients were consistently found for three predictors in the lagged models across all three statistical techniques. First, the positive impact of pedestrian stops was consistently larger than the effect of traffic enforcement in the lagged models. One exception is that the lagged effect of pedestrian stops was not larger than the lagged effect of traffic enforcement in the AR2 model. Second, the effect of pedestrian stops was also consistently larger than the effect of quality of life arrests in the lagged models. Third, the impact of traffic enforcement was also larger than the impact of quality of life arrests. It is noted that the effect of pedestrian stops was larger than the effect of traffic enforcement in the contemporaneous AR1 and AR2 models, but this difference was not found for the lagged random effects model or the more stringent mean centered models. Overall, the substantive results are consistent across all three statistical techniques.

Table 14. All violent crime and hot spot mean centered individual police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.2279	0.0959	0.2929	0.2136	0.4015	-1.1512	0.1143	0.3163	0.2171	0.4606
MC pedestrian stops	0.0181***	0.0035	1.0183	1.0066	1.0300	-----	-----	-----	-----	-----
MC traffic stops	0.0083	0.0039	1.0083	0.9954	1.0214	-----	-----	-----	-----	-----
MC QOL arrests	0.0232	0.0194	1.0235	0.9602	1.0909	-----	-----	-----	-----	-----
MC felony arrests	0.0078	0.0585	1.0079	0.8315	1.2217	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0170***	0.0035	1.0171	1.0056	1.0289
MC traffic stops lag	-----	-----	-----	-----	-----	0.0049	0.0040	1.0049	0.9919	1.0182
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0543	0.0238	0.9472	0.8758	1.0244
MC felony arrest lags	-----	-----	-----	-----	-----	-0.0179	0.0674	0.9822	0.7869	1.2260
Month – February	-0.2062	0.1070	0.8137	0.5722	1.1572	-0.3099	0.1190	0.7336	0.4958	1.0853
Month – March	-0.0721	0.1126	0.9305	0.6424	1.3476	-0.1357	0.1234	0.8731	0.5817	1.3105
Month – April	0.0251	0.1121	1.0254	0.7091	1.4829	-0.0422	0.1230	0.9587	0.6397	1.4369
Month – May	0.1399	0.1100	1.1501	0.8010	1.6515	0.0681	0.1209	1.0705	0.7192	1.5933
Month – June	-0.0452	0.1139	0.9558	0.6570	1.3905	-0.1267	0.1246	0.8810	0.5846	1.3277
Month – July	0.1925	0.1095	1.2123	0.8454	1.7384	0.1090	0.1202	1.1151	0.7509	1.6560
Month – August	0.2167	0.1094	1.2419	0.8666	1.7799	0.1094	0.1201	1.1157	0.7515	1.6564
Month – September	0.2107	0.1095	1.2345	0.8611	1.7698	0.0800	0.1203	1.0833	0.7293	1.6092
Month – October	0.1926	0.1095	1.2124	0.8456	1.7383	0.0891	0.1198	1.0932	0.7371	1.6213
Month – November	-0.0914	0.1147	0.9126	0.6258	1.3310	-0.2061	0.1242	0.8137	0.5407	1.2246
Month – December	-0.8261***	0.1351	0.4377	0.2807	0.6827	-1.0270***	0.1403	0.3581	0.2256	0.5682

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 14. All violent crime and hot spot mean centered individual police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					**Model B cont.**				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1024	0.0790	1.1078	0.8542	1.4367	0.1366	0.0819	1.1464	0.8756	1.5009
Year – 2011	-0.0375	0.0810	0.9632	0.7377	1.2575	-0.0100	0.0839	0.9900	0.7511	1.3050
Year – 2012	-0.7287***	0.0985	0.4826	0.3490	0.6673	-0.7250***	0.1009	0.4843	0.3475	0.6751
Year – 2013	-0.7816***	0.0998	0.4577	0.3295	0.6356	-0.7785***	0.1027	0.4591	0.3274	0.6437
PFPE Foot patrol	-0.0226	0.1612	0.9776	0.5752	1.6617	0.0846	0.1591	1.0883	0.6448	1.8371
PPTE Foot patrol	0.2679	0.2124	1.3073	0.6499	2.6294	0.3199	0.2101	1.3770	0.6897	2.7489
PPTE Offender-focused	-0.0925	0.2878	0.9116	0.3537	2.3500	-0.0987	0.2880	0.9060	0.3512	2.3370
PPTE Problem solving	-0.0736	0.3827	0.9290	0.2637	3.2730	-0.0825	0.3822	0.9208	0.2618	3.2386
Unit length	-0.0003	0.0001	0.9997	0.9995	1.0000	-0.0003	0.0001	0.9997	0.9995	1.0000

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 15. All violent crime and hot spot mean centered individual police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.2130	0.0990	0.2973	0.2147	0.4117	-1.1512	0.1173	0.3163	0.2150	0.4653
MC pedestrian stops	0.0143***	0.0037	1.0144	1.0023	1.0267	-----	-----	-----	-----	-----
MC traffic stops	0.0083	0.0040	1.0083	0.9951	1.0218	-----	-----	-----	-----	-----
MC QOL arrests	0.0220	0.0196	1.0223	0.9583	1.0905	-----	-----	-----	-----	-----
MC felony arrests	0.0107	0.0577	1.0107	0.8359	1.2222	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0145***	0.0036	1.0146	1.0026	1.0268
MC traffic stops lag	-----	-----	-----	-----	-----	0.0035	0.0041	1.0035	0.9901	1.0172
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0546	0.0238	0.9469	0.8754	1.0241
MC felony arrest lags	-----	-----	-----	-----	-----	0.0018	0.0656	1.0018	0.8074	1.2431
Month – February	-0.1906	0.1066	0.8265	0.5819	1.1739	-0.2706	0.1187	0.7629	0.5163	1.1274
Month – March	-0.0637	0.1048	0.9383	0.6646	1.3248	-0.1133	0.1165	0.8929	0.6085	1.3102
Month – April	0.0370	0.1096	1.0377	0.7235	1.4883	-0.0150	0.1209	0.9851	0.6618	1.4664
Month – May	0.1527	0.1083	1.1649	0.8156	1.6639	0.0951	0.1196	1.0998	0.7420	1.6300
Month – June	-0.0340	0.1132	0.9665	0.6659	1.4029	-0.0990	0.1241	0.9057	0.6021	1.3625
Month – July	0.2089	0.1090	1.2323	0.8609	1.7638	0.1395	0.1198	1.1497	0.7752	1.7051
Month – August	0.2314	0.1088	1.2603	0.8811	1.8028	0.1417	0.1196	1.1522	0.7774	1.7077
Month – September	0.2212	0.1082	1.2476	0.8740	1.7810	0.1064	0.1189	1.1123	0.7522	1.6448
Month – October	0.1988	0.1076	1.2199	0.8563	1.7379	0.1085	0.1176	1.1146	0.7568	1.6415
Month – November	-0.0912	0.1083	0.9129	0.6392	1.3037	-0.1908	0.1168	0.8263	0.5626	1.2136
Month – December	-0.8369***	0.1350	0.4330	0.2777	0.6752	-1.0144***	0.1409	0.3626	0.2281	0.5766

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 15. All violent crime and hot spot mean centered individual police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1015	0.0850	1.1069	0.8368	1.4641	0.1331	0.0880	1.1424	0.8551	1.5261
Year – 2011	-0.0726	0.0894	0.9299	0.6930	1.2479	-0.0434	0.0925	0.9575	0.7062	1.2983
Year – 2012	-0.7600***	0.1085	0.4677	0.3273	0.6683	-0.7518***	0.1110	0.4715	0.3272	0.6795
Year – 2013	-0.7949***	0.1097	0.4516	0.3147	0.6481	-0.7953***	0.1130	0.4514	0.3112	0.6548
PFPE Foot patrol	-0.0462	0.1666	0.9548	0.5518	1.6522	0.0464	0.1640	1.0475	0.6106	1.7970
PPTE Foot patrol	0.1975	0.2213	1.2184	0.5883	2.5233	0.2447	0.2191	1.2772	0.6210	2.6268
PPTE Offender-focused	-0.0959	0.3074	0.9085	0.3304	2.4983	-0.1015	0.3075	0.9035	0.3285	2.4852
PPTE Problem solving	-0.0450	0.3945	0.9560	0.2611	3.5007	-0.0503	0.3936	0.9510	0.2604	3.4727
Unit length	-0.0003	0.0001	0.9997	0.9994	1.0001	-0.0003	0.0001	0.9997	0.9994	1.0001

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table 16. All violent crime generalized estimating equations first-order autoregressive error models equality of coefficient Wald tests

	Contemporaneous Model	**Lagged Model**
	χ^2 (*df*)	**χ^2 (*df*)**
Table 12: Individual count predictors model		
Omnibus test	12.22(3)**	16.96(3)***
Pedestrian stops vs. Traffic stops	12.09(1)***	11.39(1)***
Pedestrian stops vs. Misdemeanor arrests	n.s.	8.09(1)**
Pedestrian stops vs. Felony arrests	n.s.	n.s.
Traffic stops vs. Misdemeanor arrests	n.s.	4.86(1)*
Traffic stops vs. Felony arrests	n.s.	n.s.
Misdemeanor arrests vs. Felony arrests	n.s.	n.s.
Table 14: Individual hot spot mean centered predictors model		
Omnibus test	3.05(3)	12.03(3)**
Pedestrian stops vs. Traffic stops	---	3.98(1)*
Pedestrian stops vs. Misdemeanor arrests	---	8.53(1)**
Pedestrian stops vs. Felony arrests	---	n.s.
Traffic stops vs. Misdemeanor arrests	---	5.99(1)*
Traffic stops vs. Felony arrests	---	n.s.
Misdemeanor arrests vs. Felony arrests	---	n.s.

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table 17. All violent crime generalized estimating equations second-order autoregressive error models equality of coefficients Wald tests

	Contemporaneous Model	**Lagged Model**
	X^2(*df*)	**X^2(*df*)**
Table 12: Individual count predictors model		
Omnibus test	8.21(3)*	14.18(3)**
Pedestrian stops vs. Traffic stops	8.12(1)**	8.80(1)**
Pedestrian stops vs. Misdemeanor arrests	n.s.	7.87(1)**
Pedestrian stops vs. Felony arrests	n.s.	n.s.
Traffic stops vs. Misdemeanor arrests	n.s.	5.09(1)*
Traffic stops vs. Felony arrests	n.s.	n.s.
Misdemeanor arrests vs. Felony arrests	n.s.	n.s.
Table 14: Individual hot spot mean centered predictors model		
Omnibus test	1.31(3)	10.20(3)*
Pedestrian stops vs. Traffic stops	---	n.s.
Pedestrian stops vs. Misdemeanor arrests	---	7.99(1)**
Pedestrian stops vs. Felony arrests	---	n.s.
Traffic stops vs. Misdemeanor arrests	---	5.76(1)*
Traffic stops vs. Felony arrests	---	n.s.
Misdemeanor arrests vs. Felony arrests	---	n.s.

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table 18. Percentage increase in expected monthly violence counts per standard deviation unit increase in statistically significant predictors

	Random Effects	GEE AR1	GEE AR2
	IRR*SD	IRR*SD	IRR*SD
Total enforcement	19.60	43.50	36.22
Total enforcement lag	16.26	41.50	39.81
MC total enforcement	8.61	16.05	13.72
MC total enforcement lag	n.s.	11.49	8.93
Pedestrian stops	12.34	28.13	26.49
Traffic enforcement	n.s.	20.82	20.94
QOL arrests	n.s.	n.s.	n.s.
Felony arrests	n.s.	n.s.	n.s.
Pedestrian stops lag	12.40	27.72	26.35
Traffic enforcement lag	n.s.	20.56	19.99
QOL arrests lag	n.s.	n.s.	n.s.
Felony arrest lags	n.s.	n.s.	n.s.
MC pedestrian stops	7.76	12.46	9.80
MC traffic enforcement	n.s.	n.s.	n.s.
MC QOL arrests	n.s.	n.s.	n.s.
MC felony arrests	n.s.	n.s.	n.s.
MC pedestrian stops lag	7.98	11.67	9.96
MC traffic enforcement lag	n.s.	n.s.	n.s.
MC QOL arrests lag	n.s.	n.s.	n.s.
MC felony arrest lags	n.s.	n.s.	n.s.

Notes: Numerical values are the percentage increase in expected monthly violence counts per standard deviation unit increase in the predictor for effects where $p < 0.001$. All models specified with a negative binomial probability distribution. All models include controls for the month, year, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and hot spot length in feet.

Abbreviations: GEE = Generalized estimating equations, AR = autoregressive, IRR = Incident rate ratio, SD = standard deviation, MC = hot spot mean centered, QOL = Quality of life, n.s. = not statistically significant

Qualitative Results

The results of the qualitative analyses addressing research questions three and four described in Chapter 4 are outlined below. Recall these results complement the empirical findings. In the discussion of the results, the qualitative data will be drawn on further to expand the quantitative findings (Morse, 1991; Palinkas et al., 2011).

Because the number of police commanders in the PPD is small, additional measures were employed to protect the study subjects' identities when reporting the qualitative results. No potentially identifying information, such as geographic identifiers or the names of special units, is provided. Additionally, potentially identifying information was also occasionally altered to further protect interviewees' identities. For example, each interviewee was assigned a pseudonym and the gender of some commanders may have been changed. The patterns and themes identified are illustrated by observational and narrative interview accounts which are verbatim and indicative of the most common patterns.

Even though the police commanders studied exercised discretion when developing the strategies and implementing the tactics they use to address crime problems, analysis of the field observations and interviews revealed that commanders shared common beliefs of what they thought they were doing when allocating resources to crime hot spots. Commanders also expressed similar rationales for believing their tactics would effectively address violent crime. When addressing violent crime hot spots, PPD commanders expressed the beliefs that they were: (1) "locking down" crime places, (2) disrupting high risk offenders, and (3) educating potential victims. Police enforcement actions played a vital role in "locking down" crime places and disrupting high risk offenders. Educating potential victims involved sharing crime prevention information with the community through different mediums. Police commanders' rationales for focusing on these objectives included: (1) making potential offenders "think twice", (2) removing potential offenders' and victims' opportunity to offend or be victimized by denying use of crime places, (3) getting potential offenders "off the street", and/or (4) target hardening.

Locking Down Crime Places

Police commanders emphasized the importance of "locking down" high crime places. While the importance of geography is implied, the commanders studied focused on both places with historically high levels of crime as well as places where multiple crimes had recently occurred but not necessarily concentrated over long periods. In other words, police commanders were interested in both short-term and long-term hot spots. Of course, it is possible that some short-term hot spots overlapped with some long-term hot spots in practice.

For example, Captain V stressed the importance of locking down a long-term violent crime hot spot in his district.

> There are certain areas in this district we're never going to move out of. We're just going to be there because that's where the history has been. And if it stops, if it drops down there, we're always going to be there because we know that it's always been there, two years ago, it's been there three years ago, so we're going to [be there]... (Interview, Captain V)

To lock down these historic crime hot spots, every PPD Captain had at least one "grid" that was designed by centralized crime analysts using historical data (three to five years of data), but most captains reported focusing on numerous grids that were identified locally using both crime and intelligence analysis as well as the commanders' personal knowledge and experience.

There was also a continuous emphasis on locking down places experiencing recent upticks in crime. When two or more crime events (e.g., robberies) occurred close in space (i.e., within a few blocks) and time (i.e., within a few days to a few weeks), police commanders would also focus on locking down those areas. The short-term focus was likely driven by the crime strategy meetings which typically focused on the previous 14 and 28 days, though there was no indication the police commanders studied disagreed with this temporal scale. For example, during one observed crime strategy meeting, one captain was questioned about what she was doing to address street robberies to which she immediately noted, “there have been two robberies on [street block] about a week apart” and indicated that area was her priority.

Regardless of the temporal extent of the hot spots focused on, locking down crime places involved using two tactics simultaneously: (1) increasing police presence and (2) generating activity. Locking down a crime place always purportedly started with police commanders deploying officers to the area in order to increase police visibility. When Captain V described his most recent success addressing violent crime, a strategy designed to address an area that had historically experienced high levels of gang violence, he explained:

> Deployment wise, we increased our deployment, we increased our visibility in that area, we got some feet on the ground… We didn’t solve the problems and walk away and then get the problem back again. But we’ve been in there. We still got the feet on the ground. We got foot beats down there and constantly hit that area, [Intersection]… and also officers assigned that PSA [Police Service Area] know if they are not answering priority jobs [Part I crimes in progress or officer assist calls], routine patrol, routine patrol that area. We want a more visible presence. We got cars, if you’re heading back to headquarters and you got a couple minutes, make a run through it. The more visibility [the better]. There’s a Dunkin Donuts there, right at [Intersection], you want to get a cup of coffee, go in there. I'm being serious. It gives a more visible presence, *so people get to see an increase*. We have a [public] housing, PHA [Public Housing Authority], a rec center there, that they use [gang members], we’ve been going in there and also using the bathroom, *just getting used to it*. So the visible presence but with a calculated move [in a historically violent area]… it worked, worked, and worked well so we're happy with it (Interview, Captain V, Italics added for emphasis).

Captain O put it much more simply, “We pick the areas where we have the most shootings, the most robberies, and the most property crimes and we put additional cops in those areas to bring down the crime. That’s what we do.” Captain L echoed this sentiment, “We’re tracking certain areas and being, you know, putting more resources in the areas where crime historically has been high and where violence has been."

When officers are deployed to lock down crime places by being more visible, it is also assumed they will be simultaneously "generating activity". In police parlance, generating activity means conducting enforcement actions, stopping pedestrians and cars, enforcing traffic laws, and arresting law breakers. After asking Captain V if he expected his officers to do anything special when deployed to the gang violence hot spot he discussed above, he responded, "We focus on activity. Activity is huge." The importance of generating activity to lock down crime places was also stressed during the crime strategy meetings. The following field note excerpts from the crime strategy meetings represent common exchanges stressing the importance of officers generating activity amongst the police commanders studied.

> The captain started by saying his main focus during this period [the last two weeks] was to concentrate on his violent crime grid areas. One executive commander then stated, 'I don't see the increase in activity we talked about.' The captain noted, 'we had an increase in Part I arrests, but I think I'm going to be moving some guys around to get the results we want.' The executive commander responded, 'Here's the thing. This place is firing up. I don't have time to wait. These areas need to be locked down. They needed to be locked down last week. You need to get your guys banging these areas [generating activity].' After a brief, (theatrical) pause, another executive commander questioned, 'You understand?' The captain responded, 'Yes sir.' And the other executive commander moved the meeting along by stating, 'Get it fixed' and shifted the focus to burglaries. (Observation 8)

In sum, among the commanders studied, there was a clearly expressed belief that they were deploying resources to high crime areas to lock down those areas by increasing police presence and activity levels to at least the executive commanders' subjective minimum threshold.

Police commanders' first conveyed rationale for locking down crime places was to make offenders "think twice". Captain Y explained how police presence and activity work together to achieve this effect.

> It's the presence, man. And I hear about it at the community meetings… You know, maybe they've seen a cop three more times than they usually see it, but the perception is, 'Hey man, the cops are around.' … But I like activity and I just think the more active officers are, and if it's channeled the right way in the right place… I don't like empty activity. Don't drive by a bus stop and stop everybody just to get numbers, you know, and that's just going to turn the community against us. But when you're stopping the guys that need to be stopped, we know who they are. They are all out on the corner every day, right? And it's easy in this district. You know, that mere presence, you know, really does act as a deterrent. So it has to be good and focused, channeled activity. It just can't be empty activity for the numbers… That's what I tell my guys, 'that 30 minutes you're in an area on a car stop, you know, there's no bad guys around. You know nothing bad is going to happen.' It's that presence, and the more active you are, you know? And believe it or not, the number one community complaint is that we don't target the bad guys. I try to reinforce to my guys that, that activity is not just empty activity, man. Don't stop cars for me at [Intersection], if you're a guy who likes traffic enforcement, 'God bless you, I want you to do that. But can we target that in our high crime, high problem areas where I have more of a presence?' They are still going to blow the stop signs, they're still going to make illegal turns, now I'm getting more bang for my buck because you're producing activity for me and then you're actually maybe deterring crime. That's the way I kind of look at it… (Interview, Captain Y)

Moreover, police commanders perceived that focusing enforcement actions on potential offenders communicates to them that the police are honing in on them and they should "think twice" about offending. Captain M explained, "If you stop somebody you're announcing, one, your presence and, two, you're acknowledging that person is on the corner, whoever it may be, and, so both of you are on notice." Further, Captain V suggested stopping potential offenders "lets those individuals know that we know what you're doing and now you're on our radar."

Overall, the rationale for increasing police presence and activity seems simple; create the perception of police omnipresence which in return should encourage offenders to "think twice" about offending (O. W. Wilson & McLaren, 1963). Furthermore, if enforcement actions are focused on high risk persons then those potential offenders know they should "think twice" about offending. As Captain O put it, "When they see a lot of cops around there, they get a little scared of something like that… And the other thing is stopping them… so that they know by stopping them we're looking [at them]." Because, as Captain Z stressed, "if we [the police] can get a sustained presence in an area to where the guys know, 'Hey the cops are around. Hey, they're going to stop us!' Maybe they won't carry that gun" or offend more broadly.

Police commanders also demonstrated the perception that locking down crime places – by increasing police presence and activity – will deny potential offenders' access to crime places thereby reducing potential offending and victimization opportunities at those locations. The studied commanders provided numerous examples of how increasing police presence would encourage suspicious persons to leave an area and reduce future offending and victimization opportunities in the area. In terms of removing suspected offenders from a location, Captain O noted, "When they [potential offenders] see the cops all around here, cops on a bicycle, cops on foot, they may go elsewhere." Captain Z gave a more general example of how police presence may remove suspicious people from an area who may later offend and/or be victimized: "My foot beats were off yesterday, I drove by [Intersection], all the junkies were on the corner, all the drunks were on the corner. You know, you go by when the foot beats are in there, they're gone." Alternatively, Captain O explained how his officers use pedestrian stops to force presumed drug dealers suspected of driving violence out of certain areas.

> I want them to stop the bad people. I don't want them stopping somebody who may be, you see some middle aged couple or something and they missed the yellow light or they go through a red light or something like that. I'm more looking for; we have known drug corners and known drug areas. I want my officers to focus on that. Cars are driving around there, people are hanging out on corners, and you could ride by say a group of males on a corner and if you come back here half hour, forty minutes later and they're still there, that's reason for a stop. They're obstructing the highway, three or more people, and we can stop them for that, and we can search them, and find out where they live, what are they doing here, *and tell them they can't hang here, and you tell them to leave…* We tell them, basically, *'you can't stay here*, go hang in front of your own house… if you don't live around here, hang in front of your house. You don't hang in front of somebody else's house…' (Interview, Captain O, Italics added for emphasis)

Regardless of whether potential offenders or victims leave crime places voluntarily because of increased police presence or due to having been told to leave during the course of police enforcement actions, the expressed rationale for denying potential offenders access to crime places is simple: “you remove the guy you remove his potential to commit violent crime or be a victim (Interview, Captain M).”

Generating Quality Activity

As detailed above, qualitative analysis revealed findings that police commanders expressed shared beliefs that they were locking down crime places by increasing police presence and activity in order to make offenders “think twice”. By denying individuals access to certain locations, commanders perceived locking down hot spots would also remove citizens’ potential opportunities to offend or be victimized. The qualitative data supporting those components of police commanders’ violent crime fighting strategies further suggest there was a subjective minimum quantity of activity expected by police commanders. In addition to a minimum quantity of activity, police commanders also stressed the importance of the quality of police activity – as some quotations from the previous section began to allude to. Quality activity was expressed as police enforcement actions that focused on the “right places” and the “right people”. The “right places” refers to crime hot spots. The “right people” refers to potential offenders. Generating quality activity is rationalized by the same crime prevention benefits that were discussed about general activity above, but additionally quality activity should also sometimes lead to arrests. This expressed expectation of some increase in arrest certainty was central to police commanders’ belief that they are also disrupting high risk offenders.

In practice, the focus on generating a minimum level of activity and quality activity proved to be a balancing act. As alluded to previously, the qualitative data demonstrated that the executive commanders would frequently point out when police commanders' activity levels were "insufficient" and police captains would refute this criticism by emphasizing the quality of their officers' activity.

> An executive commander asked the captain to give an overview of his district's activity. The captain noted he has been concerned about two areas. He described them as two grids, a few square blocks bounded by four street segments. The executive commander then interrupted him, 'I don't see enough activity. You need to make sure your officers are doing what they need to be doing.' The executive commander then urged the captain to do an analysis of his activity to make sure performance is where it needs to be. The captain noted that his officers have been patrolling his two grid areas with his lists of known offenders. The executive commander responded, 'Well, I should be seeing more activity on the map then.' The captain acknowledged that there had been a significant drop in activity, but noted, 'I'd rather my guys only make 100 stops of the offenders on my list than 500 any ol' body's. Like the good people. The church going ladies. My people are trying to stop the right people.' The executive commander then responded, 'I hear you, but that's still too much of a drop. It's getting to the time where a lot of people are going to be outside [referring to summer] and we need to make sure we're sending the right message out there.' (Observation 5)

However, executive commanders also stressed the importance of generating quality activity at times.

> An executive commander then moved the discussion to shootings. Shooting events were shown on the map. The executive commander then called for the district's activity to be displayed on the map as the captain gave an incident by incident overview of recent shootings. The executive commander asked about a specific job [shooting event], 'This job on [100 street block], it was a neighborhood dispute, right? Did we resolve that?' The captain answered that nobody was talking and they had been unable to solve it. The DC responded that the district needed to get its weekend activity up, adding 'Make sure your people are doing what they should be doing. A car stop at 9am on a Sunday ain't going to cut it'. (Observation 7)

Regardless of the need to meet the executive commanders' subjective minimum threshold for the quantity of activity, police captains also repeatedly emphasized the importance of quality activity during the interviews. Captain L pointed out:

> You know, I'd rather have lower activity and have it done the right way than somebody just producing numbers, which in effect, you know, are really useless. You know, I could stop every grandmother walking up and down [Avenue] and have a whole bunch of ped [pedestrian] stops, but in reality, what did I do, other than waste time and paper? (Interview, Captain L)

Captain Z echoed this sentiment and elucidated specifically what quality activity meant.

> I like activity and I just think the more active officers are, and if it's channeled *the right way in the right place*… I don't like empty activity. Don't drive by a bus stop and stop everybody just to get numbers, you know, and that's just going to turn the community against us. *But when you're stopping the guys that need to be stopped*, we know who they are. They are all out on the corner every day, right? … So it has to be good and focused, channeled activity. It just can't be empty activity for the numbers… (Interview, Captain Z, Italics added for emphasis)

In other words, quality activity was described as police enforcement actions focused on both the "right places" and the "right people". Captain V reiterated this point and spoke at length about generating quality activity focused on the "right places and the "right people".

> We use our activity strategically because we can't be everywhere. So what we do is we try to concentrate the activity where the crime is. We try to concentrate in those areas… And we just don't want to be stopping the old lady going to church on Sunday morning. It counts as a car stop, and you look at the numbers it says a car stop, they [the executive commanders] don't know if there's a car stop, the old lady going to church, or is it a car stop that got four knuckle heads out there probably committing a crime. So it's just not making the stop, it's making the vehicle investigation, and making a pedestrian stop. Who are you stopping? And what cars are you stopping? [Are] these stops then going to make the quality of life better for the people of the [District]? … We're not just stopping people to generate numbers; we're stopping people to prevent crime... (Interview, Captain V)

Similarly, Captain M asserted the need to be strategically focused on the "right places" and the "right people".

> You know, the cops are there for a reason typically. Might be some manager like me says, 'I got guys hanging out on [Street block] and robberies over there, you know, I want you to stop guys who are hanging out [on Street block].' So I'm giving cops direction and they're following up by saying, 'Hey, here's a guy on the corner of [Street], so I'm going to stop him.' You know, for this and that reason, and, you know, you need probable cause, or actually you don't, you can

> just have mere encounters and talk with people … But it really should be supported by information [about the 'right places' and 'right people']... (Interview, Captain M)

Alternatively, Captain O described how commanders use the descriptions of offenders – provided by robbery victims – to ensure officers are generating quality activity.

> We're not going to stop a regular person walking down the street. We're going to make sure we have descriptions of those people in the same area [where robberies had hypothetically just occurred][32] and I expect my cops to stop them. We can just have a mere encounter and just talk to them and say, 'what are you guys doing around here? You live around here?' Get their ID checked and let them go. That's all we do. And, you know we'll pat them down to see if they have guns on them. If they match that description [of offenders from recent robberies] we'll do something like that, but like I said before I want quality stops. I don't want to stop people just walking down the street or something like that. It could be two kids walking down the street going to play basketball or something like that. I don't want my cops stopping people for that… (Interview, Captain O)

This emphasis on generating quality activity – focused on the "right places" and the "right people" – also resulted in the other component of quality activity that was stressed by the police commanders studied, making arrests. For example, Captain O emphasized the importance of arrests when prompted directly about what makes a quality pedestrian or traffic stop.

> A quality car stop or a quality ped stop would be something that maybe results in an arrest. I mean if I have my officers stop 100 people in, say a week, the whole squad, I would expect to have maybe 25 arrests, whether they'd be all warrants, bench warrants or something… it's got to be a good stop and that's what I tell my cops. I say, 'Listen, they sometimes get on me downtown, our car stops or ped stops are down' and I tell them all the time, 'I'd rather have quality car stops and ped stops that may result in an arrest, or results in a bench warrant, or something, rather than just stopping people for the sake of numbers.' That doesn't help me because people sometimes have bad encounters with police and I don't want them to have that. Stop the right people. That's all I ask them [district officers] to do. (Interview, Captain O)

Captain X also noted that quality activity can help get wanted offenders off the street.

[32] During Captain O's interview, he frequently referenced a hypothetical scenario, albeit one he commonly deals with. He used the scenario, which involved an area in his district had experienced numerous robberies, in order to clearly demonstrate to the author how he might deploy his resources.

> [T]here are people, unfortunately, I think there's somewhere in the area between 40 and 50,000 people who are wanted on bench warrants for failing to show up for court and things like that, so you also have that residual, you know, that crossover, you're able to get people who, you know, are wanted off the streets also. (Interview, Captain X)

Furthermore, an observed discussion that took place during a crime strategy meeting provided particular insight into the intersecting importance of quality activity and arrests.

> The commanding officer for the homicide unit then detailed how some officers had made a "quality ped stop" in the area of some recent shootings. The officers stopped a guy who was believed to have been involved in the shooting based on intelligence. After a foot pursuit, the guy was caught with two guns. Ballistic evidence was then used to link the guns to the recent shootings. The guy was arrested for the shootings. (Observation 1)

This pervasive belief that quality activity will subsequently result in arrest appears to be central to Captain M's suggestion that if a hypothetical law was passed prohibiting officers from conducting "ped stops" then "we'd have to encourage people to surrender more, because we would have very little effectiveness".

Disrupting High Risk Offenders

In addition to discussions of the importance of quality enforcement actions in a more general sense, the commanders also believed that the generation of quality activity was vital to disrupting high risk offenders in crime hot spots. In the context of the present study's focus on violent crime, high risk offenders included repeat robbers and people (potentially) engaged in retaliatory violence.[33] In short, police commanders used crime and intelligence analysis to identify high risk places and people in order to deploy officers to generate quality activity focused on the most high risk offenders. In addition to the crime reduction and prevention benefits of police presence and activity previously discussed, commanders expressed the belief

[33] Though the present study focused on violent crime it is noted that police commanders were also concerned with high volume, repeat burglary, automobile theft, and theft from automobile offenders as well as other crimes.

that quality activity focused on high risk offenders may also result in their arrest and incarceration. The incapacitation effect of increased arrests was also described as a means of getting high risk offenders “off the street” and reducing future offending and crime levels. Disrupting high risk offenders was believed to be imperative because police commanders believed those individuals would continue to offend until they were “off the street”.

Repeat Robbers. The importance of identifying repeat robbery offenders and then working to disrupt their criminal behavior was apparent in both the field observations and narrative interviews.

> The executive commander then drew the captain’s attention to two areas on the robbery map displayed on the projector. The captain acknowledged the first area. He noted, ‘there have been two robberies on that block about a week apart.’ The robberies happened on a Friday and a Saturday, so his plan is to have his officers in the area this Friday/Saturday to make an arrest. He noted there were some cameras in the area, so detectives have been trying to get some of the tapes to see if they could identify any suspects. The executive commander gave a brief lecture to the captain and detective unit commander on communication and urged them to talk more and work a little faster on getting surveillance tapes after a pattern has developed. Another (lower ranking) district commander then tried to ease the tension a bit by noting that they were well aware that these two robberies were related and were looking for two Hispanic males based on victims’ descriptions of the offenders from both robberies. The executive commander then questioned, ‘you have enough resources to be out there?’ The captain responded, ‘yes, we’ll be out there.’ (Observation 3)

Captain O described a similar process.

> I actually will put a crime bulletin [report] out. It will be on the roll call board, each lieutenant will get a copy of it, but I’ll personally go to roll call, or have my lieutenants go to roll call, or my sergeant that was here, or the lieutenant that was here, and go to roll call. I’ll say, ‘Listen, we got this guy, these two guys doing robberies in PSA [Police Service Area] Two.’ And I’ll say, ‘This is the description, the times are from five o’clock in the afternoon till one o’clock in the morning. And then this is the descriptions, so I want a car in that area.’ Tell the line squad that they have to have a car in that area along with my two tactical teams I’ll put in that area. I have visible police presence. Sometimes when they see all the cops around they stop robbing. Unfortunately they’ll probably go elsewhere, but I’m hoping that my cops see two guys that match

> that description walking down the street, we'll stop and get ID from them, usually sometimes when my cops get out of the car these guys will just run, right away, they'll start running then we know they're up to something so we'll bring them in, maybe get them fingerprinted and photographed, find out who they are, and see if we can match them up to other robberies in that area. (Interview, Captain O)

The commonly expressed rationale for disrupting repeat robbers was that they would continue to offend unless they were removed from the street through arrest and incarceration. The importance of getting repeat robbers "off the street" emerged throughout the qualitative data in numerous ways. First, arrests of repeat offenders were frequently celebrated. An illustrative example of this was a celebration which occurred during an observed crime strategy meeting.

> When discussing a cluster of robberies, the executive commander then noted that the [district] was able to arrest two guys in the area for multiple robberies and that those offenders may even 'go for jobs all over the city', so the district should be credited with two good arrests. (Observation 2)

Also, evident was a shared belief that the arrest of repeat offenders was central to resolving crime problems. For example, executive commanders frequently urged local commanders to focus on arresting repeat robbers in order to resolve robbery hot spots during observations of crime strategy meetings.

> The captain started by noting a recent robbery pattern. The robbery pattern was identified based on the fact the description of the robber was the same for multiple events that were close in space. An executive commander noted that the times were different on the jobs, but the captain insisted that the events were related based on the offender descriptions. The executive commander then asked if the detectives had anything and the detectives noted they didn't. The executive commander then questioned, 'what's your deployment like?' The captain noted that she was using bike teams and her five-squad in the area. The executive commander responded, 'This is an odd area. Give me more.' A [Special Unit] commander then chimed in that 'there's no video in the area.' The executive commander then asked for the district's activity to be displayed on the map, 'satisfied?' The captain responded, 'they're doing things, so…' The executive commander then interrupted, 'There's no reason to think he's in custody [unknown suspect for the robbery pattern] so there's your problem.' (Observation 6)

Likewise, the following discussion clearly illustrated the police commanders' pervasive belief that disrupting repeat offenders by getting them off the street is imperative.

> The executive commander then instructed the captain to get his [the repeat robber's] picture out to his patrol officers to make sure they know to get him 'off the street'. The captain then noted, 'We will. That's how it works. Get one of these guys off the street and the pockets disappear.' (Observation 3).

Similar to findings from the field observations involving PPD commanders at different ranks, the interviewed police captains also explicitly emphasized the importance to arresting repeat offenders in order disrupt them. Also, captains elaborated on their expressed belief that repeat robbers would not simply stop offending on their own. Captain X explained:

> They'll feed in that area and they'll keep hitting it, hitting it, and hitting it until they're caught. Just had one, two weeks ago, you know, where the guy was arrested for two robberies, and, so, just reading over the crime reports that I do every day, as soon as I saw he was arrested, his description, the location, you know, I got right on the phone with the captain from upstairs [Divisional Detective Captain] and I said, 'I know there's at least four other ones'. And then here as they looked and reached out and then, you know, now they're up to about 16 or 17, not just here but, you know, up in [Neighborhood] where the guy's from. (Interview, Captain X)

Captain V also shed light on the shared assertion that repeat robbers would not only continue to offend, but they would also continue to target an area unless they were disrupted through arrest.

> You got to lock these guys up. You got to be aggressive in locking them up. And that's with us putting our feet on the ground. Getting out there. Cars, bikes, foot beats. Whatever we need. And that's also cooperating with our detectives, so they can get out there and we can get some information and these jobs worked so we can cut down. It's a process... (Interview, Captain X)

Thus, the logic for focusing on repeat robbers is simple; if particular offenders are responsible for a high volume of offenses then the police should identify those offenders, target enforcement actions toward them, arrest them, and remove them from the street in order prevent offending and reduce robbery levels in the future.

Retaliatory Violence. Similar to concerns surrounding repeat robbers, police commanders also emphasized the importance of focusing on people with the potential to engage in retaliatory violence. Demonstrated across both observational and interview narrative accounts, this concern emerged out of the common belief that rival violent offenders would continue to target each other until – just like repeat robbers – they were “off the street”. The following field notes excerpts demonstrate the importance of focusing on retaliatory violence.

> The executive commander then moved the discussion to homicides. The commander of one [Special Unit] briefly described the parameters of each homicide event: location, modus operandi, motive, any relationships among people involved. The homicides in this district were attributed to two groups battling with one another. Some guys involved in an earlier shooting were caught on phone calls from the local jail discussing how they had recently retaliated against the other group. A consent search on the house of one of their girlfriends returned a bunch of ammunition and drug paraphernalia. A different [Special Unit] commander suggested that at least one of the groups involved in this battle was a serious player with easy access to guns and territory all over the city. The overarching discussion amongst the commanders centered on where the families of these groups lived and whether they should expect retaliatory shootings in other areas of the city. One executive commander instructed everyone present [the district and special unit commanders] to try to place more pressure on these groups. The district captain noted that the recent shootings were her fault because she did not realize the possibility of retaliation in time and moved her officers from the area. As soon as her officers moved, the most recent shooting occurred. The captain assured the executive commander that her people would stay in the area and make sure nothing else happened. (Observation 1)

The emphasis on retaliatory violence is also well illustrated by a crime strategy meeting discussion where participants collectively determined that a domestic homicide required no further police focus because retaliation was deemed unlikely.

> An executive commander asked about another shooting event on the map. The captain said the event was a domestic where a husband shot his wife and the husband was in custody. The executive commander then responded, ‘No need to focus on that one. Let’s move on to the next district.’(Observation 1)

In other words, because the homicide had been solved and was not likely to spur retaliation, the commanders collectively believed it was unnecessary to spend any more time discussing a potential strategy for addressing any future violence stemming from the event.

During the interviews, captains also discussed how they deployed their resources in order to address retaliatory violence. Captain M described a recent strategy he used to address an area with high levels of gang violence.

> So what we did with that is we identified the gang members... We do kind of a biographical profile of these gang members… Then we made the cops in the patrol sector, PSA [Police Service Areas], and the tactical teams I use a lot, and we say this is where we need you to be because there's gang friction here. I need you guys to be in the area of [street block] and I want you stopping people there, and not just people, but the right people. These are the gang members [gesturing towards a pile of papers on his desk like they were list of gang members]. These are the guys on the corner, these are the guys hanging out in the alley, these are the guy on the steps, you know. And I need you as officers to go out and stop those guys based upon probable cause and interfere with their operation [narcotics sales] so to speak. And that's what we do basically. And then in doing so we usually glean results in terms of, we get gun recoveries, we get narcotics recoveries, and you know even minor violations like traffic violations and all that, all builds our information base. And then the officers that're knowledgeable just work on that and continuously, maybe for weeks. And in doing so, one we have officer presence there. So we reduce the chance for a crime to happen. Two, we know these guys. If you look at the history of violence particularly in gangs, gangs are kind of easy in that because if there's a history of violence it's, we're pretty certain that it's going to continue because they don't stop and go home. So we look for ways to intercede and the presence there and in doing those enforcement efforts denies them the opportunity to go out and shoot someone else or get shot themselves while they're on the corner. So because another gang is not going to come over with the cops hanging around all the time, you know, they say it's 'hot out', or whatever, you know, 'the heat is on', that kind of stuff. So I mean that's our basic interdiction strategy. (Interview, Captain M)

Captain M's remarks demonstrate a number of key points. First, the previously discussed beliefs on using police presence and activity to make (specific) offenders "think twice" and deny them the use of places in order to reduce offending and victimization opportunities were reiterated. Second, the use of quality activity focused on high risk gang members in hopes it would generate arrests is illustrated. Third, police commanders' commonly expressed belief that offenders with the propensity to commit retaliatory violence will continue to engage in violence unless the police stop them was introduced.

Additional remarks by Captain M further illustrate the shared belief that retaliatory violence will continue until the police disrupt the offenders involved.

> If you look at gang violence, you can even do it for regular shootings, sometimes you can trace shootings back 10 years. A course of shootings. I mean because one victim knows another victim. We've had shootings so long that people can't remember what the original argument was over, but they do remember the last shooting was a guy from [street block] shot by a guy from [street block]. So, 'we don't like them guys in general, we're going to go to [street block] and shoot them.' So they might not even know the original cause of the argument they just want to be engaged in the, in the friction, and we have done that study in the past and I think there's a link between a lot of shootings, a tremendous amount of shootings we get the same, we got repeat offenders and we got repeat victims all the time and a lot of times people, you know, look at the police and say, 'this guy is a victim, you know, why are you picking on him?' Well this guy has been a victim 7 or 8 times, you know, it didn't happen by accident, and he knows more than he's telling us… A lot of our shooting victims we get, you know, we know are involved in the drug trade or we know this or we know that and they just tell us they don't know who shot them, they just heard a noise and they felt pain in their leg, you know, well you know, 'what were you doing out there at 3 o'clock in the morning? There's nothing there but a car wash, you know.' (Interview, Captain M)

Captain V expressed similar sentiments.

> We're always going to be where we're having shootings at. That's going to be one of the grids we're in. We're going to lock that area down. We're going to get in that area right after the shooting. We get in that area, we're conducting ped stops, we're conducting vehicle investigation, we gain intel, we're working with central detectives, we're trying to get that information out there to lock it down. We want a visible presence, so if I was, god forbid, to have a shooting across the street tonight, we want more visible presence there [points out the window]. We don't want a retaliation shooting. We don't want this guy who is shot, now he's going to come back. (Interview, Captain V)

But Captain V then went on to discuss the particular importance of getting offenders at risk to engage in retaliatory violence off the street. Captain V demonstrated how intelligence, particularly intelligence gathered through social media, helps police commanders focus their efforts to do so.

> When somebody gets shot and we know the victim, and we're able to get access to the victim's Twitters page, or whatever page, we can find out who he runs with. We'll get information about, 'yeah, such and such was shot and we want to retaliate, or whatever' so it's good. It's a crime fighting tool and it's great…. Now we know that such and such was shot by such and such and such and such is planning on retaliating at this particular place, so it's huge. Now we are using that knowledge and we're using it wisely. So you're preventing, now you're being proactive with it, and not just waiting for the shoe to drop. If you know Criminal A was shot by Criminal B now Criminal C wants to go back and shoot up Criminal B because Criminal C and Criminal A are friends, now we can intercept that so now we can avoid Criminal C shooting Criminal B and also now we can lock up Criminal B for shooting Criminal A. We get all that because of social media. I mean we get that, it's huge. (Interview, Captain V)

Overall, addressing retaliatory violence is a major focus of the studied police commanders. They shared the common belief that the best way to address retaliatory violence was to use police presence and quality activity based on the rationalization that it would make offenders "think twice" about offending and reduce offending and victimization opportunities by denying people the use of high crime locations. Further, the importance of disrupting high risk offenders – hopefully by arresting and incarcerating them – was stressed because the belief they would continue to engage in violence unless the police stopped them.

Educating Potential Victims

The final emergent component of police commanders' efforts to address violent crime was their shared belief that educating the public on how to protect themselves from victimization was important. While educating potential shooting victims was not discussed within the qualitative data, education emerged as a commonly identified approach for addressing property crime and robbery.[34] The commanders' rationale for educating victims centered on "target hardening". It was believed that potential victims would take precautionary actions to protect themselves from victimization if they were aware of the victimization potential they faced and some possible actions they could take to reduce it.

Educating potential victims involved various activities that took place across numerous mediums, such as talking with citizens at community meetings, talking with students at schools and local universities, distributing flyers around neighborhoods, calling residences via the reverse 911 system, and even writing articles for neighborhood-based newspapers. Captain L described using a variety of means to educate citizens from his district on how to better guard themselves against victimization.

> The other part is also working with the community because each lieutenant has their own PSA and their PSA meetings with the community. And I have a town hall meeting, and a [District] workshop that we have here… We like to give people information, we try to educate them on what's going on in their area. Certain areas are hit heavy... So when people from the community come in, dependent on where they're from and what PSA, they have their own unique problems which is unique to them and their own quality of life problems, and we try to get the neighbors involved, if they want to get involved, we have town watch which is very good. It comes in and trains. Yeah. And we try to get them involved, even if it's not a town watch per se, if they just keep an eye on their own block. And I've also, several times, put out, robo calls, reverse 911 calls out to the people in the district, you know? Education is a lot worth it. That's why I try to do an article in the [neighborhood] paper, that's why I do the reverse 911 calls, community meetings, we try to let people know. Anything that we can do to get the message out, and other meetings we go to, like last night I went to [neighborhood] partners' meeting. Gave them an overview of the crime in the district and different things we've done which have been successful, and, which things that, you know, us and the community working together could help alleviate a little bit better than what we've done so far. (Interview, Captain L)

In addition, Captain L discussed handing out educational flyers to local restaurants when robberies of delivery drivers spiked.

[34] This point is still discussed for a number of reasons. First, educating potential victims was an important component of police commanders' strategies to address robbery hot spots. Second, educating potential victims may have important implications for the design of future hot spots policing strategies.

> We give out flyers for everything, you know burglaries, auto thefts, theft from autos, even to some of these pizza shops, when we're having problems with pizza delivery men getting robbed. Just to give them pointers; make sure you call back before you leave, make sure it's legitimate, you know, make sure you have the phone number recorded, you know, stuff like that. 'Cause the driver might get it using his cellphone and when he's robbed they take his money and cellphone. So well that number you called back is on the cell phone that was stolen. So make sure the businesses have it. Just little things like that… (Interview, Captain L)

Others described comparable initiatives oriented towards educating juveniles and young adults about their common victimization risks. Captain V reported working with the [University] Police Department to distribute crime prevention information to students because they were frequently robbery victims in his district.

> A lot of times we try to tell the kids, 'know your environment, walk in pairs, don't be out by yourself. Certain areas where it's dicey, maybe have three or four. Don't, maybe not walk. Maybe jump in a cab. If you've been drinking don't stumble down the street' because a lot of times that opportunity may lead to something bad happening. But even then, when we have an increase near [University] with robberies, we increase our presence in the area and make sure we get boots on the ground, increase our presence, we're constantly in communication with [University] police, we'll send them their messages out to the students [typically via email]. So constantly, we [the police] still want to address it [using the means previously described] but also you want to make sure that you're not, don't put yourself [in the situation] to be a victim if you can, if you can, you cannot be a victim. (Interview, Captain V)

Captain M also described an education campaign designed to reduce juveniles' robbery risk due to being distracted by their cell phones.

> What we're seeing now is that in the recent history, juveniles are carrying these cellphones, so what used to be a $60 cellphone is now a $400 computer or $600 computer and, you know, the numbers go up from there… So what we find is juveniles are ignoring their environment. Totally. And they're totally absorbed by the virtual world. In other words, if they're getting out of school and walking to the bus, they're looking at their phone and engaging that instrument the whole time they're walking. They're oblivious to the environment entirely, and that's the reality of the situation… They're more concerned about the virtual world than the actual world, so what we're doing now is recognizing that, you know, a basic in policing, we don't want anybody to be a victim of anything. And we don't even want them to fear being a victim of something, so what we're trying to do for juveniles now, and it's going to take a while, is to constantly

> educate and reinforce them on different ways how not to be a victim. Because if you're a juvenile walking down the street with your $500 cellphone, you're coming out of school, you're absorbed in your Facebook, or whatever, Instagram, you know you're a target because people see the phone, they see that you're distracted and you're not paying attention to your environment, so those factors right away just send the antenna up for a would be robber. I can walk up, it's a juvenile anyway, so generally they're smaller people, and I can punch that kid in the head and take his cellphone and I'm out of here, it happens a lot. Easy target, so what we're trying to do is go to our schools, there's [number] schools here in the [district], go to our schools, we created posters about describing how not to be a victim and we just use simple things. We're not going to get them to give up their cellphones. That's not going to happen. We kind of ceded that battle, but what we can do is say, 'you should be aware of your environment', just reinforce that, 'you should walk home with a friend or a couple of friends when you can, when it's available to you, you shouldn't take your cellphone out or display any electronic devices, iPad or anything else, computer, until you are at a safer harbor...' And, you know, we're going to just keep doing that for years. So that's a battle that we're engaged in right now at the beginning of the school year we made posters, we hung them up in every school here in the [District], we made flyers and pamphlets to hand out to each student, saying the same things as on the posters, and then what we're doing is going to the general assemblies that each school has normally a couple times a year, we're going to them and repeating the same thing. We think, you know, here that if we constantly repeat that message eventually somebody will hear, but it won't be this week, and it might not be this year, but it could be four years from now. So that's what we're looking at. We're trying to plant those seeds now, just constantly reinforce it until it becomes, you know, normal... (Interview, Captain M)

Summary of Qualitative Results

Findings from the qualitative analysis suggest that the police commanders studied had commonly held and expressed beliefs about what they were doing to address violent crime hot spots as well as shared rationales for why their preferred actions were perceived as effective. The findings demonstrate that police commanders believed they were doing three things: (1) "locking down" crime hot spots, (2) disrupting high risk offenders, and (3) educating potential victims. Police commanders rationalized these beliefs based on four explanations of their perceived effectiveness: (1) making offenders "think twice", (2) denying potential offenders and victims certain places in order to reduce crime opportunities, (3) getting high risk offenders "off the street", and (4) target hardening.

First, police commanders stressed the importance of “locking down” crime places by increasing police presence and activity. In return, offenders, especially repeat offenders who were often the targeted recipients of enforcement actions, would begin to “think twice” about offending in the area. Additionally, it was found that police commanders internalized the belief that “locking down” crime places would consequently deny potential offenders and victims the opportunity be present in high crime places and better ensure that future crimes would not occur. This crime reduction benefit was achieved when potential offenders and victims would voluntarily avoid places where police presence was high or would simply leave once officers used enforcement actions to encourage them to do so.

Moreover, the findings demonstrate that the commanders studied believed police activity can be of varying levels of quality. Specifically, high quality activity involved police enforcement actions focused on hot spots and high risk offenders. Quality activity then might lead to the arrest of active or wanted offenders. In practice, local commanders had to balance generating sufficient activity to satisfy the standards of executive commanders while still focusing their officers’ efforts on generating quality activity. The importance of generating quality activity proved paramount within the qualitative data. Commanders stressed that they believed that the same crime reduction benefits achieved through “locking down” crime hot spots would be enhanced through quality enforcement actions that would both make high risk offenders “think twice” and potentially incapacitate them through arrest and incarceration.

The generation of quality activity also proved important to police commanders’ expressed belief that they were disrupting high risk offenders. The findings suggest that commanders specifically emphasized focusing on and disrupting repeat robbers and people with the propensity to engage in retaliatory violence. This shared belief was rationalized based on police commanders' expectation that both types of offenders would continue to offend unless they were stopped by the police. This rationalization meaningfully contributed to commanders' focus on deploying their resources in a manner in which they believed would increase the likelihood of arresting those offenders in the hopes of getting them "off the street".

Finally, educational efforts were identified as another component in addressing hot spots. Police commanders demonstrated their belief that it was important to increase public awareness of potential victimization risks as well as educate potential victims on how to better protect themselves. Commanders identified a variety of mediums used to educate citizens on how to protect themselves from property crime and robbery victimizations (e.g. community meetings, school visits, informational flyers, and reverse 911 calls). Overall, the findings demonstrate a shared belief that by educating citizens on what they could do to protect themselves from victimization would then lead to them engaging in target hardening behaviors and be less likely to become a future victim thereby translating into reductions in hot spot crime levels as well.

CHAPTER 6: DISCUSSION

Chapter 5 detailed the results of the quantitative and qualitative analyses designed to address four research questions. (1) Do four police enforcement actions focused on offenders or potential offenders reduce violent crime in hot spots? (2) Are any one of these four police enforcement actions more effective than the others? (3) When police commanders allocate resources to crime hot spots, what do police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots? This chapter starts by discussing possible explanations for the observed quantitative results. Next, the pros and cons of the policing strategy that emerged during the qualitative analysis are discussed in the context of the criminological theory and crime control literatures. The theory and policy implications of the findings are then discussed. The qualitative data are drawn upon in some parts of the discussion to provide a deeper understanding of the findings. The study's limitations and conclusion follow.

Research Questions 1 and 2

When all police enforcement actions are considered together, it was found that enforcement actions actually linked to higher monthly violent crime levels. When police enforcement actions were considered individually, only pedestrian stops (and sometimes traffic stops) remained positively linked to monthly violent crime counts. Additionally, the Wald Tests found the effect of pedestrian stops exceeded those of traffic enforcement and quality of life arrests.

The next question becomes, why would pedestrian stops (and traffic enforcement) increase monthly violent crime counts? There are at least five possible explanations: (1) an anticipatory effect, (2) over-deterrence, (3) escalation, (4) unintended enticement and self-fulfilling prophecies, and (5) temporal scaling. These explanations are elaborated below. Because the traffic enforcement effects did not hold in the more rigorous hot spot mean centered models, the effects of pedestrian stops are mostly focused on but the explanations may also make sense for the less consistent traffic enforcement effects.

Anticipatory Effect. The anticipatory explanation may follow a complex process. First, police anticipate violent crime is about to break out in violent crime hot spots using crime and intelligence analysis. The PPD's ability to anticipate violent crime spikes based on crime and intelligence analysis is supported by the qualitative data. For example, Captain Z described how an arrested citizen provided intelligence that a new group of drug dealers was trying to move onto a block previously occupied by another group.[35]

> Well all of a sudden we're seeing beefed up presence over there. So, my cops, they noticed it, they make a gun arrest, a young Spanish kid. They ask him why he's got a gun, he says 'it's getting dangerous around here, can you see all them black guys [making a pointing gesture]?' So, another organization moved in and [was] trying to open up... So, when you drive out there and you actually look at it, nothing [is] showing up in the numbers [official data] because we don't have anything going on out there. But when you go out and look… 'wow, all right, they're setup'. They're watching me when I came in because they don't recognize the car… They're looking at me right away, like, 'alright, is this someone that's going to shoot at us?'… So, but just things like that so, why, I always rely on my numbers and my mapping that human piece of the intelligence process is, you know, what I see visually on the street and what my guys are telling me. (Interview, Captain Z)

Officers are then deployed to locations where future violence is anticipated. After their deployment, officers immediately generate higher levels of pedestrian stops (and traffic enforcement). Regardless of police commanders' correct anticipation of future violent crime, pedestrian stops (and traffic enforcement) still failed to produce measurable reductions in

[35] In many instances police commanders discussed how they often use intelligence collected from different sources, such as arrested offenders, social media, or tips from the community, to anticipate when and where violence will to break out in the future and then deploy their resources in those locations.

monthly violent crime counts. This failure could be explained by different dynamics: (1) dosage, (2) over use of enforcement, (3) police legitimacy, (4) temporal displacement, (5) imprecise measurement, and (6) lack of a proper counterfactual.

First, it may be that some offenders are so motivated that police simply are not able to increase pedestrian stop (or traffic enforcement) levels high enough to alter their decision making. In other words, the dosage of these actions may increase, but not to a level that changes offenders' decisions to offend. This explanation assumes there is a threshold effect for pedestrian stops (and traffic enforcement). Other researchers have previously suggested a threshold effect exists for the relationship between clearance rates and crime levels (Chamlin, 1991; Kane, 2006; Tittle & Rowe, 1974). This explanation could be explored with different research designs in the future as long as police commanders have additional resources available.

Second, it may be that pedestrian stops (and traffic enforcement) are ineffective because they are overused and have become normalized in violent crime hot spots. If potential offenders experience, witness, or hear about people (and cars) frequently being stopped then those actions may not actually signal that the certainty of punishment has increased. This dynamic may be exacerbated if law abiding citizens are frequently the recipients of police enforcement actions because then stops may not be associated with criminal behavior as clearly. Further, pedestrian stops require the lowest legal burden to conduct (compared to traffic enforcement and arrests). Therefore, police may be able to quickly increase pedestrian stops shortly after a crime problem arises even if they will not be effective. It follows that pedestrian stops will dramatically increase even though they have little effectiveness.

Third, and somewhat similar to the normalization explanation, it may also be that police legitimacy is low in high crime places that experience frequent pedestrian stops (and traffic enforcement) (Brunson, 2007; Brunson & Miller, 2006; Gau & Brunson, 2010). Lower levels of police legitimacy is hypothesized to link to a lower likelihood of obeying the law (Tyler, 2003, 2004). Therefore, even as pedestrian stops (and traffic enforcement) increase, offenders who do not view the police as legitimate will not stop offending when the motivation to offend remains high.

Fourth, temporal displacement may occur if offenders wait until the police leave to commit crimes (Reppetto, 1976). In fact, Captain Z described a scenario where two groups in a dispute had a shoot out shortly after his officers left an area they had been heavily patrolling in order to reduce gun violence.

> Around the spring time it really took off to the point where I could not leave the area unattended. There always had to be a cop there, and they were still shooting, with cops around the corner. They're waiting for our guys to pull out of sight and they were doing their business. (Interview, Captain Z)

As the quotation from Captain Z demonstrated, potential offenders may recognize higher levels of pedestrian stops (and traffic enforcement), but simply wait until the police are no longer present to offend. This point has also been made about offenders in Baltimore who were said to wait to offend during police shift changes (Moskos, 2008). In other words, the processes anticipated by the police to result in future violence (e.g., retaliation) may be too strong to disrupt through pedestrian stops, and offenders may simply wait for more opportune times to offend. More pedestrian stops (and traffic enforcement) also means more paperwork for police and that may actually translate into less time for police to be on the street:

> A ped stop used to be a simple 48 [form] with the name, address, and date of birth on there, and that was it, and the reason for the stop but that was it. You just write down a quick note. Well now it's a little more elaborate form, takes longer, and each one has to be entered into a database… It takes time, certainly manpower intensive, 'cause I mean, you're kind of writing it down, you are writing it down, and you're duplicating effort by entering it, entering it into a database… it's very, very time consuming. (Interview, Captain M)

Fifth, it is also possible that (at least some of) the pedestrian stops (and traffic enforcement) conducted during the study were not effective because they did not target the "right people". The quality of police enforcement actions was emphasized by police commanders in the qualitative data. Recall the pedestrian stops (and traffic enforcement) variables used in the present study only capture the quantity not the quality of the actions taken. If officers are not conducting quality pedestrian stops (or traffic enforcement) then it may be unreasonable to expect them to have any measureable crime control benefits even if they are actively increasing the volume of actions in the area. Street-level officers may be even more apt to generate higher numbers of low-quality pedestrian stops (and traffic enforcement) when their supervisors are pressuring them to concentrate on a particular area where violence is anticipated.[36] On the other hand, the crime control effects of the quality pedestrian stops (and traffic enforcement) police were generating may be going undetected due to the imprecise measures used in the present study.

Lastly, the quasi-experimental nature of the study means that there was not a counterfactual of what would have happened if the police did not conduct any pedestrian stops (or traffic enforcement). Therefore, it may be that violent crime may have increased even more than was observed had the police not conducted any pedestrian stops (or traffic enforcement). This scenario was observed during the Philadelphia Foot Patrol Experiment, but the study's experimental design allowed the researchers to detect the crime reduction benefits of foot patrol (Ratcliffe et al., 2011).

[36] It is important to point out that stopping someone who is not likely to be involved in a violent crime in the near future and conducting an illegal pedestrian or traffic stop are not synonymous. Officers could easily meet the legal requirements to execute the enforcement action without targeting serious violent offenders.

Over-deterrence. A second explanation is that the police enforcement actions generate over-deterrence and disrupt guardianship in hot spots (Grabosky, 1996). It is possible pedestrians (or drivers) who are stopped typically serve as guardians in violent crime hot spots. When the police increase pedestrian stops (or traffic enforcement), they may succeed in discouraging people from using the space, regardless of those individuals' motivation to offend. Once those residents and potential guardians leave the hot spot then offenders are free to capitalize on the prime offending opportunities in the area. Even if pedestrian stops (and traffic enforcement) are only targeted against potential offenders and encourage them to leave the area, they may still provide positive benefits to the area, such as guardianship, despite their involvement in crime as well (Pattillo, 1998).

Escalation. A third explanation may be that police enforcement actions ultimately escalate competition over offending locations among rival offenders. The competition process would occur when increased levels of pedestrian stops (and/or traffic enforcement) in a hot spot discourage offenders from using an area. Next, rival offenders may notice the void in territoriality and attempt to take over the area, perhaps after the police activity decreases. Finally, a "turf battle" may then transpire once police activity subsides and the original offenders return and attempt to regain control over the area.

The overlap between drugs and violent crime has been demonstrated empirically (Lum, 2008). Violence stemming from competition over drug corners has been demonstrated empirically as well (Taniguchi et al., 2011), and there are certainly instances of multiple groups attempting to control particular areas in Philadelphia. Captain Z noted:

> We have three very distinct organizations operating on three small blocks along [Avenue]. Two actually get along. If one shuts down, they'll send their customers to the other one and vice versa. The third actually doesn't like the

> other two, and that's been a good majority of the shooting. (Interview, Captain Z)

Therefore, it is possible that if the police were successful at using pedestrian stops (and traffic enforcement) to dissuade potential offenders from using a particular space then violence may have increased later on when those offenders return and rival groups have moved in to claim that space as well.

Unintentional Enticement & Self-Fulfilling Prophecies. Fourth, increasing pedestrian stops (and traffic enforcement) may have increased violent crime through unintentional enticement or self-fulfilling prophecies (Grabosky, 1996). For example, if the police informed people they were conducting pedestrian stops on them because of an increase in robberies in the area, then they could have unintentionally enticed those people to commit robberies as well if those people change their perceptions of robbery opportunities in the area. Likewise, if the police inform a gang that they are stopping them because they have the potential to retaliate then that may encourage retaliation if the gang believes it will help them maintain their reputation (Anderson, 1999).

Temporal Scaling. The monthly temporal scale employed in this study may also explain the observed positive impacts of police enforcement. Taylor (2015) discussed two issues with temporal scaling that may be relevant to the monthly periods employed here: (1) time horizons and (2) unity of time horizons. Time horizons relates to a lack of clarity on how long it takes for a variable to change. Unity of time horizons relates to whether or not predictors change with the outcome during the same temporal unit. It may be that the cycle of increased enforcement and subsequent decrease in violent crime counts occurs at a different temporal scale than the monthly periods employed in this study.

In the literature, deterrence theory does not detail the temporal scale at which deterrence effects should be observed (Cousineau, 1973), and deterrent effects for arrests and crime levels have been found for temporal units ranging from a day (D'Alessio & Stolzenberg, 1998) to a year (Kubrin et al., 2010). In practice, the temporal scale of policing is complex. In order to appease executive commanders, local police commanders must demonstrate they are addressing crime problems in response to crime strategy meetings which focus on both the previous 14 and 28 days. Additionally, some police captains may attempt to appease executive commanders by focusing on shorter temporal scales in order to demonstrate that they are addressing crime problems prior to crime strategy meetings. For example, as detailed in the qualitative findings, one police captain noted during a crime strategy meeting, "there have been two robberies on [street block] about a week apart" and indicated she was focusing her resources there before the crime strategy meeting. Finally, the qualitative data also revealed that police commanders consistently focus on places that have been long term crime problems.

Therefore, in the context of Taylor (2015), police may be implementing police enforcement actions at temporal scales smaller than months, such as weeks or days. Given the fact that pedestrian stops are the easiest police enforcement action to implement, this would support why they consistently linked to higher levels of violence when the other actions (mostly) did not. Further, the unity of time horizons for police enforcement actions and violent crime may occur at shorter temporal units as well. It follows, multiple cycles of increased police enforcement and lower violent crime levels could occur within a month; perhaps, introducing simultaneity bias into the models using the monthly temporal scale. If the previous point is true then lagging the predictors by one month will not solve these important theoretical limitations. Next, failing to control for the effects of ongoing hot spot predictors, or ecological continuity, confounds variation in violent crime due to long term predictors and changes in police enforcement effects, or ecological discontinuity (R. B. Taylor, 2015). Thus, the models may be further misspecified. Since, like many theories (R. B. Taylor, 2015), deterrence theory does not explicitly state the appropriate temporal scale at which police enforcements should reduce crime (Cousineau, 1973), it was impossible to address these issues *a priori*. Additionally, the present study was necessary in order to empirically demonstrate how Taylor's (2015) discussion of these ideas would apply in this context. It may be possible to employ different temporal units in the future, but the micro spatial units employed here may create analytical challenges due to excess zeros in the outcome when combined with more micro temporal scales (Twisk, 2003).

The Present Study vs. the Philadelphia Policing Tactics Experiment

Given there is some overlap in how police commanders described what they believe they are doing when they allocate resources to crime hot spots and the measures used in this study with the offender-focused policing treatment that was found to be effective in the Philadelphia Policing Tactics Experiment (PPTE), the observant reader might ask why the results of the present study are not aligned with those from the PPTE. There are several potential differences between this work and the PPTE, however, which may explain those differences.

First, the present study examined individual street blocks and intersections and essentially "ignored" nearby locations; whereas, the PPTE used "grid areas" that were on average the size of 22 American football fields. It may be the spatial scale used in the present study does not capture the true spatial dynamics of violence. In other words, while urban violence may be concentrated geographically, the social dynamics that drive violence and/or facilitate deterrence may not be strictly isolated to only a single street block or intersection, but also play out in the surrounding areas. If this is true, then the street block and intersection units used in this study would not adequately capture the true nature of violent crime and the impacts of hot spots policing.

Second, differences in the dosage and quality of policing may explain the difference in the findings of the two studies. The PPTE was a sustained effort spanning at least five months in the target hot spots. Further, the PPTE was a calculated use of criminal intelligence to identify the offenders believed to be responsible for violent crime in the target hot spots. The police then "made frequent contact with these prolific offenders ranging from making small talk with a known offender to serving arrest warrants for a recently committed offense. The most frequent tactic used was surveillance followed by aggressive patrol and the formation of partnerships with beat officers (Groff et al., 2015, p. 34)." In contrast, the dosage of hot spots policing examined in this study is more aligned with day-to-day policing in Philadelphia but is also more piecemeal.[37] Police commanders must address their violent crime hot spots while still addressing other crime problems, requests from external sovereigns, as well as many other contingencies and issues. Given resource constraints, it can be difficult to obtain sustained dosages of policing at hot spots while dealing with the wide range of constraints also placed on police commanders. PPD officers do their best to address violent crime hot spots in between carrying out a range of other duties. Further, the extent to which police commanders actively and effectively collect and analyze criminal intelligence and crime data to drive hot spots policing on a sustained basis remains an open question. Despite its importance to police commanders in the qualitative data, the present study was unable to measure the quality of enforcement. Anecdotally, the PPD's analytical capacity and business processes do not reflect the ideal operations that many police reformers would endorse (Boba & Santos, 2011; Ratcliffe,

[37] Likewise, monthly temporal units were examined to attempt to more accurately reflect the realities of how hot spots policing is conducted outside of experimental evaluations. The PPTE also examined bi-weekly observations.

2007; B. Taylor, Kowalyk, & Boba, 2007). Thus, it could be argued that day-to-day policing has not reached the point to where the highest risk individuals in the highest crime places are adequately focused on for sustained periods of time. Overall, the PPTE was likely found to be effective because it involved a sustained dosage of policing that was more analytically driven than what may currently be practical under non-experimental circumstances in the PPD given resource constraints (i.e., number of officers), the wide range of demands placed on the PPD, and the city budget's minimal investment in analytical training.

Research Questions 3 and 4

The qualitative component was conducted to purposively allow the police commanders studied to provide their beliefs regarding what they think they do in crime hot spots and rationales for why those actions work in their own words. On the whole, the hot spots policing strategy and rationalizations of effectiveness given by the police commanders studied is consistent with major ideas in the academic literature. On the other hand, some components of the policing strategy and rationalizations of effectiveness given by the police commanders are also limited when considered in light of important findings in the literature.

Police Commanders' Beliefs & Rationales & the Academic Literature

Before thinking about how to use these findings moving forward, it may be useful to consider how police commanders' beliefs and rationales align with the academic literature (Lum, 2009; Veigas & Lum, 2013). Locking down crime hot spots with police presence and enforcement actions was at the core of studied police commanders' strategy. Increasing police presence and enforcement actions was rationalized on the premise that it would both make offenders "think twice" and deny potential offenders and victims access to certain locations in order to reduce crime opportunities. As was argued in the literature review of this dissertation, increasing police presence and activity has long been a fundamental component of policing (Weisburd & Eck, 2004). The rationalization that these tactics will make offenders “think twice” runs parallel with deterrence theory. Police commanders also distinguished between making the wider offender population “think twice” and making specific offenders “think twice” by directly generating enforcement actions against them. Thus, whether or not the police commanders intended to, they embraced the ideas of general and specific deterrence (Zimring & Hawkins, 1973).

Locking down crime places using police presence and enforcement was also rationalized based on the idea it could reduce opportunities for crime by denying potential offenders and victims access to certain places. While the police commanders did not note it themselves, these ideas are consistent with situational crime prevention (Clarke, 1980). Controlling access to locations has typically focused on controlling access to specific facilities, such as apartment buildings, but dissuading potential offenders from being present on certain street blocks and intersections where violent crime is more likely to occur is certainly a form of access control (Clarke, 1995, pp. 110 - 111). If those people would become victims of violent crime as well then removing them from the location will also translate into removing potential violent crime targets (Clarke, 1995, p. 116). The overlap between offending and victimization is well established in the literature (Lauritsen, Sampson, & Laub, 1991; Vecchio, 2013).

Police commanders’ interest in generating quality activity against the “right people” to disrupt high risk offenders by getting them “off the street” through incarceration is also consistent with criminological theory and the empirical literature on offending and desistance. Wolfgang and colleagues’ (1972) seminal work suggested that roughly six percent of offenders are responsible for the majority of crime (53 percent), so police commanders’ belief in high rate offenders is certainly warranted. Further, desistance from offending does not just happen, but rather is thought of as a long, complicated process (Maruna, 2001). The desistance process may be initiated by life-changing events (e.g., getting married) (Laub & Sampson, 2009), but still involves substantial changes in the (ex-)offender's view of his or herself (Maruna, 2001). Therefore, police commanders' belief that offenders will continue to offend unless they are stopped by the police is quite reasonable. Finally, the belief that police need to arrest high risk offenders and get them "off the street" is the quintessential definition of selective incapacitation (Greenwood & Abrahamse, 1982).

Police commanders' belief in educating potential victims is also aligned with the situational crime prevention technique of target hardening (Clarke, 2008). In fact, many police commanders used the term "target hardening" themselves during the qualitative data collection. Clarke (1995) considered target hardening, reducing the vulnerability of a target to be victimized, to be the most obvious method of crime reduction and prevention. Again, it follows that police commanders' efforts to educate citizens on how to reduce their vulnerability to (robbery) victimization is well aligned with criminological theory.

Thinking Critically About Police Commanders' Beliefs & Rationales

> *"The only thing more powerful than knowing what to do is doing it."*
>
> *-- Mark Sanborn*[38]

The congruence between police commanders' beliefs regarding what they thought they were doing in crime hot spots and their rationales for expecting those actions to be effective and criminological theory does not automatically preclude police commanders' actions will

[38] This quotation is painted on a wall in the room where the Philadelphia Police Department holds its crime strategy meetings.

translate into crime control. This section looks more critically at the police commanders' perspectives.

The reliance on police presence and enforcement actions to lock down crime places is susceptible to the classic concern of dosage. In fact, the first hot spots policing experiment was initiated because the authors believed the Kansas City Preventive Patrol Experiment's null findings (Kelling et al., 1974) were due to inadequate dosage rather than a true null finding (Sherman & Weisburd, 1995). And while police departments are typically able to commit significant resources in order to generate high levels of police presence to produce positive effects under special or experimental conditions (Lawton et al., 2005; Ratcliffe et al., 2011; Telep et al., 2012), high dosages of police presence and enforcement actions may not always be feasible in practice. For example, during a crime strategy meeting, one captain argued that he simply just did not have enough resources to be able to answer 911 calls and lock down his crime hot spots.

> The executive commander pointed out two small areas (roughly two blocks by two blocks each) with multiple robberies that were on opposite sides of the district. The executive commander asked 'how do you manage your resources with these two areas?' The captain said he's been trying to move his bike patrols between two areas, but it is hard to cover both frequently. He said that one of the areas was actually where his narcotics teams were working, so that helps. The other area doesn't have a narcotics problem so he wasn't deploying his narcotics officers there. The executive commander then shot back, somewhat confrontationally, with, 'OK, what else? How about that area right there [pointing to the other area]? What are you doing?' The captain responded by saying, 'Well I'm trying to have my patrol cops hit those areas but they are busy chasing the radio. By the time two squad comes in the radio queue is already backed up. Two squad starts just trying to clear out all the calls. I just don't have any other beats to send there.' (Observation 1)

In other instances, police captains noted they had fewer officers due to summer vacation, officers turning down overtime for personal/family reasons (e.g., holidays), or breakdowns in communication amongst commanders during scheduling. Additionally, police commanders noted that generating activity when assigned to hot spots results in paperwork for officers and they often have to come off the street for a considerable amount of time to complete it. Thus, officers have to balance generating activity and potentially having to leave the hot spot or refraining from generating activity and remaining present in the hot spot. The lack of coverage in a hot spot is important because commanders often blamed the occurrence of shootings and robberies in their hot spots due to brief lapses in presence. Captain O illustrated this phenomenon quite succinctly when talking about how he would deploys his officers to a robbery hot spot.

> This area is getting hit with robberies being committed by two males, 19 to 25 years old, general description [modus operandi and offenders' appearance]. So I want a car in this area. And we'll have two tactical teams in that area. And you have to stay in that area. You just can't roam because it's boring because it only takes a minute for somebody to pop out of a house and somebody goes and robs them then they're gone again. So that's why they got to stay in that area. (Interview, Captain O)

Overall, relying on police presence and activity to address crime problems requires that police commanders always have adequate staffing to maintain high enough dosages of policing.[39]

The selective incapacitation of high risk offenders also faces limitations. Critiques of selective incapacitation, albeit in other contexts, have long questioned the criminal justice system's ability to correctly predict future offending (Auerhahn, 1999). Captain L noted similar concerns when talking about using truancy enforcement to get repeat juvenile burglars in his district "off the street".

> Captain L: It kind of is because; we know there's only a small percentage of people that are responsible for the crime. Not every kid that cuts school is going to commit a crime…

[39] Of course, this conceptualization of hot spots policing is in contrast to previous findings (Koper, 1995; Telep, Mitchell, & Weisburd, 2012), yet these studies did not focus on serious violent crime.

> Author: But you know there's some people out there that, small percentage of people, that if they're not stopped they're just going to keep going?
>
> Captain L: Right. And the hard thing is, being able to identify them… (Interview, Captain L)

Prediction errors are typically thought of in two ways: (1) false positives or overprediction and (2) false negatives or underprediction. The former prediction error involves predicting a person will offend in the future when in fact they will not; whereas, the latter error involves predicting a person will not offend when they will. Invoking sanctions against false positives raises serious ethical concerns regarding “harming” citizens who do not deserve it; whereas, failing to invoke sanctions against false negatives potentially raises public safety concerns if those offenders “harm” the public (Auerhahn, 2003; Zimring & Hawkins, 1995, pp. 61 - 67). The extent to which these problems will plague the predictions about future offending depends on the quality of crime and intelligence analysis in police departments. Moreover, the criteria used to identify high risk offenders and predict future offending has implications for the effectiveness of selectively incapacitating high risk offenders. The qualitative data suggested that police commanders mostly based their predictions of high risk offenders’ future offending on past offending (e.g., robbery chains involving similar offender descriptions or modus operandi) or intelligence predicting retaliation (e.g., gun violence amongst drug dealers who are likely to retaliate). Thus, predicting future offending by high risk offenders using these methodologies requires at least some crime to happen before high risk offenders can be identified. Relying on selectively incapacitating high risk offenders to address crime problems means the police may make predictions errors and still have crime occur or accept that some crimes will have to occur before prediction can occur.

Another potential limitation of selectively incapacitating high risk offenders is that it can be difficult to actually keep them “off the street”. An accused offender must be determined guilty before s/he can be incarcerated for a long period of time. While awaiting trial, many accused persons will be released on bail. When prompted, Captain M noted his skepticism that the criminal justice system effectively detains high risk offenders after they are arrested.

> Author: So one thing that is interesting as you were talking about these gangs [that] start shooting back and forth at each other and so on, do you think it matters if you, you know, I mean obviously you want to arrest them for the serious violent crime they commit, they're off the street, they're in jail just one less bad guy out there...[40]
>
> Captain M: Right, for a short period of time.
>
> Author: Yeah? Because they get out?
>
> Captain M: They get out chronically. Everybody we lock up for a shooting offense has multiple prior offenses, including guns and other shootings and murders. I always hear a big misnomer across the country, I think, people are in jail for non-violent crimes, well I would love to see where that's happening, because it is not happening here, we don't keep people in jail for violent crimes, let alone, you know, a marijuana violation.
>
> Author: How long is it going to take if you get locked up for robbery or gun possession, you would be out in?
>
> Captain M: Well, it's person specific, and the, you know, bail commissioner sets the bail and the judge can reduce that bail and even the bail commissioner can reduce that bail but, in general, you commit a violent crime with a gun, and you know, you just, you say, 'I can't pay my bail' and they keep you for a week longer and they have another bail hearing and ultimately it ends in a bail reduction, even if you do post bail or bond, you should be aware, nobody pays it in Philadelphia, so it really has no teeth. So... if you get a five thousand dollar bail you post ten percent, five hundred bucks, you never have to pay that back, so it cost you five hundred dollars to get out. That's our system, so you can be out as soon as you have five hundred bucks. (Interview, Captain M)

The perception that violent offenders are frequently released prior to court processing is likely why the executive commanders frequently urged local commanders to work with the District Attorney's Office to ensure gun offenders received high bail during the crime strategy meetings.

> The captain started with an overview of shootings and noted that there was one arrest for one of the shootings, one clearance based on a self-inflicted wound,

[40] The author was going to finish the statement with a question of whether it mattered if the offenders were arrested or simply the recipients of pedestrian stops or traffic enforcement.

> and one clearance based on a narcotics arrest. The executive commander noted that the district had done good work and they needed to work with the DA's [District Attorney's] office to make sure the guys stay in jail. (Observation 7)

Alternatively, captains were also questioned when violent offenders from their districts were frequently released on bail.

> The executive commander then asked the crime analysts to put up prison releases on the map. The executive commander noted, 'I'm seeing a lot of your gun offenders getting out…' The captain noted, 'I didn't even know you could check that.' The executive commander then responded, 'You have a lot of guys with high bails who are out. You need to challenge your DA [District Attorney's] Bureau Chief about why these guys are getting out with high bails. Let's make sure the DA [District Attorney's] is doing what they're saying they're doing.' (Observation 6)

As the following field notes excerpt demonstrates, the release of high risk offenders was certainly believed to lead to more violence.

> The captain quickly provided a description of the circumstances surrounding the shootings. The focus is on one particular shooting. The victim of that shooting was named as a suspect but not arrested for a shooting that occurred last year. The victim is a known drug dealer and he refused to cooperate with police. The commanders all agree that this shooting has the potential to result in retaliation. The captain noted some of the guys likely to be involved in the retaliation for the previous shooting are part of his high risk offender list. He noted that they were able to get the guys believed to be responsible for the shooting into custody on illegal gun possession charges, 'but a judge let them out [for whatever reason] and the shootings started.' (Observation 2)

Overall, the balance between reducing and preventing crime by getting and keeping high risk offenders "off the street" or crime control and meeting the legal rights of accused persons or due process poses a serious limitation to the idea of selectively incapacitating unadjudicated high risk offenders (Packer, 1964).

If the police are successful in getting high risk offenders "off the street" then the crime control benefits of the tactic depend on those offenders not being replaced by new offenders (Blumstein, 1993; Miles & Ludwig, 2007; Piquero & Blumstein, 2007; Zimring & Hawkins, 1995).

The following field notes excerpt demonstrates that this limitation was not lost on the police commanders studied.

> Shootings were displayed on the projector map. The captain started by noting that one was self-inflicted and that the guy was arrested on a VUFA [illegal firearm possession] charge. He noted that the guy was suspected to be involved in a previous shooting, so it was good they got him off the street. In addition, the captain discussed his use of bike enforcement to address the shootings. Because he believes that offenders are using bikes to escape shooting scenes, he has been instructing his officers to enforce bike/traffic regulations. He noted that this approach has led to a number of VUFA arrests, albeit he raised some concerns that the gang members keep getting younger and younger and that he was concerned that the gangs may be recruiting new members to stay together. (Observation 4)

In other words, the crime reduction and prevention benefits of selectively incapacitating high risk offenders could be mediated by new offenders who replace them and begin to offend (Klein, 1993).

As mentioned previously, when the police increase presence and enforcement in a concentrated area, especially a geographically small area, citizens' perceptions of procedural justice and police legitimacy may be damaged (Brunson, 2007; Brunson & Miller, 2006; Gau & Brunson, 2010). While it is certainly possible for police departments to conduct enforcement actions in procedurally just ways (Mazerolle, Antrobus, Bennett, & Tyler, 2013), police departments have to be aware of the potential damaging effects that high levels of police presence and enforcement can have on the community. The police commanders in the present study were certainly aware of the contentiousness of enforcement actions.

> Your stop has to be based on reasonable suspicion or probable cause. And the big thing is, once your stop is completed, you know, take that extra step and explain to the person, 'This is why I stopped you'. And, you know, you treat them on that human level, you know, on that same level as far as, you don't talk down to them, you don't think you're superior or anything like that, just because you're in the police department. You know, it's the same thing. It's, you know, the principle, you know, of legitimacy and procedural justice. Yeah, I stopped you, I patted you down, you're not wanted, you're not carrying any

> guns, this is the reason why I stopped you, and I hope you understand why because you were just out here, we're trying to prevent people from getting injured. And that's, if the officers, and we always put it out to them, you know, take that extra step and explain to them this is the reason why you were stopped and the majority of the time, you know, the people are saying I understand. (Interview, Captain X).

On the other hand, as Captain L stated, "We only need one mistake to become the front page of The Daily News too." When the community members perceive lower levels of procedural justice and police legitimacy, they are less likely to cooperate with the police to fight crime, be satisfied with the police, and obey the law (Haberman, Groff, Ratcliffe, & Sorg, 2014; Tyler, 2006; Tyler & Fagan, 2008). It seems likely that a reliance on police enforcement actions increases the probability that the public will have negative experiences with police officers and in return negatively impacts their perceptions of procedural justice, legitimacy, and satisfaction with the police.

Implications for Theory

First, the results may have important implications for deterrence theory. Simply increasing the quantity of enforcement was not found to lower monthly violent crime levels. Therefore, offenders' perceptions of punishment certainty may be more complex than a simple function of how many actions the police take. Since the police have long relied on enforcement, residents may expected pedestrian stops (and traffic enforcement) to occur in hot spots; especially, if law abiding citizens are also frequently stopped (Brunson, 2007).[41] If everyone experiences pedestrian stops (and traffic enforcement) in high crime places and they rarely result in legal sanctions then offenders may not be sensitive to short-term increases in enforcement or perceive it as an indicator of increased punishment certainty. Therefore,

[41] This dynamic is analogous to Sherman's (1990) idea of deterrence decay, but may be working at a longer temporal scale. Sherman (1990) argued that the deterrence effects of police crackdowns could decay over time as people get used to them or realize they overestimated the perceived increase in punishment certainty.

drawing on the findings of police commanders' emphasis on quality enforcement, it may be that police enforcement actions only generate deterrence if they are used in a parsimonious way that signals to the public that the police know about criminal activity in the area and the perpetrators are going to receive serious punishment. Police enforcement actions implemented more selectively would appear as rare events that signal a drastic change in police activity and the likelihood of punishment. In terms of deterrence theory, it may be that the certainty of punishment is more a function of the quality of police actions when they are taken rather than the sheer quantity of actions taken.

Next, contrary to the singular theoretical explanations of crime control emphasized in the academic literature, police commanders suggested the mechanisms of different crime control theories work simultaneously to control crime. Recall police commanders believed they were increasing police presence and enforcement actions in crime hot spots in order to generate deterrence; however, their goal was also to focus police enforcement actions on high risk offenders in order to arrest them and generate incapacitative effects. At the same time, police commanders emphasized the importance of denying potential offenders and victims access to certain places and helping citizens become less vulnerable to victimization to reduce crime opportunities (i.e., situational crime prevention). Therefore, similar to the principles of problem-oriented policing, police commanders draw on the mechanisms of multiple crime control theories simultaneously in practice. Based on this notion, the more relevant question for deepening our theoretical understanding of crime control might not be which actions are most effective, but rather which combination of actions are most effective? In other words, assuming that only one theoretical mechanism needs to be adjusted through the implementation of different tactics may be too narrow of a view. In practice, effective crime control may be about adjusting the correct combination of mechanisms. The fine lines among the mechanisms of crime control theories may be of academic but not necessarily practical utility.

Implications for Policy

No crime control benefits were observed for police enforcement actions when examining their impact on monthly violent crime counts in high crime street blocks and intersections. In the context of the interpretations offered above for the quantitative findings, police enforcement actions, particularly pedestrian investigations, may at best have no crime control benefits for hot spot monthly violent crime counts and at worst set in motion mechanisms that actually increase monthly violent crime counts in hot spots. Unfortunately, the research design of the present study cannot empirically determine which explanation is most valid. Nonetheless, a strict (yet somewhat naïve) interpretation of the quantitative findings is that they should not be relied upon to generate reductions in hot spot monthly violent crime counts.

Most proponents of evidence-based policy (Lum, 2009; Lum et al., 2011; Sherman, 1998), however, would likely advise against crafting policy based on a single study and suggest reviews of the entire evidence-base and even meta-analyses are needed to guide evidence-based policy making (D. B. Wilson, 2001; Young, Ashby, Boaz, & Grayson, 2002). Therefore, the present findings can also be considered in the context of previous research on pedestrian investigations. Some studies have indirectly implied that police enforcement actions, including pedestrian investigations, can effectively reduce crime, especially when applied to crime hot spots (Boydstun, 1975; Ratcliffe et al., 2011; Sherman & Rogan, 1995; Weisburd, Telep, & Lawton, 2013). Other studies directly measuring the impact of pedestrian investigations, in addition to this one, however, have found pedestrian investigations were not effective for reducing crime (Rosenfeld et al., 2014; Rosenfeld & Fornango, 2014). Overall, the evidence on the effectiveness of pedestrian investigations for reducing crime might best be considered mixed. This leaves police commanders with essentially three options: (1) develop partnerships with academics to rigorously test their use of police enforcement actions (especially pedestrian investigations) in more depth, (2) adopt other tactics with less inconclusive evidence-bases, such as focused deterrence (Braga & Weisburd, 2011), or (3) do what they have always done without conclusive evidence that it is effective.

Other Potential Outcomes of Police Enforcement Actions

In addition, the complex nature of policing and the policy process further complicates drawing strict policy implications based solely on the empirical crime control benefits of police enforcement actions and/or pedestrian investigations (Head, 2010; Sanderson, 2003; Young et al., 2002). Police strategizing is complex. In fact, the qualitative findings revealed the police commanders studied had the common belief that hot spots policing requires multi-faceted strategies that draw on numerous criminological theories of crime control. Further, police departments must simultaneously balance numerous organizational objectives and goals in practice. While crime control may receive the greatest attention, the police are also responsible for maintaining order and initiating the justice process, among other outcomes. Suggesting the police should or should not use specific tactics strictly due to the comparative effectiveness of different tactics, as is implied by research questions one and two, may be too simplistic of a view on police policy making (Head, 2010). Therefore, the alternative functions of police enforcement actions that emerged in the qualitative data are discussed before specific policy recommendations are discussed.

First, police enforcement actions were believed to be important for helping the police maintain positive relationships with the community. The police captains studied noted that the first component of maintaining police-community relations is demonstrating the police are addressing their concerns. For example, Captain O noted the importance of acting on community members' concerns stressed at community meetings.

> We go to community meetings a lot. We have a good relationship with the community. They're the ones that give us the information about what's going on in their areas and what's going on on their block, if they have a bad family on the block or something like that. So they give us the information, they want to see a police response. So if I go to a meeting and tell them there's going to be somebody out there and I don't do what the community asks me to do then they lose faith in the police and they're going to say, 'we're not going to talk to the captain, or we're not going to talk to lieutenant, because every time we do the cops do nothing about it.' So when they give me that information, it's important that we act on it so that people know that, 'yeah they were really out there, that was good, they're out there.' (Interview, Captain O)

However, the community members are typically more concerned about public disorder than serious crime.

> Captain L: Violent crime is something that we have to work with but also I want the old lady to be able to go to the store and not have to trip over the drug dealers. Not have to come home from work after working eight hours and can't even get to her door because the corner boy is hanging on her front porch. That stuff is important to people who live here. Sometimes that's more important than the violent crime. Because my quality of life is important to me. I think that's huge.
>
> Author: That's what they talk to you about, right?
>
> Captain L: That's what they're more concerned about. They're concerned about. They're more concerned about, 'why can't I go to the store, why can't I walk, why are people breaking in?' The things that affect me personally. A lot of times I'm not going to be affected by somebody who's shot or something like that. That's important to us [the police] because we have to deal with the violent crime but I don't want to ever not remember the quality of life of individuals in the community… (Interview, Captain L)

Captain O also explained the importance of dealing with quality of life issues.

> I mean, we still have quality of life issues in this district where people talk about people playing loud music, people sitting on somebody's steps, maybe smoking some weed, people hanging in front of abandoned houses. So we still have to address; most of my complaints in this community come from quality of life issues, abandoned houses, abandoned cars, people hanging along the corner, people playing loud music. They're the type of things that I get a lot more of at community meetings. So it's important for me to have officers to address those problems throughout the district and they do. (Interview, Captain O)

As Bittner noted (1974, p. 30), the ability to use coercive force is vital for dealing with situations where "something-ought-not-to-be-happening-about-which-something-ought-to-be-done-NOW!" When disorderly situations arise, the police might conduct a pedestrian stop on the individual who decides to sit on the old lady's stoop and/or potentially arrest him for disorderly conduct when he refuses to leave or shows up the next day. If the community cares about the guy on the stoop then police enforcement actions are necessary at least some of the time.

And for whatever reasons, sometimes the community just wants to see bad guys given a hard time.

> I was at a meeting last night, [street block], first time I think ever we've had a community meeting there, and they were so mad because we weren't aggressive, more aggressive. These are black and Hispanic neighborhoods complaining that we're not aggressive enough with the bad guys. To me, that's a big deal because you'll never see that in the paper, you know, they're never going to come out and put that in the news because it doesn't play, right? But that's the complaints we got, 'you got to be tougher with these bad guys, you got to be tougher.' (Interview, Captain Y)

Therefore, police enforcement actions might also be used to maintain or improve police-community relations when minor disorder occurs.

Police enforcement actions can also be used to contribute to public safety. Traffic enforcement may be an action that can be used to address crime hot spots, albeit not based on the results of this study, but it is also tied to public safety concerns. This point was raised in the interviews. Captain M stated, “There’s a safety aspect to our jobs too... We don't want people blowing red lights. That’s why we write tickets.” Captain O made a very similar point.

> I don’t want somebody traveling at a high rate of speed on these side streets and so forth, going through stop signs and so forth. So I want them to be stopped. I also want them to be issued tickets because I want to make sure that they know that they broke the law, they got a ticket for it, and if they don’t pay the ticket they go to court. Their license could be suspended. We do a lot of live stops where somebody has a suspended license or no driver’s license at all, we take their cars, and we take a lot of them just because of that reason, because they're going to end up hurting somebody, somebody going shopping, or somebody coming home from work, some family in the car, we can’t have that. (Interview, Captain M)

Alternatively, during a crime strategy meeting, the police commanders discussed how they were using police enforcement actions to try and figure out what was driving a spike in heroin overdoses.

> The executive commander then questioned the room, ‘Anyone know anything about these sudden deaths?’ [Referring to a recent increase in heroin overdose deaths].The [Special Unit] commander stated they didn’t know yet, but were analyzing the cases to determine if fentanyl was present in their blood streams. The district captain for the area noted that she was also instructing her officers to conduct pedestrian stops on known drug users in order to confiscate bags of heroin and send them in for testing. The executive commander then responded, ‘Well that’s our charge too. Let’s get whoever is putting this stuff out there off the street.’ (Observation 3)

Police departments also use enforcement actions to investigate crimes and gather intelligence. For example, after a call for service reporting a crime in progress comes in, patrol officers will typically speed to the area in an attempt to stop pedestrians and vehicles matching the description(s) of the offender(s) given by the caller. Sometimes pedestrian or vehicle investigations result in the identification and arrest of the offender. This is important because regardless of what the criminal justice system ultimately does with convicted offenders (e.g., incapacitation vs. rehabilitation) very few people would disagree with the idea that the police should make an effort to capture (serious) law breakers. Nonetheless, most citizens would probably be upset if the police decided to just ignore calls about crimes in progress.

Even if police enforcement actions do not result in the arrest of the recipient, people also sometimes provide intelligence that can be used to guide future policing strategies (Ratcliffe, 2008). For example, during one of the crime strategy meetings, a captain explained how arrests for minor level offenses might lead to information about more serious offenders.

> The executive commander started by noting, 'I'm disappointed with your narcotics activity.' The captained argued the map was a little deceiving as, 'there are multiple arrests for some dots. They're just stacked on top of each other.' He then noted that narcotics arrests were up for the year and they were doing a lot of surveillance to arrest drug dealers. The executive commander then questioned, 'Do you think these are the right arrests?' The captain responded, 'We are getting a lot of information from these arrests. We use these arrests to develop intel. We just made an arrest and found out that [a particular corner] was being rented out to a new group, so we're keeping an eye on that place and trying to arrest the new main guy.' Another executive commander then explained how the arrested guy told them the drug boss lives on the block and uses binoculars to look out his window and monitor the operation. This way it keeps him isolated from the street. The district was working on figuring out a way to investigate him. (Observation 6)

Captain Y explained how traffic enforcement may also return intelligence.

> And you never know what's going to happen, during a car stop, people talk to you. You know, you might stop the guy that's from [Suburb] buying his heroin. He's going to tell you something, you know, what is going on. (Interview, Captain Y)

Captain V explained more broadly how enforcement actions can also return intelligence.

> We get intel where that person lives, what car they're driving, where they hang out, that's good intel we can use later on because what if we have a shooting there? That maybe gives us some suspects to look at. You know Joe Smith, this is where he hangs out, where he does his dirt, this is the car he drives, this is the time he's out there. And that could be gotten from a good ped investigation. A good 75-48A [form required to document a pedestrian stop], we can go back, you know what, 'I remember stopping this guy. I remember these guys were out there.' And that would give us intel if a crime is committed. So that's good. It's always good to get that. Intel is huge and the more intel you have on these bad

> guys the easier it is to deal with them if something does happen. (Interview, Captain V)

Further, conducting quality pedestrian stops on the "right people" is important because they have the best information.

> I'll tell you what, if you have the right personality, you know how to talk to people, these bad guys will talk. And they're not all bad; I shouldn't call them bad guys. For most of them there isn't another alternative for them. I don't think there's any other alternative for them. I mean, quite frankly, the drug game is so profitable in some of the neighborhoods, like the heroin market, which is easier to do than working at McDonald's. But the ways you talk with them, that's how we get information on the street. It isn't necessarily coming from good people, I mean, they'll tell a certain amount but they're not in a game. Where we get the best information is guys who are in the game. (Interview, Captain V)

Overall, if police enforcement actions are vital for collecting intelligence, then at least some enforcement actions may need to be conducted in order for the police to implement policing tactics that heavily rely on intelligence (e.g., focused deterrence).

Improving the Use of Police Enforcement Actions in the Future

The previous sections made two important points: (1) the evidence on the effectiveness of police enforcement actions for reducing crime is mixed and (2) police commanders believe police enforcement actions achieve goals other than crime control. This study was framed based on the long history of policing relying on police enforcement actions. The qualitative data demonstrated that police commanders still strongly believe in the effectiveness of police enforcement actions. While the present study calls that belief in question, it may be more fruitful to think about improving the use of police enforcement actions rather than calling for an outright ban on their use. In other words, suggesting to police commanders who strongly believe in the use of enforcement actions to reduce crime that they should never be used, especially if they are used to achieve goals in addition to crime control, will not likely be taken serious. Therefore, a plan to potentially improve the effectiveness of police enforcement actions is outlined below.

The evidence of the effectiveness of hot spots policing that motivated this study should provide the basis for the future of policing (Braga & Weisburd, 2010), yet the value of offender-focused policing based on criminal intelligence cannot be ignored either (Ratcliffe, 2008). Given the studied police commanders' belief in "locking down" the "right places" while focusing on getting the "right people" "off the street", an intelligence-led, hot spots policing strategy will likely be appealing to police commanders (Groff et al., 2015). While police enforcement actions may play a role in this type of policing strategy, the quantitative results suggest they should not be solely relied upon to address crime. Situational crime prevention tactics will likely also have to be incorporated in order to sustain long-term crime control. Given the police commanders studied emphasized the importance of target hardening, multi-faceted crime control strategies may be of interest to police commanders.

Police commanders could start by emphasizing the use of quality police enforcement actions in the future. In fact, it may be beneficial to drop the focus on the quantity of activity altogether. Campbell's (1979, p. 84) idea of the Corrupting Effect of Quantitative Indicators stated, "The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor." In other words, when the emphasis is on the number of enforcement actions rather than their quality, officers under pressure by their commanders to generate more enforcement may simply conduct enforcement actions on anybody. In effect, as discussed above, high usage of enforcement actions may result in those actions becoming normalized, ineffective, and causing poor police-community relations.

The ability of a police department to generate quality enforcement actions will depend on the departments' analytical ability to interpret the criminal environment (Ratcliffe, 2008). Police departments need highly skilled crime and intelligence analysts to guide operational decision-making (Ratcliffe, 2008). Crime analysts typically use mapping and statistical software to understand crime patterns and trends using official crime data. Intelligence analysts typically employ a wide range of sources, including but not limited to human sources, to understand criminal behavior (Ratcliffe, 2007). While crime and intelligence analysis are usually viewed and conducted separately, integrating both functions seems to be the most fruitful (Ratcliffe, 2007). Regardless, if analysts can create analytical products that address the what, where, who, how, and why components of crime problems, perhaps by structuring analyses around the scientific method and hypothesis testing (Chainey, 2012; Clarke & Eck, 2003; Townsley, Mann, & Garrett, 2011), then police departments will be able to direct their officers to the "right places" to generate enforcement actions against the "right people" while avoiding subjecting law abiding citizens to enforcement actions (Groff et al., 2015; Ratcliffe, 2007, pp. 21 - 24).[42] Nonetheless, if police departments can develop high functioning analytical capabilities then they can ensure that officers have the information necessary to generate quality activity.

The use of analysis to focus enforcement actions may mean the police will be able to control crime in the future. High quality analysis may make prediction problems less likely, thus making it more likely that the police will be able to make the "right" potential offenders "think twice" and/or get them "off the street" when warranted and necessary. A more selective use of

[42] The analytical capacity of the Philadelphia Police Department would be best described as "under construction". The PPD operates centralized crime and intelligence analysis units with each district also housing an officer who conducts district level analysis. The district analysts were trained by a team of Temple University researchers led by Dr. Jerry Ratcliffe, the examining committee chair of this dissertation, and included the author. PPD police commanders are undoubtedly using analysis to guide their decision making, but analysis may still be characterized as "shallow" at times and mechanisms for the tasking and distribution of analytical products and organizational decision-making have not been formalized.

police enforcement actions against only the most deserving people may also reduce the normality of seeing people engaged with the police and increase the deterrent effects of enforcement actions across the general population. In other words, people will know that if they are the recipients of an enforcement action, such as a pedestrian stop, it is because the police are aware of their criminal activity and they should refrain from offending. Likewise, focusing on the right people means there is less likelihood law abiding citizens will be the recipients of enforcement actions and have negative experiences with the police, thus improving their perceptions of procedural justice, police legitimacy, and satisfaction with the police.

Similarly, police departments can also make an effort to provide additional training to officers to improve procedural justice during the initiation of police enforcement actions (Boydstun, 1975; Mazerolle et al., 2013; Wheller, Quinton, Fildes, & Mills, 2013). Improved procedural justice during police enforcement actions combined with a more selective application may make police enforcement actions less susceptible to criticism. Furthermore, increased perceptions of procedural justice and then police legitimacy may promote the transmission of intelligence, which will then allow the police to more effectively use enforcement actions for crime control (Tyler, 2006; Tyler & Fagan, 2008).

Finally, as this section's opening paragraph introduced, the use of police enforcement actions should only be viewed as one component of hot spots policing strategies. Police enforcement actions focused on specific offenders may be effective in hot spots (Groff et al., 2015), but the police must begin to develop more holistic hot spots policing strategies. For example, Haberman and colleagues (2014), argue that a hot spots policing strategy that starts with foot patrol then utilizes crime and intelligence analysis informed by the foot patrol officers in order to facilitate problem-oriented, focused deterrence, and/or offender-focused policing may be effective for both addressing crime and improving the community's perceptions of crime and the police.[43]

Of course, an improvement in the implementation of police enforcement actions must occur alongside rigorous evaluation in order to be able to state with any confidence whether or not police enforcement actions work as hypothesized. A national investment in hot spot policing evaluations would certainly be worthwhile (Mastrofski et al., 2010). However, these evaluations must not just be individually rigorous, but must also systematically test the various assumptions and theoretical mechanisms hypothesized to drive crime control that underpin hot spots policing. For example, an evaluation of the assumptions and hypothesized mechanisms of the hot spots policing model that emerged from the qualitative findings of this study would go a long way in developing more insight into the effectiveness of police enforcement actions. Thus, it is likely that mixed-methods process and outcome evaluations will be needed. Measurement will also be important for the research program, and outcomes in addition to mere crime levels will need to be focused upon. For example, if police enforcement actions are hypothesized to make offenders "think twice", then this effect and outcome should be measurable with surveys or qualitative interviews of community members (Corsaro & Brunson, 2013). If these more nuanced evaluations occur in multiple locations over time, then a strong and large enough evidence-base will be generated that provides a definitive conclusion on the usefulness of police enforcement actions for hot spots policing.

Limitations

The study's results and the above discussion must be considered in light of its limitations. Limitations of both the quantitative and qualitative components are now discussed. Potential directions for future research are noted where applicable.

[43] This hot spots policing model remains unevaluated.

Limitations of the Quantitative Methodology

The importance of the quality of activity from the qualitative data was a major finding of this dissertation. The present study simply used counts of police enforcement actions for independent variables. It is possible that the results may be different and more nuanced insight could be gained from improving the measurement of the independent variables. One approach may be to track each police enforcement action all the way through the criminal justice system in order to develop measures that capture the outcome of the enforcement actions. For example, pedestrian stops that lead to arrests for illegal firearm possession and then lead to high risk offenders being incarcerated may be more effective than pedestrian stops that terminate after the stop. More refined measures may aid in understanding the importance of incapacitation for police enforcement actions as well (Zimring & Hawkins, 1995). Unfortunately, the data to address this limitation were not available, so future research will have to consider how to refine the measurement of police enforcement actions.

All studies that focus on the geography of crime are susceptible to the modifiable areal unit problem (MAUP) (Openshaw, 1983). The MAUP "is where the results of any geographic aggregation process, such as counts of crimes within a set of geographic boundaries, may be as much a function of the size, shape and orientation of the geographic areas as it is the spatial distribution of the crime data (Chainey & Ratcliffe, 2005, pp. 151 - 152)." Using a different spatial unit of analysis may have returned different results. Additionally, the spatial design of the study effectively de-spatialized the potential mechanisms transmitted through the independent variables. In other words, only considering the level of crime and police enforcement actions in the focal unit and ignoring the occurrence of crime and police enforcement actions in the surrounding street blocks and intersections may not be fully capturing how the hypothesized processes work. Future research may need to consider how police enforcement actions in the surrounding street blocks and intersections (e.g., spatially lagged predictors) also contribute to the level of crime in the focal street block/intersection (see Braithwaite & Johnson, 2015 for an example of a research design that may be useful in the future).

The potential temporal scaling limitations of this study were already mentioned. Months may not be the appropriate temporal unit. Different temporal units may provide different results when studying the link between police enforcement actions and hot spot violent crime levels. This is the modifiable temporal unit problem. Similarly, a one month lag also may not be the appropriate lag structure. It may be that the theoretical mechanisms proposed in this study may work at shorter or longer time periods and lag structures. Again, using different temporal units and lags may produce different results. Taylor (2015) makes two related recommendations to address temporal scaling problems. First, clearly explicate how different theoretical mechanisms will work across different temporal scales. Second, systematically investigate the impact of different temporal units (and lag structures) on a study's results. The researcher can then eliminate theoretical explanations that do not coincide with the study's results. The temporal scaling explanation for the present findings suggests Taylor's (2015) methodology should be considered for future studies of police enforcement actions.

Also, the internal validity of quasi-experimental studies is always a concern (Shadish et al., 2002). Omitting important independent/control variables can lead to biased statistical estimates. If other initiatives or programs implemented in the hot spots had important effects on violent crime then controlling for those effects may alter the relationships among police enforcement actions and monthly violent crime counts.[44] On the other hand, the internal validity of quasi-experimental studies can be improved when extraneous causes are ruled out (Nagin & Weisburd, 2013). It is possible that some crime reduction initiatives taking place in Philadelphia during the study period were not controlled for and biased the models' parameter estimates. Likewise, other social processes that impact violent crime patterns may also have been omitted from the study. For example, retaliatory shootings are a well-documented problem in Philadelphia (Ratcliffe & Rengert, 2008), so a time variant measure capturing ongoing disputes among Philadelphians may help improve model specification. If these findings were replicated using even stronger designs in other places then policy-makers will be able to become even more confident in the validity of the results (note Rosenfeld et al., 2014 arrived at different conclusions than this study).

Limitations of the Qualitative Methodology

Any time a researcher conducts field observations he/she should be worried about reactivity. Reactivity occurs when research subjects change their behavior due to the presence of the researcher (Padgett, 2008). Because it is unrealistic to believe the PPD would change their style of policing and jeopardize the public's safety or their jobs due to the presence of a researcher, reactivity during the crime strategy meeting field observations should have been minimal yet still possible.

It is also important to recognize police personnel may be wary of outsiders, so it is possible that interviewees were not truthful during the interviews (Mastrofski & Parks, 1990). There is no way to completely eliminate untruthfulness, but measures were taken to minimize

[44] Note efforts to minimize the problem have been taken by controlling for the tactics of the Philadelphia Foot Patrol Experiment (Ratcliffe, Taniguchi, Groff, & Wood, 2011) and the Philadelphia Policing Strategies Experiment (Groff et al., 2015).

it. All subjects were informed of their rights as research subjects and promised confidentiality (per IRB guidelines). The subjects were informed no personal identifying information would be included in the interview transcripts or any subsequent publications or presentations. The interview data were corroborated with the field observation data. The researcher used the relationships he developed with PPD personnel during previous projects to make contact with the interview subjects and develop rapport. The researcher conducted the field observations over a three month period prior to starting the interviews, and many captains at least recognized the author when he arrived for the interviews. Overall, there were absolutely no indications that the interview subjects were being dishonest.

The fact that only one situation was observed (i.e., crime strategy meetings) should also be noted because hot spots policing strategizing may have taken place in other (unobserved) settings. Because it is reasonable to assume that district commanders want their bosses to know about all of the hard work they are doing, however, it is believed that crime strategy meetings provided a holistic overview of how hot spots policing tactics were conceptualized and implemented in practice. After corroborating the field observations with the interview data, there was nothing to indicate the qualitative data were unrepresentative of how police commanders implemented and thought about hot spots policing.

Finally, readers should note the qualitative findings are not necessarily generalizable to other settings. While it is important that researchers recognize limited external validity, the qualitative findings are still useful for developing insight and building theory for future studies. In other words, the qualitative findings from the present study can be tested in future studies, possibly with quantitative methods.

Summary

Over time hot spots policing has become a promising and widely adopted policing strategy (Braga et al., 2012; Police Executive Research Forum, 2008). However, the empirical evidence on the effectiveness of hot spots policing is limited because it provides little guidance on exactly what police should be doing in hot spots. Furthermore, while police predominantly use enforcement actions to address crime problems, the literature has failed to examine their effectiveness in micro-level hot spots and rarely examined more than one action at a time.

Based on these gaps in the literature, a mixed-methods study was conducted to answer four research questions. Quantitative data were analyzed to address the first two research questions: (1) Do four police enforcement actions focused on offenders or potential offenders reduce violent crime in hot spots? (2) Are any one of these four police enforcement actions more effective than the others? The quantitative results found total enforcement and pedestrian stop levels in the previous or same month linked to higher expected monthly violent crime counts. The positive effect of pedestrian stops was significantly larger than the effects of traffic enforcement or quality of life arrests. These findings were discussed in terms of (1) an anticipatory effect, (2) over-deterrence, (3) escalation, (4) unintended enticement and self-fulfilling prophecies, and (5) temporal scaling.

Qualitative data were used to answer two additional research questions: (3) When police commanders allocate resources to crime hot spots, what do police commanders think they are doing? (4) What are police commanders' rationales for what they do in crime hot spots? Field observations of crime strategy meetings and interviews with police commanders revealed police commanders thought they were doing three things in crime hot spots: (1) "locking down" crime hot spots, (2) disrupting high risk offenders, and (3) educating potential victims. Police commanders rationalized these beliefs based on four explanations of their effectiveness: (1) making offenders “think twice”, (2) denying potential offenders and victims certain places in order to reduce crime opportunities, (3) getting high risk offenders “off the street”, and (4) target hardening. Police commanders’ beliefs about effective policing were discussed in the context of the criminological theory and crime control literatures.

The implications of the results for crime control theory were also discussed. When thinking about deterrence theory, it was suggested that simply doing more actions may not mean offender decision making will be altered. Specifically, if some actions are frequently used in hot spots then they will be expected by potential offenders and may have little impact on offender decision making. Therefore, it was suggested deterrence may be better achieved by quality enforcement actions that are parsimoniously used against the “right people” in the “right places”. Further, it was suggested that police commanders do not see clear lines across theories and actually draw on multiple crime control theories when designing their hot spots policing strategies in practice. Therefore, policing theory should focus on which combinations of actions can achieve the greatest levels of crime control not which individual actions are the most effective.

The results also had important implications for policy. Because the police use enforcement actions for goals other than crime control, policy regarding the use of enforcement actions may not be as simple as whether or not they statistically significantly reduce crime. Therefore, recommendations were made to potentially increase the effectiveness of police enforcement actions in the future with an emphasis on the need to use mixed-methods studies to continually develop a deeper understanding of their effectiveness. Police departments should focus on the quality of enforcement rather than the quantity of enforcement. Police departments should improve their analytical capacities in order to ensure that enforcement actions are focused parsimoniously in the "right places" and on the "right people". Officers should be adequately trained in the principles of procedural justice and police legitimacy in order to minimize the likelihood that the public will have negative experiences with the police during police enforcement actions. Police commanders can use enforcement actions to achieve other outcomes, but hot spots policing strategies should include a wider range of tactics that draw on the policing effectiveness literature and span multiple theoretical frameworks.

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APPENDICES

A. Temple University Institutional Review Board Approval

TEMPLE UNIVERSITY

Office for Human Subjects Protections
Institutional Review Board
Medical Intervention Committees A1 & A2
Social and Behavioral Committee B
Unanticipated Problems Committee

Student Faculty Conference Center
3340 N Broad Street - Suite 304
Philadelphia, Pennsylvania 19140
Phone: (215) 707-3390
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Certification of Approval for a Project Involving Human Subjects

Protocol Number:	22212
PI:	Haberman, Cory P.
Review Type:	EXPEDITED
Approved On:	13-May-2014
Approved From:	13-May-2014
Approved To:	12-May-2015
Committee:	B BEHAVIORAL AND SOCIAL SCIENCES
School/College:	LIBERAL ARTS (1800)
Department:	CLA:CRIMINAL JUSTICE (18350)
Sponsor:	No External Sponsor
Project Title:	COPS ON DOTS DOING WHAT? THE DIFFERENTIAL EFFECTS OF LAW ENFORCEMENT-ORIENTED ACTIONS IN HOT SPOTS

The IRB approved the protocol 22212.

If the study was approved under expedited or full board review, the approval period can be found above. Otherwise, the study was deemed exempt and does not have an IRB approval period.

Before an approval period ends, you must submit the Continuing Review form via the eRA module. Please note that though an item is submitted in eRA, it is not received in the IRB office until the principal investigator approves it. Consequently, please submit the Continuing Review form via the eRA module at least 60 days, and preferably 90 days, before the study's expiration date.
Note that all applicable Institutional approvals must also be secured before study implementation. These approvals include, but are not limited to, Medical Radiation Committee ("MRC"); Radiation Safety Committee ("RSC"); Institutional Biosafety Committee ("IBC"); and Temple University Survey Coordinating Committee ("TUSCC"). Please visit these Committees' websites for further information.

Finally, in conducting this research, you are obligated to submit modification requests for all changes to any study; reportable new information using the Reportable New Information form; and renewal and closure forms. For the complete list of investigator responsibilities, please see the Policies and Procedures, the Investigator Manual, and other requirements found on the Temple University IRB website: http://www.temple.edu/research/regaffairs/irb/index.html

Please contact the IRB at (215) 707-3390 if you have any questions.

B. Qualitative Informed Consent Forms

Field Observations: Informed Consent Script

TEMPLE UNIVERSITY Informed Consent for Minimal Risk Social and Behavioral Research [IRB project # and consent #]:

Cops on Dots Doing What? The Differential Effects of Law Enforcement-Oriented Actions in Hot Spots

Cory P. Haberman, Department of Criminal Justice
Jerry H. Ratcliffe, PhD, Department of Criminal Justice

Cory Haberman, a student in the Department of Criminal Justice at Temple University, will be conducting a research study (under the direction of Dr. Jerry Ratcliffe) examining how the Philadelphia Police Department develops its strategies for addressing violent crime for his doctoral dissertation. A component of this study involves observing and recording what happens during crime strategy meetings. Cory will be observing crime strategy meetings from roughly May, 2014 through October, 2014. During this time, Cory will sit in crime strategy meetings and take field notes of the proceedings.

Consent for Participation in Interview Research

- If you volunteer to participate then no further action is needed from you. You will not be asked to do anything outside of your normal duties for this study. You will only be observed while performing your normal duties during crime strategy meetings.
- If you decline to participate in this study please notify your commanding officer. In that event, the researcher will not be permitted to observe any crime strategy meetings where you are present. If you decline to participate it will not have any impact on your standing with the City of Philadelphia, the Philadelphia Police Department, Temple University, the Department of Criminal Justice, or the researchers.
- If you volunteer to participate you may discontinue participation at any time without penalty. If you decide to withdraw from the study, the researcher will no longer be permitted to observe any crime strategy meetings where you are present. Your withdraw from the study will not have any impact on your standing with the City of Philadelphia, the Philadelphia Police Department, Temple University, the Department of Criminal Justice, or the researchers.
- You will not be compensated by the researchers for your participation, and the only benefit you will obtain from participating is knowing that you have contributed to the understanding of this topic.
- There are no foreseeable risks for participating in this study.
- All data collected during these observations will be anonymous. No personally identifying information will be recorded.
- Any products derived from using information obtained from these observations will not identify crime strategy meeting participants by name.
- You may contact the research team with questions, concerns, or complaints about the research and any research-related injuries by calling (215) 204-7918 or e-mailing jhr@temple.edu or cory.haberman@temple.edu.
- This research has been reviewed and approved by the Temple University Institutional Review Board. Please contact them at (215) 707-3390 or e-mail them at: irb@temple.edu for any of the following: questions, concerns, or complaints about the research; questions about your rights; to obtain information; or to offer input.

Page 1 of 1

Interviews: Informed Consent Form

TEMPLE UNIVERSITY Informed Consent for Minimal Risk Social and Behavioral Research [IRB project 22212]

Cops on Dots Doing What? The Differential Effects of Law Enforcement-Oriented Actions in Hot Spots

Cory P. Haberman, Department of Criminal Justice

Jerry H. Ratcliffe, PhD, Department of Criminal Justice

This study is examining how the Philadelphia Police Department develops its strategies for addressing violent crime. You are being asked to participate in an interview for this research study. The specific purpose of this interview is to gain a better understanding of how police commanders in the Philadelphia Police Department develop their respective strategies for addressing violence in the areas under their command. The estimated duration of this interview is approximately one hour. During the interview, the interviewer will ask you to respond to a series of questions regarding how you determine and implement crime fighting strategies in your area of command.

Consent for Participation in Interview Research

1. The researcher has explained the research study and purpose of this interview to me.
2. I understand that my participation in this study and interview is completely voluntary.
3. I understand that I will not be compensated for my participation.
4. I understand the only benefit I will obtain from participating in this research is knowing that I have contributed to the understanding of this topic.
5. I understand there are no reasonably foreseeable risks or discomforts associated with participating in this research study.
6. I understand that I may withdraw and discontinue participation at any time without penalty. If I decline to participate or withdraw from the study, no one from the City of Philadelphia or the Philadelphia Police Department will be notified.
7. I understand that most interviewees will find the discussion interesting and thought-provoking; however, if I feel uncomfortable in any way during the interview session, I have the right to decline to answer any question or to end the interview.
8. I understand that I will be audio recorded. I am providing the researcher permission to audio record me. I understand that I will not be paid for being audiotaped or for the use of the audiotapes.
9. I understand that I may ask the researcher to stop audio recording at any time during the interview.
10. I understand that after the interview the audio recording will be transcribed into a written document and any information that might identify me will be redacted.
11. I understand that the researcher will destroy the audio recording after the transcription process.
12. I understand that the researcher will not identify me by name in any reports using information obtained from this interview and that my confidentiality as a participant in this study will remain secure.
13. I understand representatives of the City of Philadelphia, including but not limited to the Philadelphia Police Department, will neither be present at the interview nor have access to raw notes or

Subject Initials: __________

Date: ____________________ Page 1 of 2

transcripts. This precaution will prevent my individual comments from having any negative repercussions against me.

14. I understand that efforts will be made to limit the disclosure of my personal information, including research study records, to people who have a need to review this information. However, the researcher cannot promise complete secrecy. For example, although the researcher has put in safeguards to protect my information, there is always a potential risk of loss of confidentiality. There are several organizations that may inspect and copy my information to make sure that the study team is following the rules and regulations regarding research and the protection of human subjects. These organizations include the IRB, Temple University, its affiliates and agents, Temple University Health System, Inc., its affiliates and agents, the study sponsor and its agents, and the Office for Human Research Protections.
15. I understand that I may contact the research team with questions, concerns, or complaints about the research and any research-related injuries by calling (215) 204-7918 or e-mailing cory.haberman@temple.edu or jhr@temple.edu.
16. I understand that this research has been reviewed and approved by the Temple University Institutional Review Board. Please contact them at (215) 707-3390 or e-mail them at: irb@temple.edu for any of the following: questions, concerns, or complaints about the research; questions about your rights; to obtain information; or to offer input.
17. I understand by signing this consent form, I am not waiving any of the legal rights that I otherwise would have as a participant in a research study.

Your signature documents your permission to take part in this research and understanding of all the information provided above.

DO NOT SIGN THIS FORM AFTER THIS DATE →

Signature of interview subject — Date

Printed name of interview subject

Signature of person obtaining consent — Date

Printed name of person obtaining consent

Subject Initials: __________

Date: __________

C. Interview Guide

Interview Guide

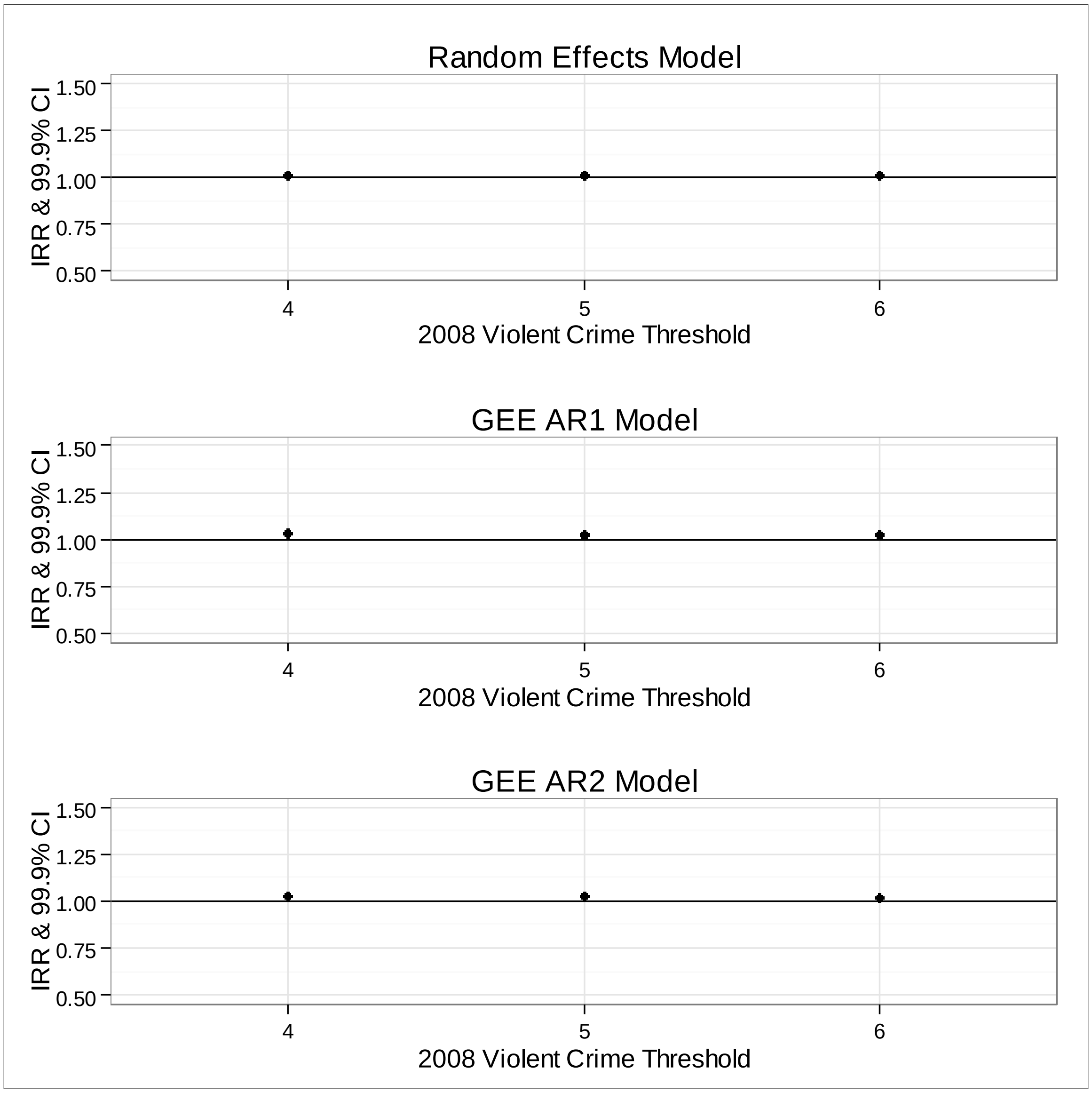
1. Can you tell me about a recent success you had addressing violent crime? How do you know you were successful?
2. How did you select that crime problem to focus on? Is that how you normally select crime problems to focus on?
3. Is that the strategy you normally use to address crime problems in your district?
4. OK, so how would you summarize your district's philosophy or strategy for addressing crime problems?
5. How did you come up with that (i.e., philosophy/strategy)? Why do you think it works?
6. Would you say arrests, quality-of-life enforcement, car stops, and pedestrian stops are an important part of your district's crime fighting strategy? Why or why not?
7. Do you think arrests, quality-of-life enforcement, car stops, and pedestrian stops are effective for reducing crime? Why or why not?
8. Do you think all of those things work the same way to reduce crime? Are they all equally effective?
9. Do you think there are differences in the quality of arrests, car stops, or ped stops? Could you give an example of a high quality or low quality arrest, car stop, or ped stop?
10. Do arrests, quality-of-life-enforcement, car stops, ped stops have benefits besides reducing crime?
11. You've probably seen people in the media recently criticizing the use of quality-of-life enforcement and ped stops in places like New York City and even here in Philly. Do you have any thoughts on that criticism? How would a city policy or law limiting how much or often officers could do these things impact policing?
12. If you couldn't use quality-of-life enforcement, car stops, or ped stops to address crime problems could you still be effective in reducing crime? What else would you do to address crime problems?
13. Once you've identified a potential crime problem that needs to be addressed, what is the process you use to address it? For example, how do you communicate your strategy to your officers? How do you ensure they do what you ask of them? Etc?
14. How do crime strategy meetings influence how you police your district?
15. As the department moves forward, what else do you think needs to be done to make it even more effective?

D. Sensitivity Analysis: Hot Spot Identification

All quantitative analyses were repeated using four and six violent crimes thresholds to identify hot spots in order to check if the results reported in Chapter 5 were sensitive to the five violent crimes threshold used (see Chapter 4).[45] All models were estimated using negative binomial probability distributions and included the month, year, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. Models were estimated using all three statistical techniques previously described: (1) random effects models, (2) generalized estimating equations with a first-order autoregressive error structure models (GEE AR1), and (3) generalized estimating equations with a second-order autoregressive error structure model (GEE AR2). Graphs displaying the police enforcement actions' incident rate ratios (IRR) and 99.9 percent confidence intervals across the hot spot thresholds for each model are shown in Figure D1 through Figure D20 below. If an IRR crosses the horizontal line at Y = 1, then the effect is not statistically significant. In order to maintain consistency the Y-axes are uniform across graphs. Because of the uniform scale and relatively small amount of variation around some of the IRR's, some graphs do not appear to display a confidence interval. This is a visual side-effect due the scale of the Y-axis. Each panel of each graph only shows the results from one statistical technique. The impact of the violent crime thresholds on the parameter estimates can been seen by comparing IRR's across each panel. In sum, the directions, relative magnitudes, and statistical significance of the IRR's were consistent across all three thresholds.

[45] The five 2008 violent crime threshold resulted in 169 hot spots and 10,140 hot spot by month observations. The four 2008 violent crime threshold resulted in 348 hot spots and 20,880 hot spot by month observations. The six 2008 violent crime threshold resulted in 96 hot spots and 5,760 hot spot by month observations.

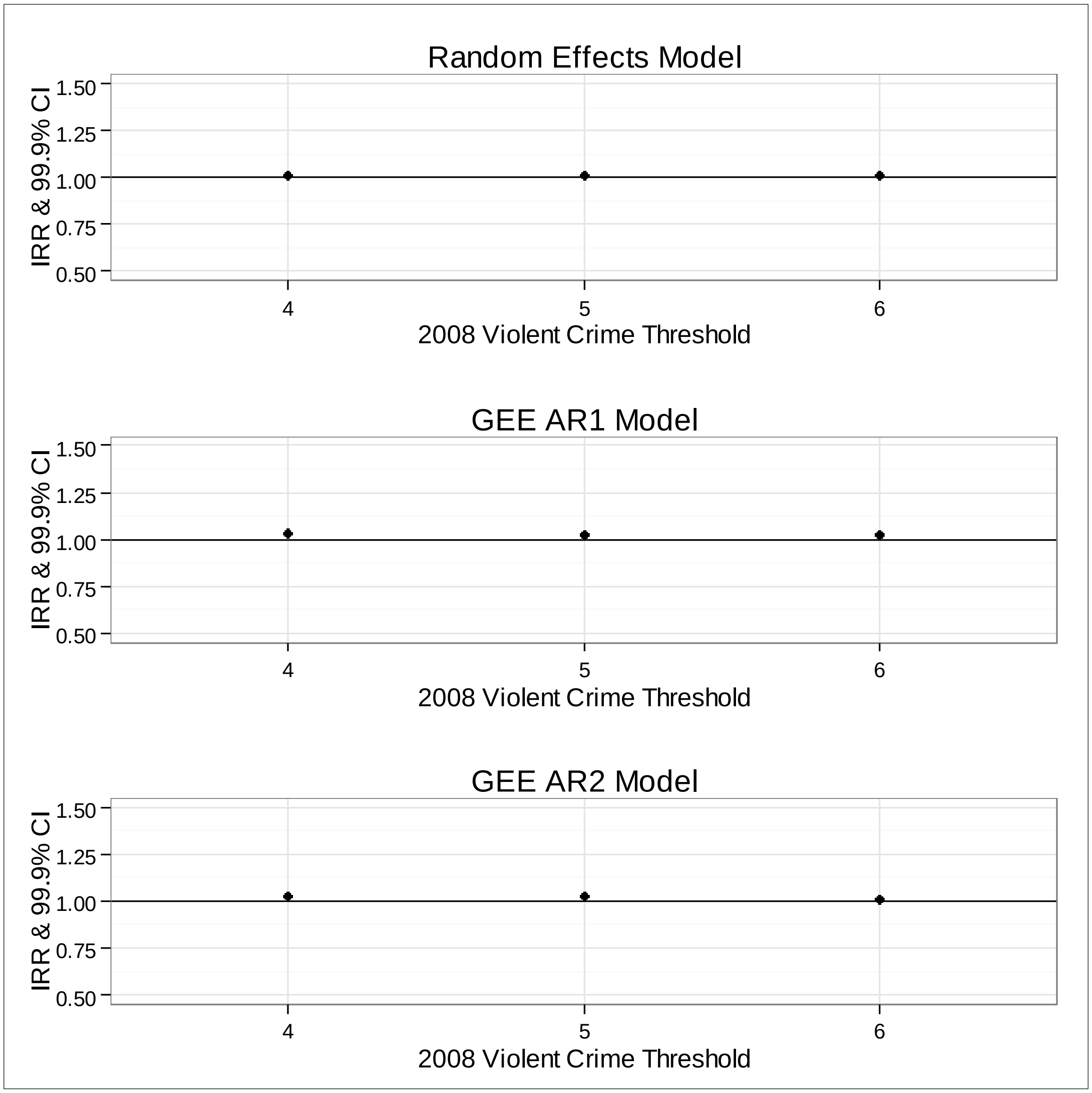
Figure D1. Incident rate ratios for contemporaneous raw monthly total enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

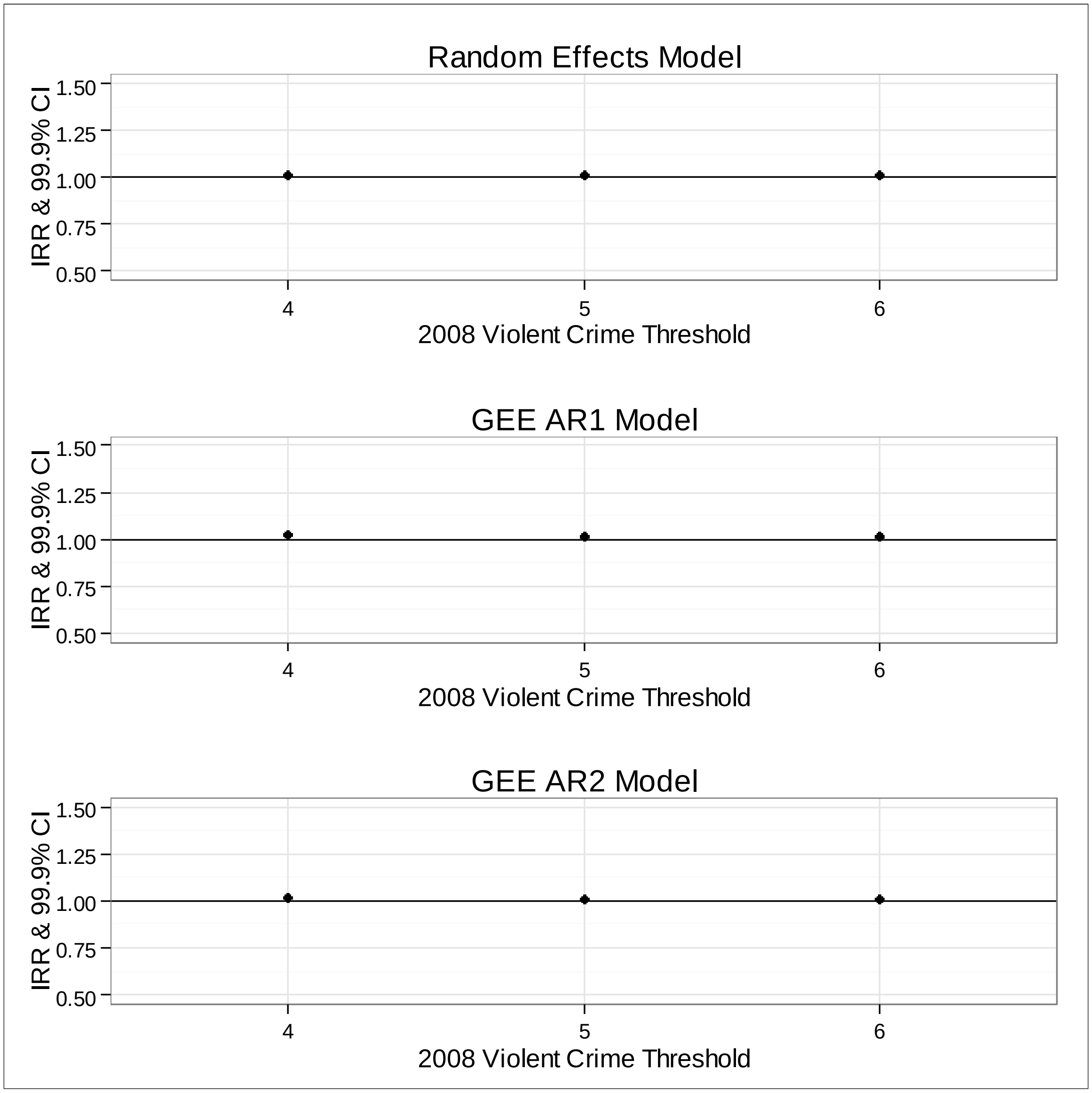
Figure D2. Incident rate ratios for lagged raw monthly total enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

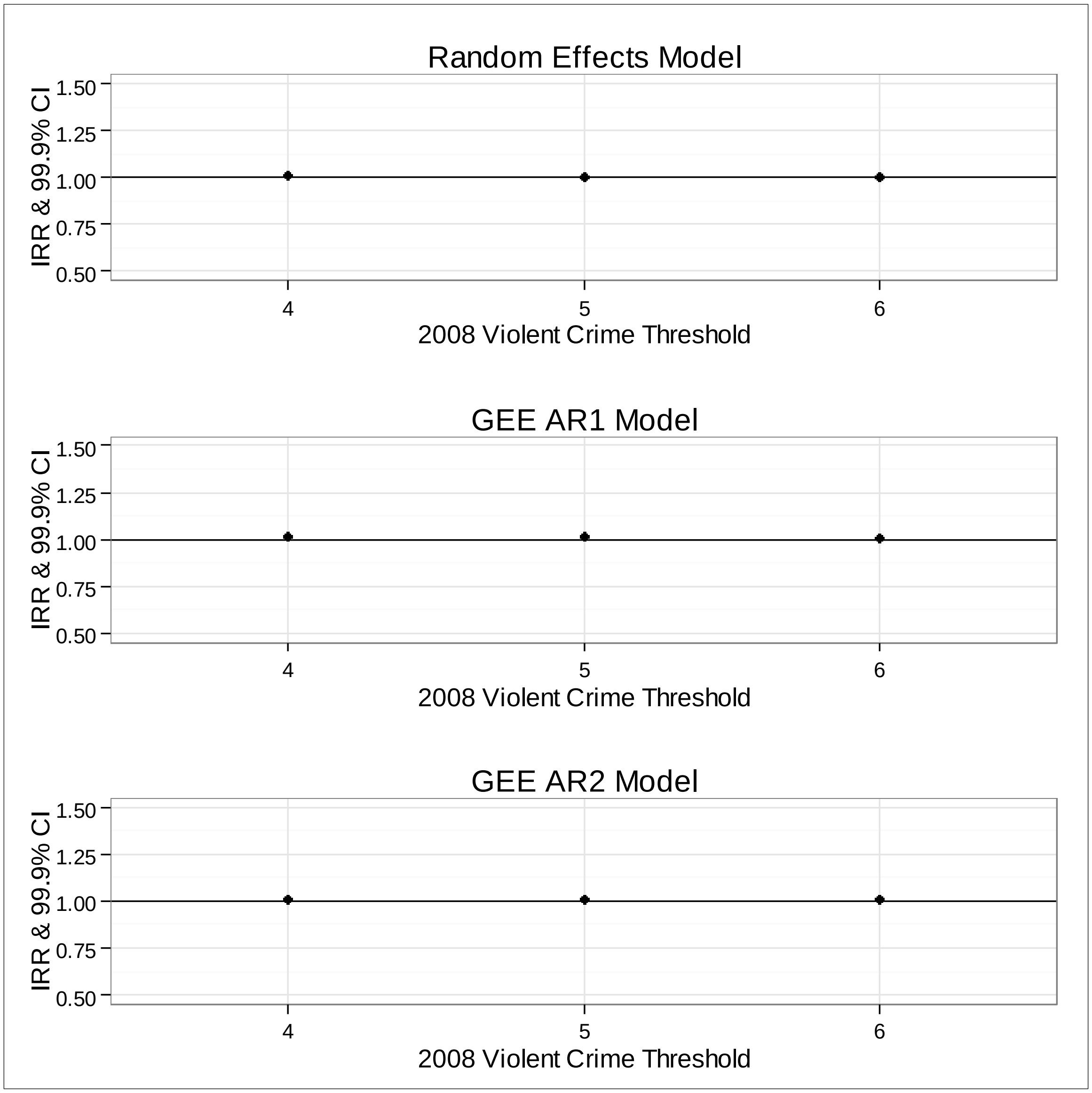
Figure D3. Incident rate ratios for contemporaneous hot spot mean centered monthly total enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

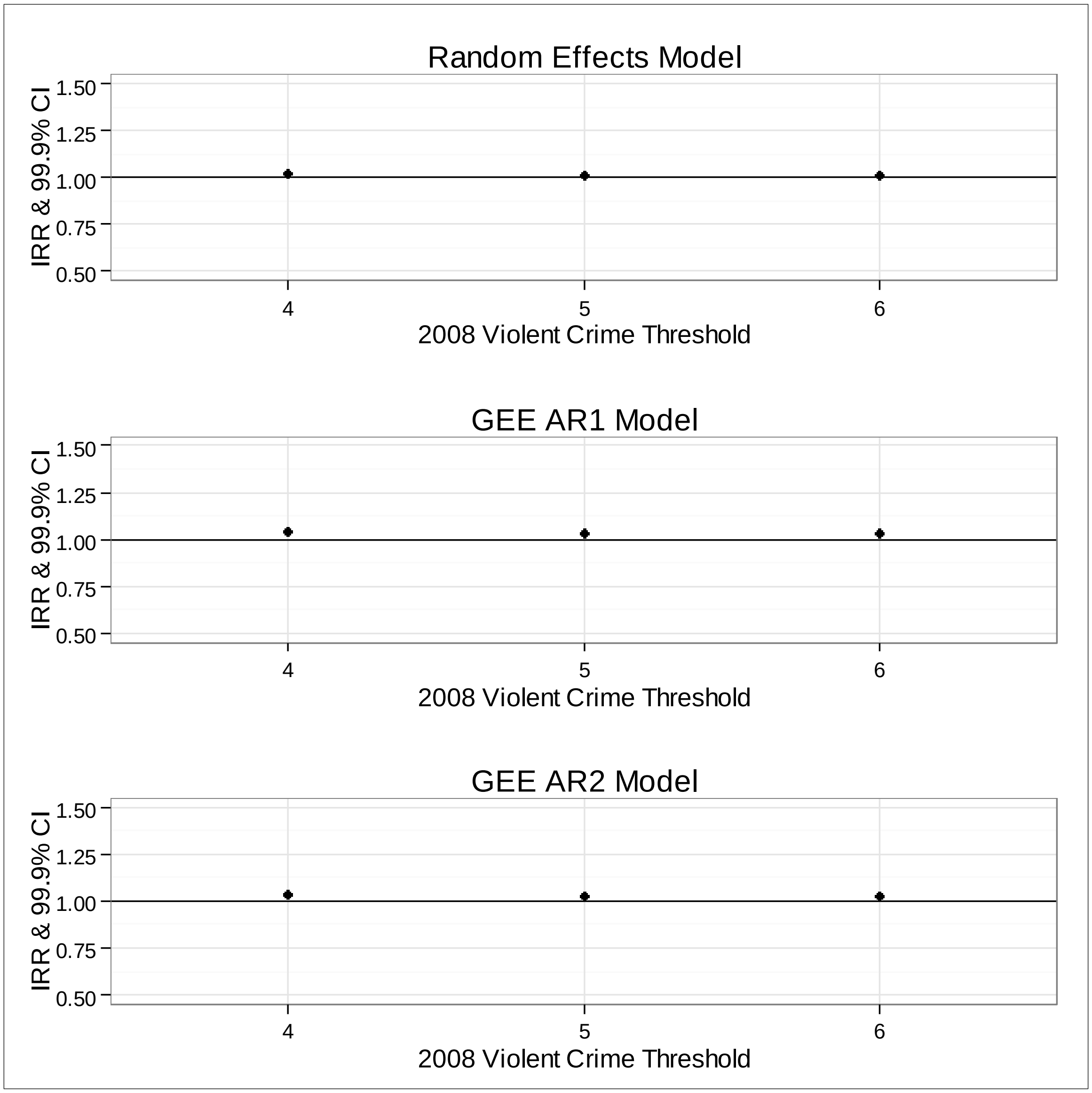
Figure D4. Incident rate ratios for lagged hot spot mean centered monthly total enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

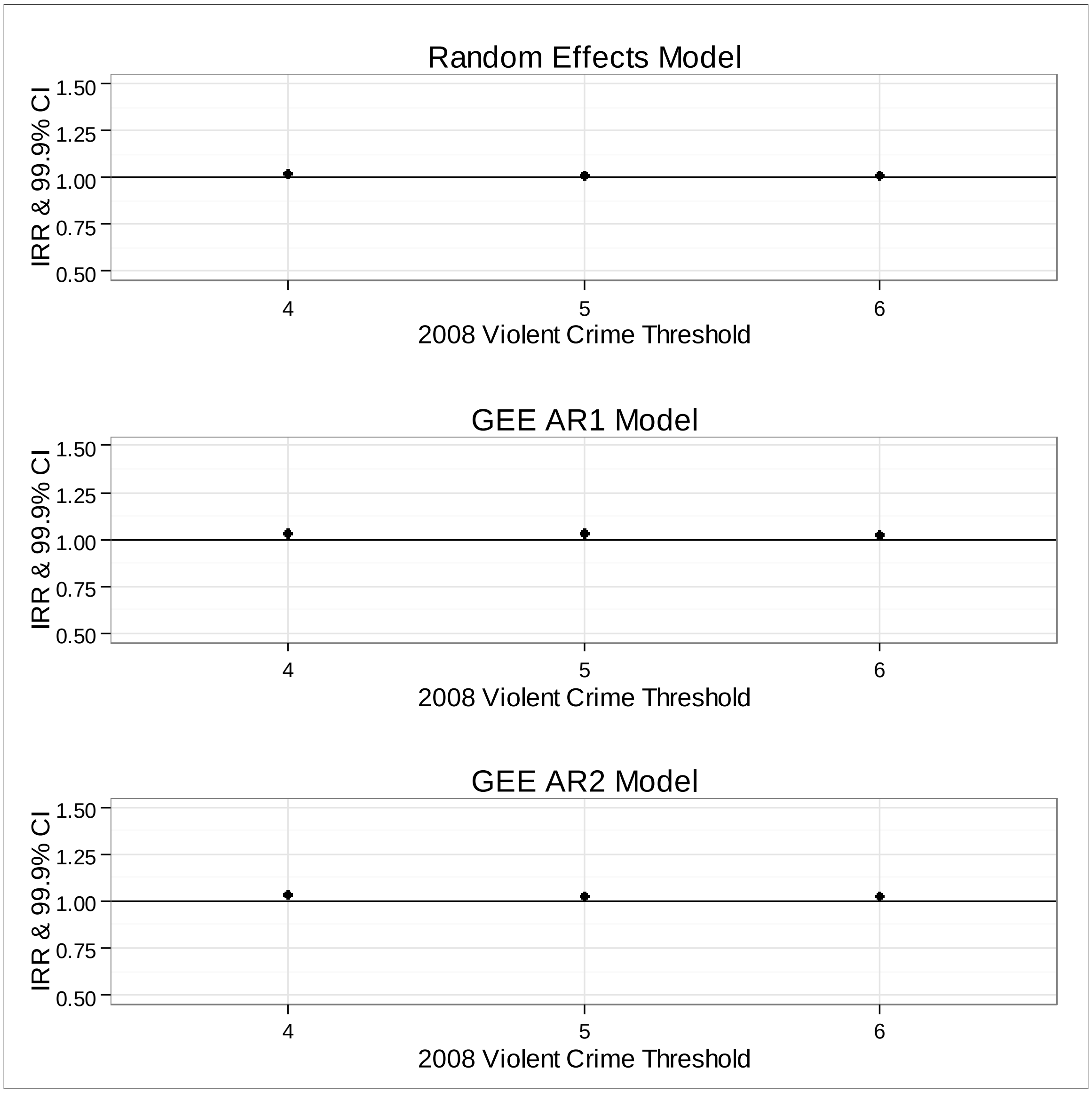
Figure D5. Incident rate ratios for contemporaneous raw monthly pedestrian stops on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

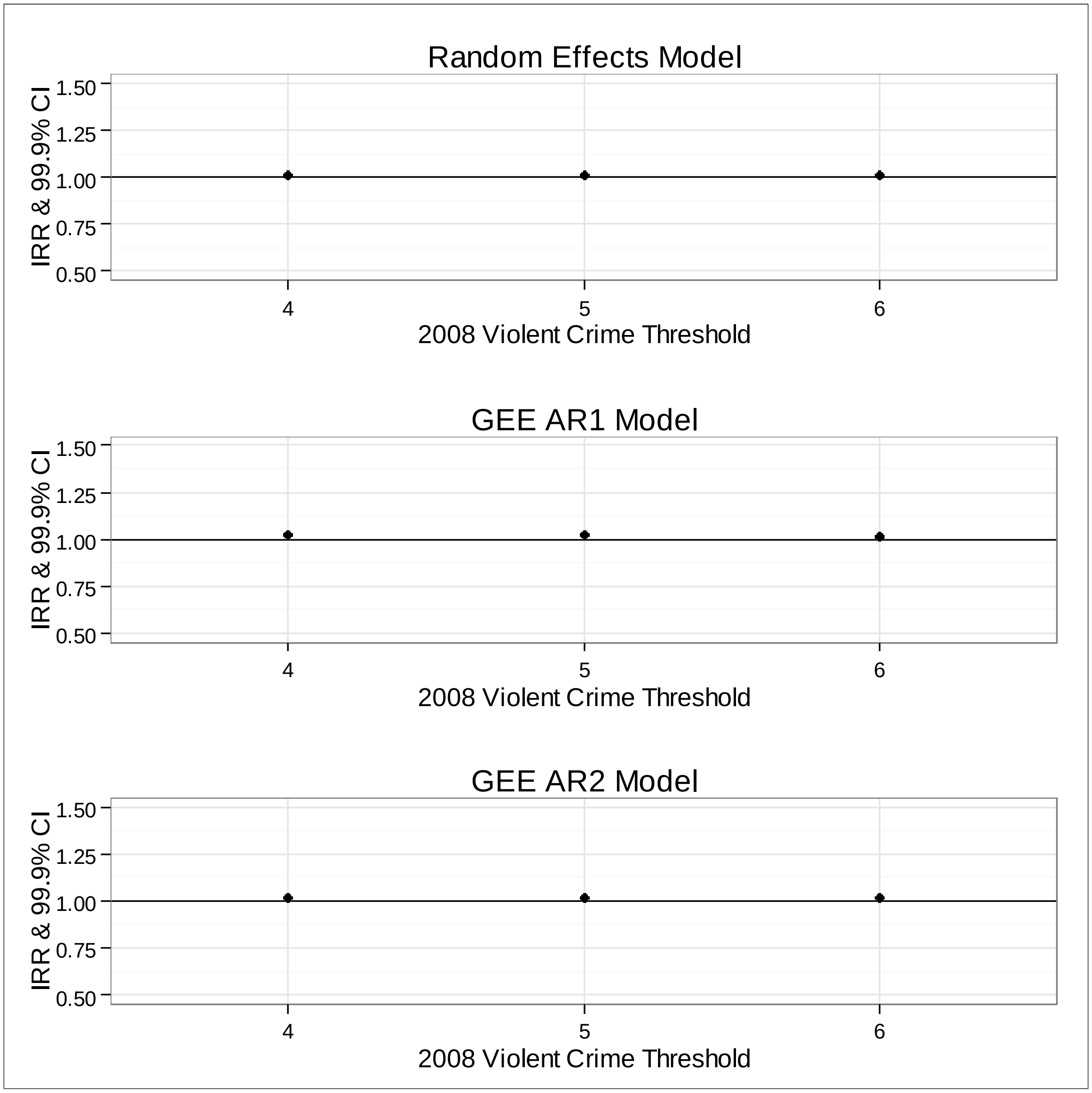
Figure D6. Incident rate ratios for lagged raw monthly pedestrian stops on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

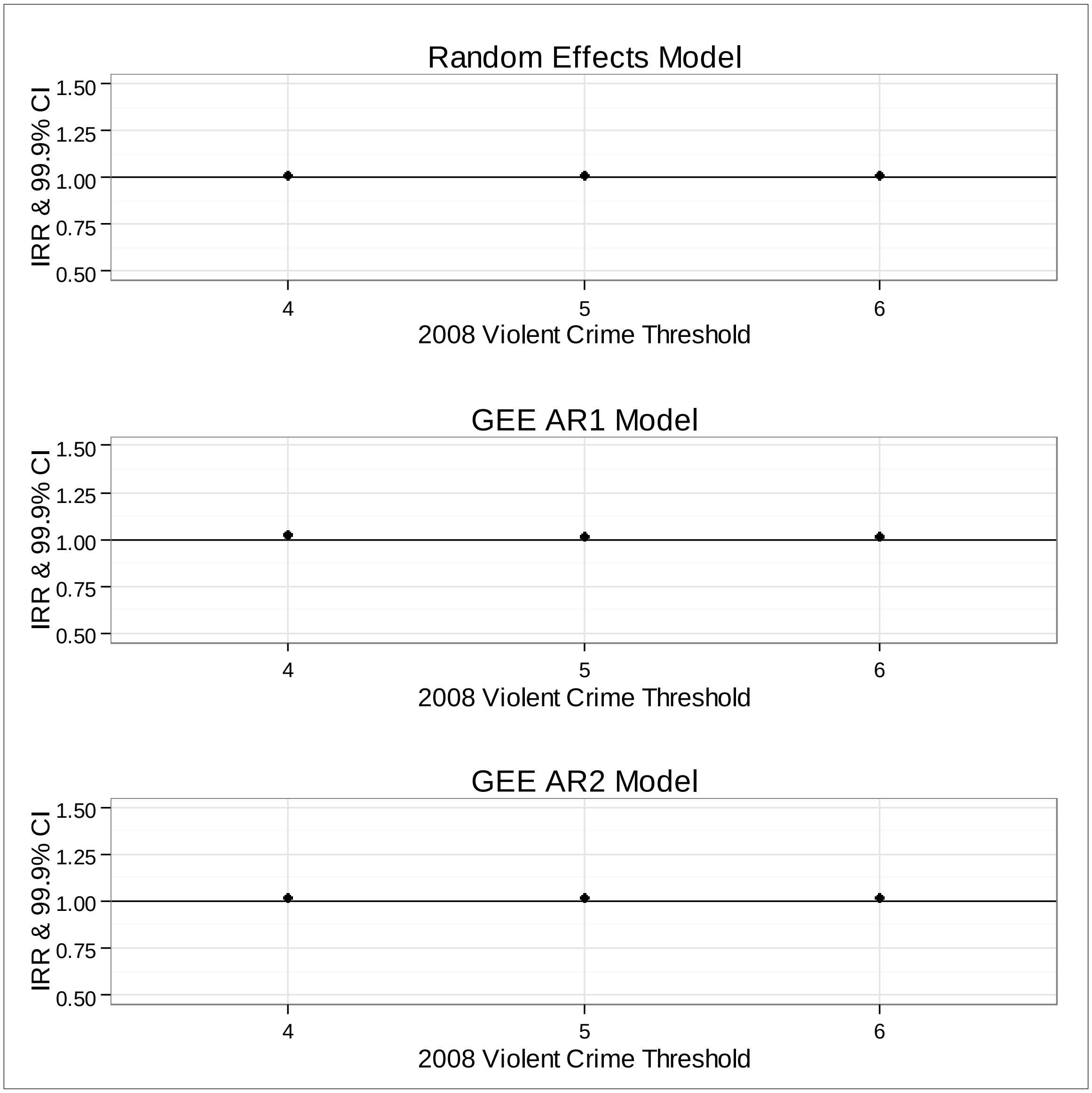
Figure D7. Incident rate ratios for contemporaneous hot spot mean centered monthly pedestrian stops on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

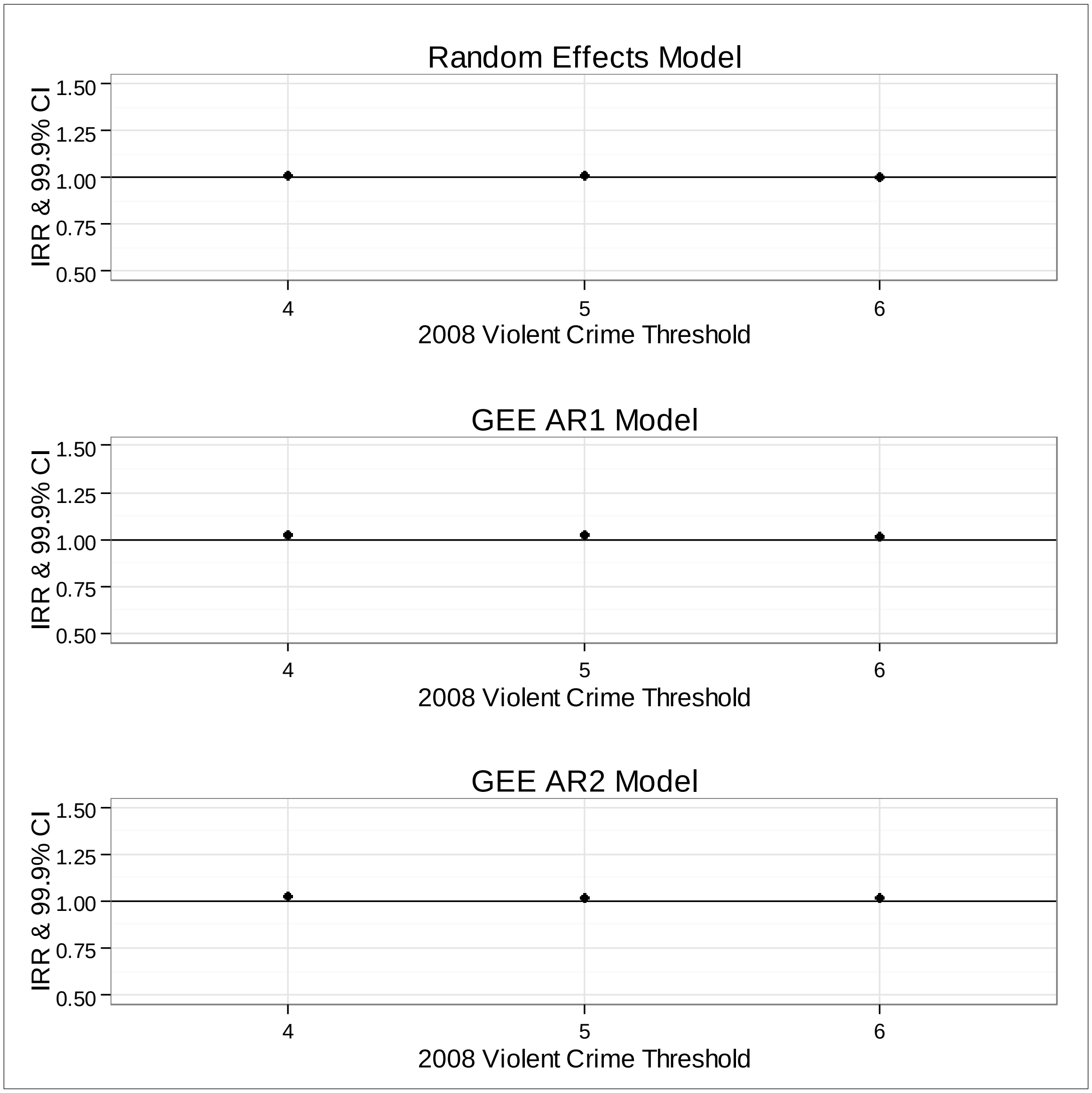
Figure D8. Incident rate ratios for lagged hot spot mean centered monthly pedestrian stops on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

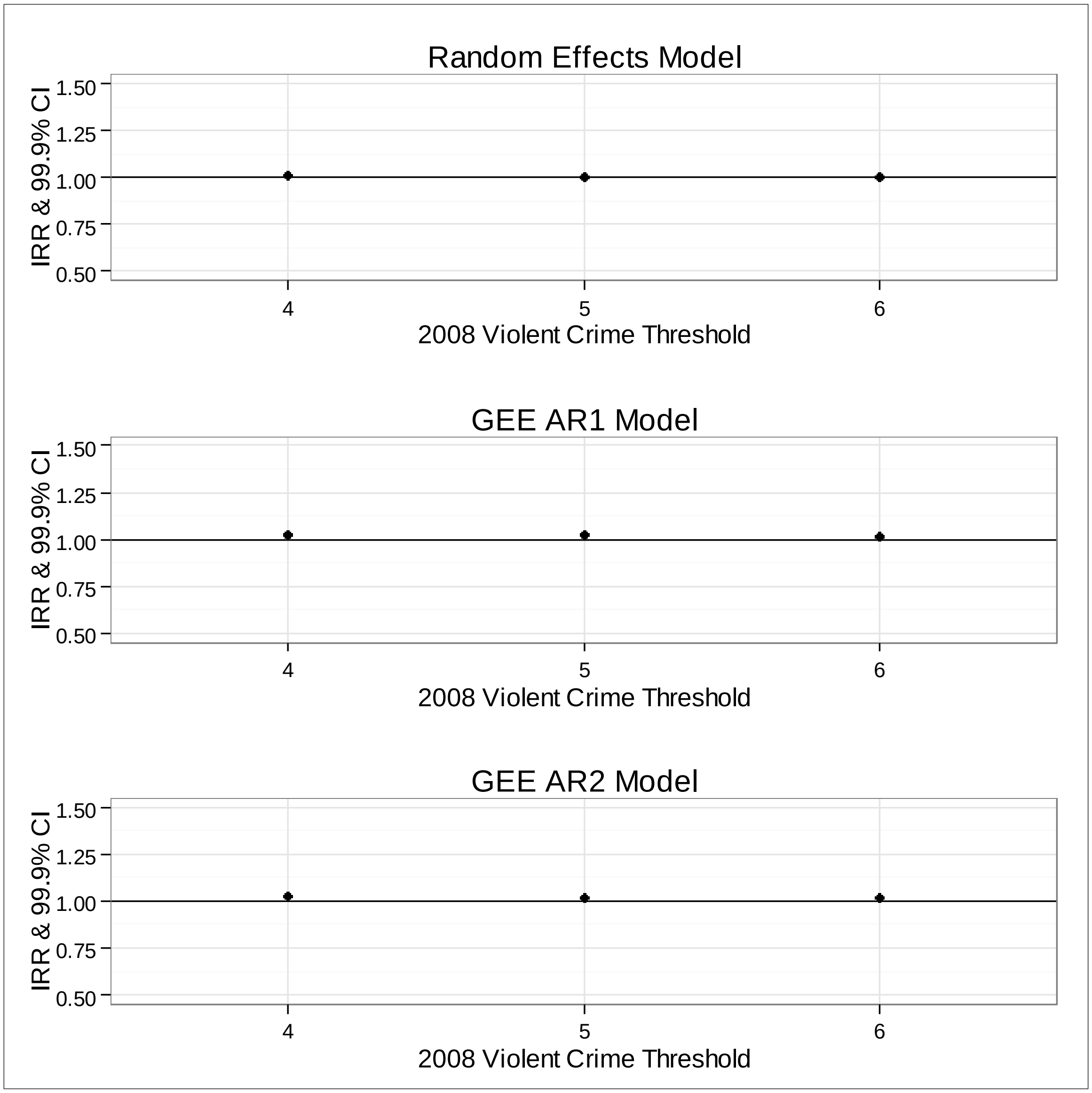
Figure D9. Incident rate ratios for contemporaneous raw monthly traffic enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

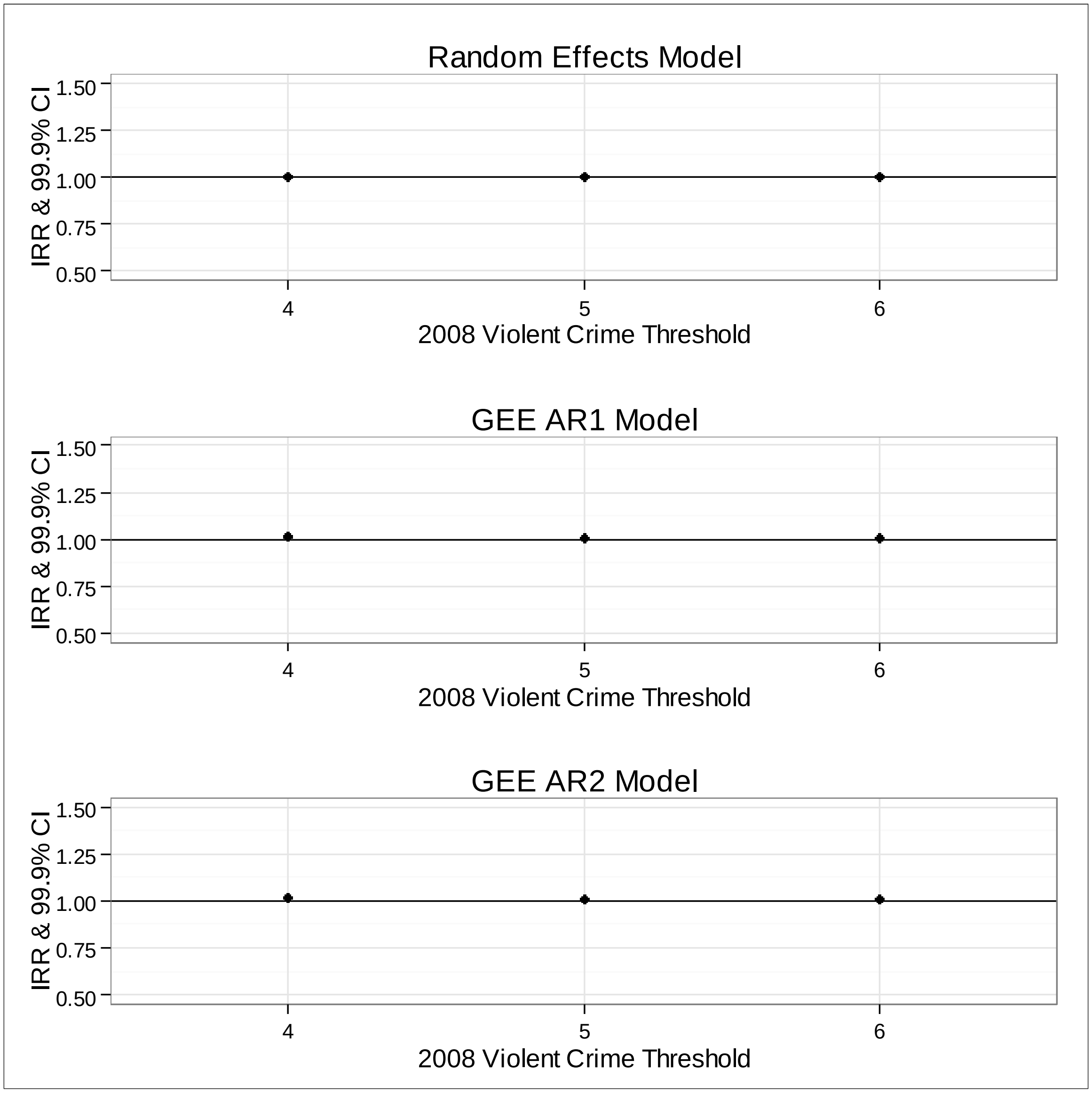
Figure D10. Incident rate ratios for lagged raw monthly traffic enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

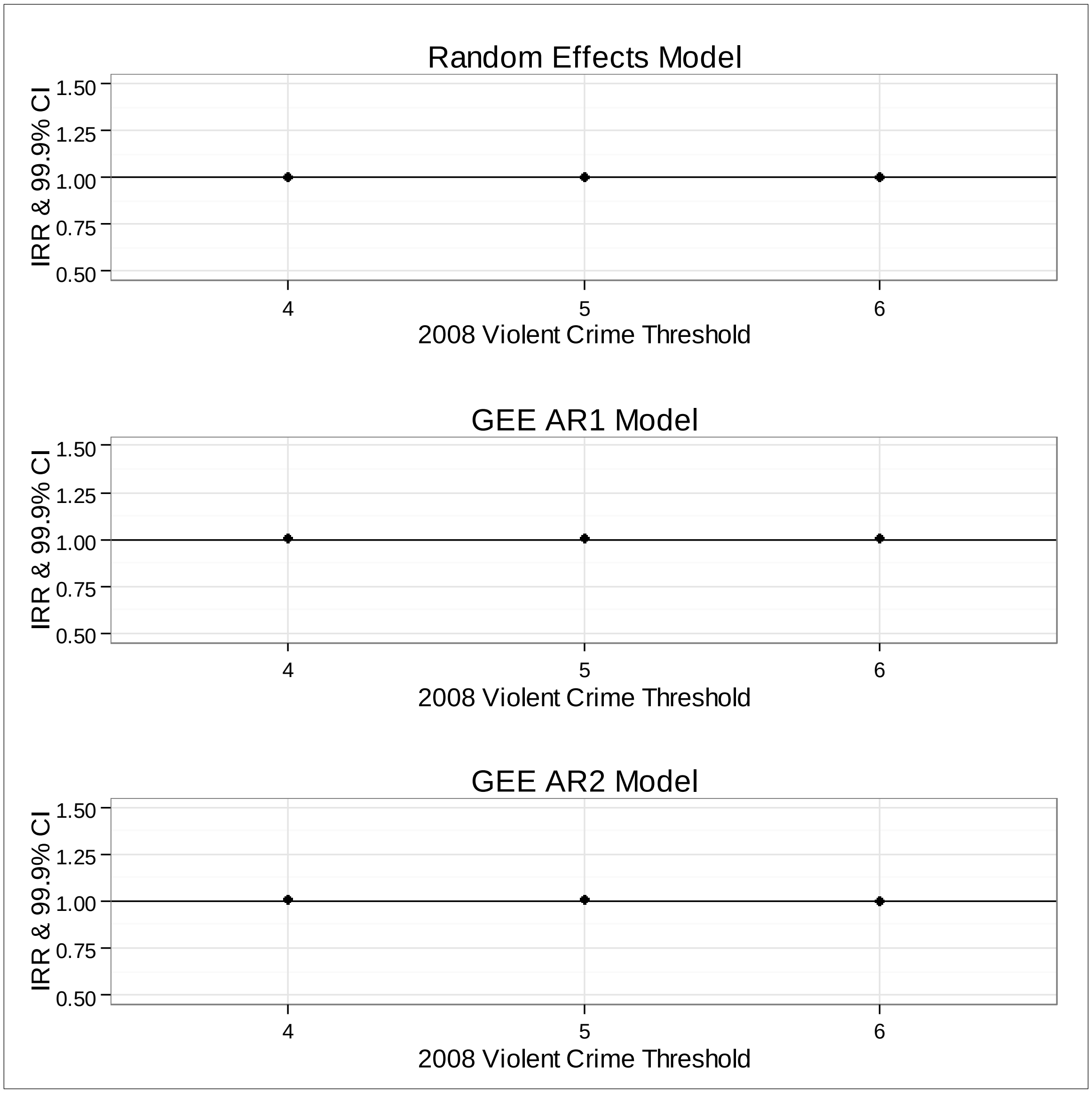
Figure D11. Incident rate ratios for contemporaneous hot spot mean centered monthly traffic enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

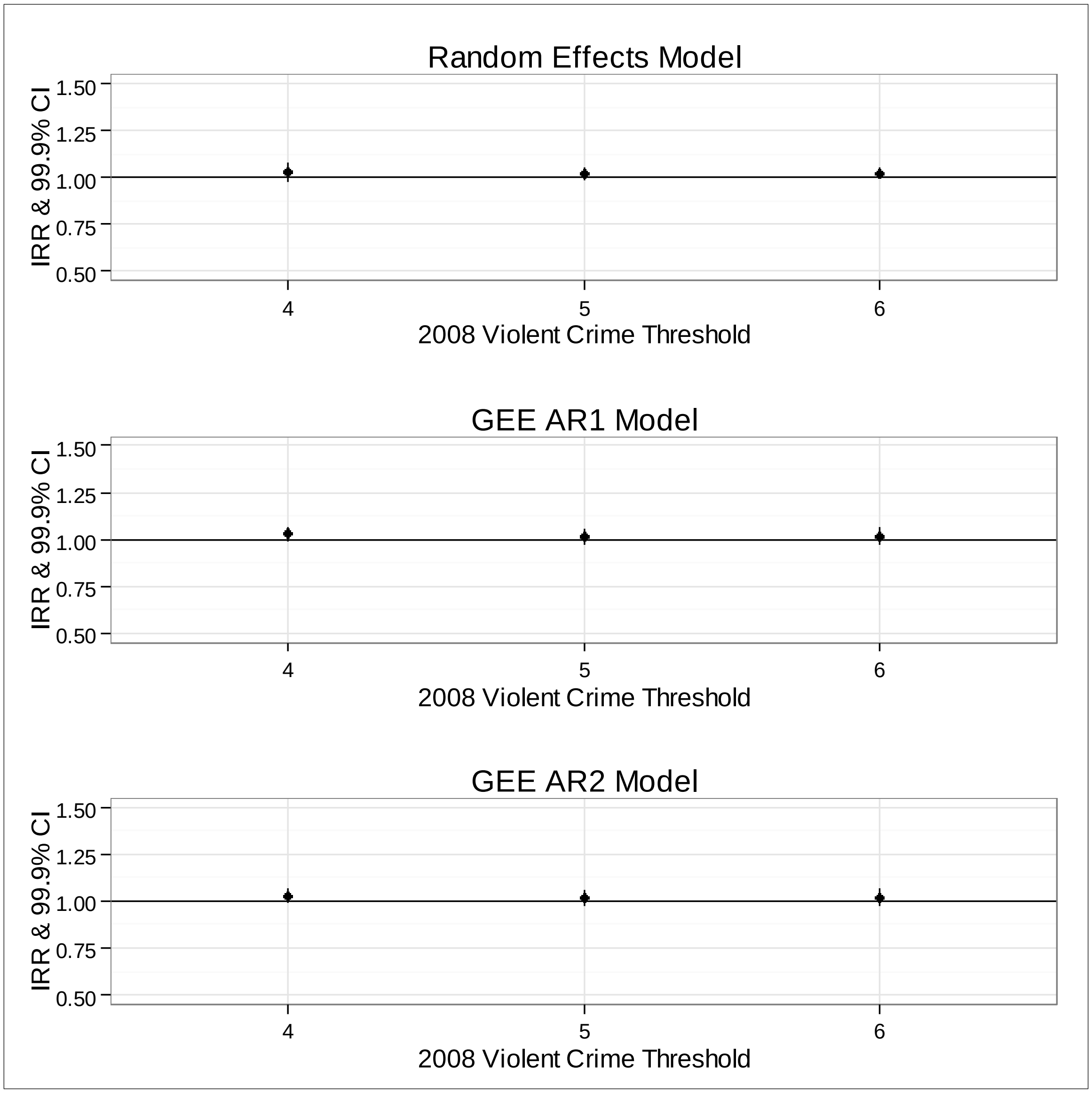
Figure D12. Incident rate ratios for lagged hot spot mean centered monthly traffic enforcement on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

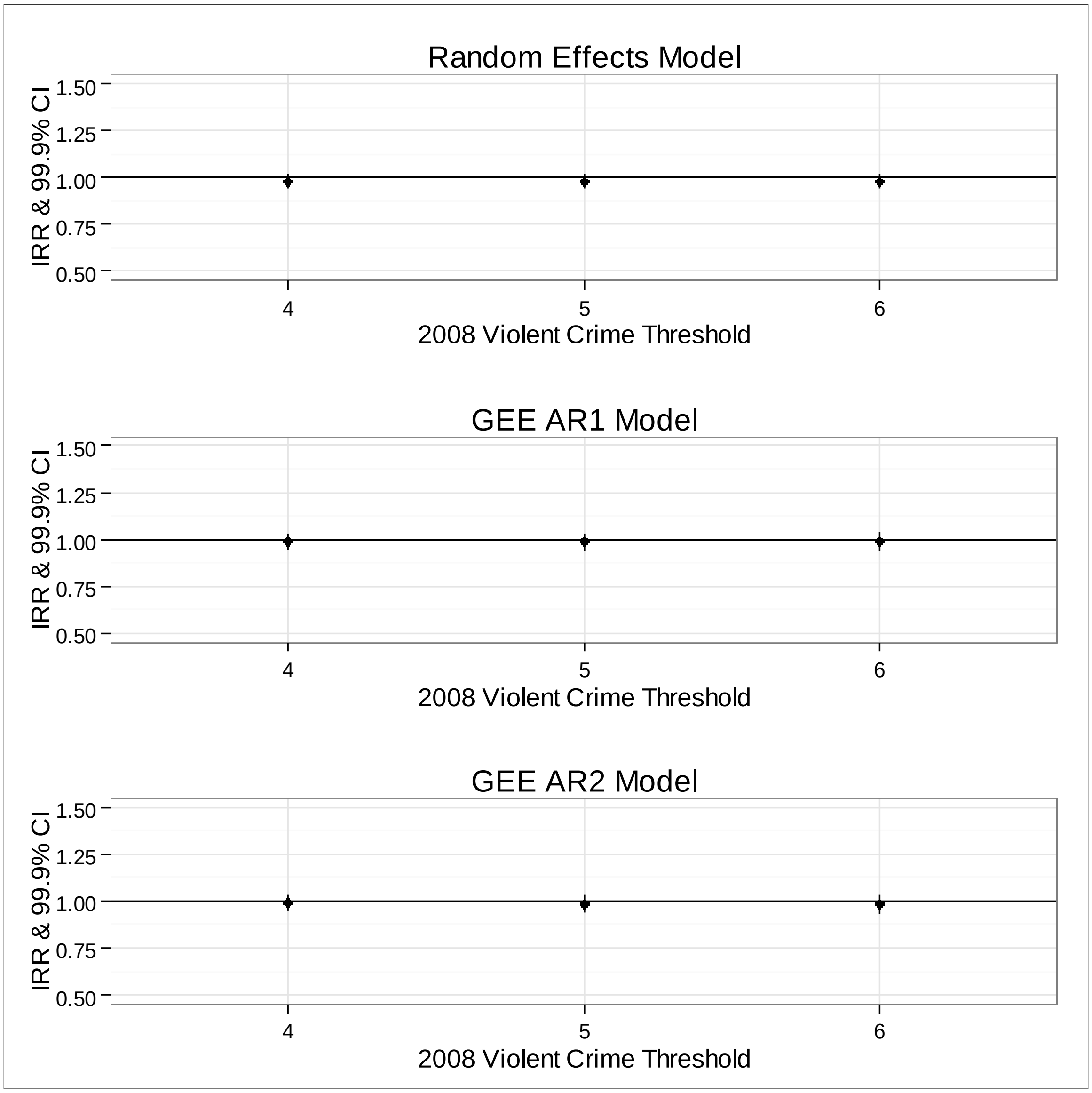
Figure D13. Incident rate ratios for contemporaneous raw monthly quality of life arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

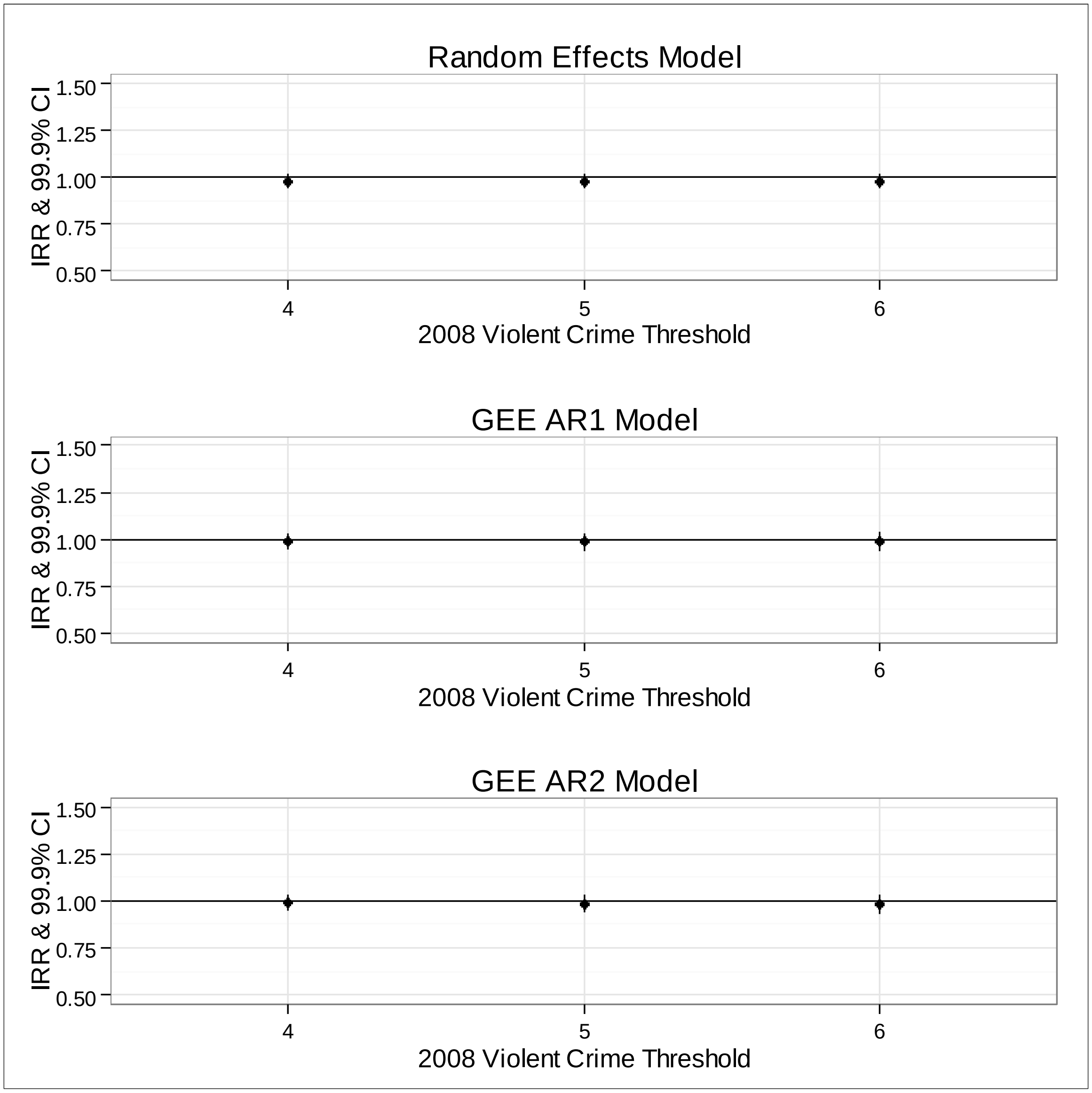
Figure D14. Incident rate ratios for lagged raw monthly quality of life arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

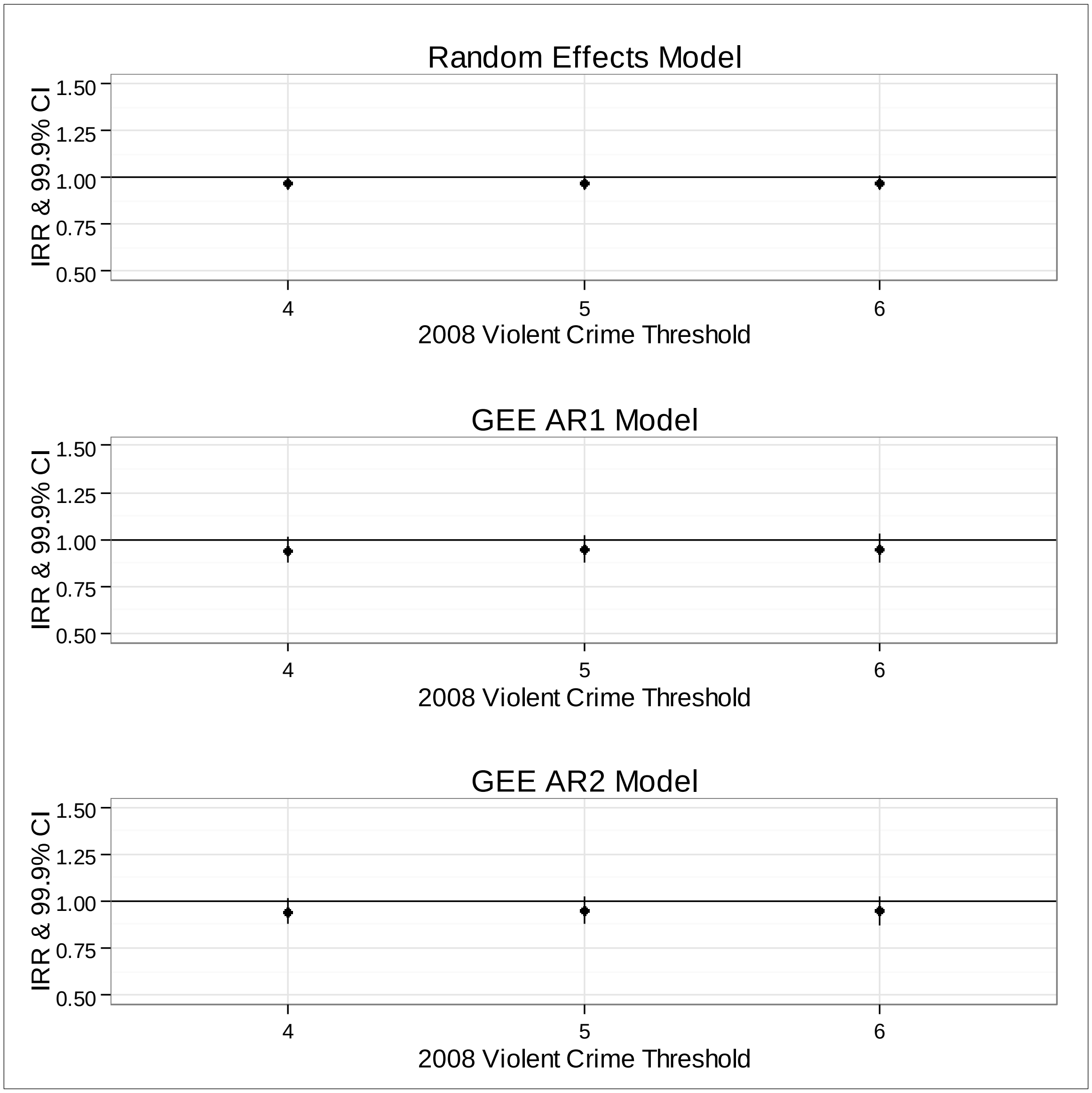
Figure D15. Incident rate ratios for contemporaneous hot spot mean centered monthly quality of life arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

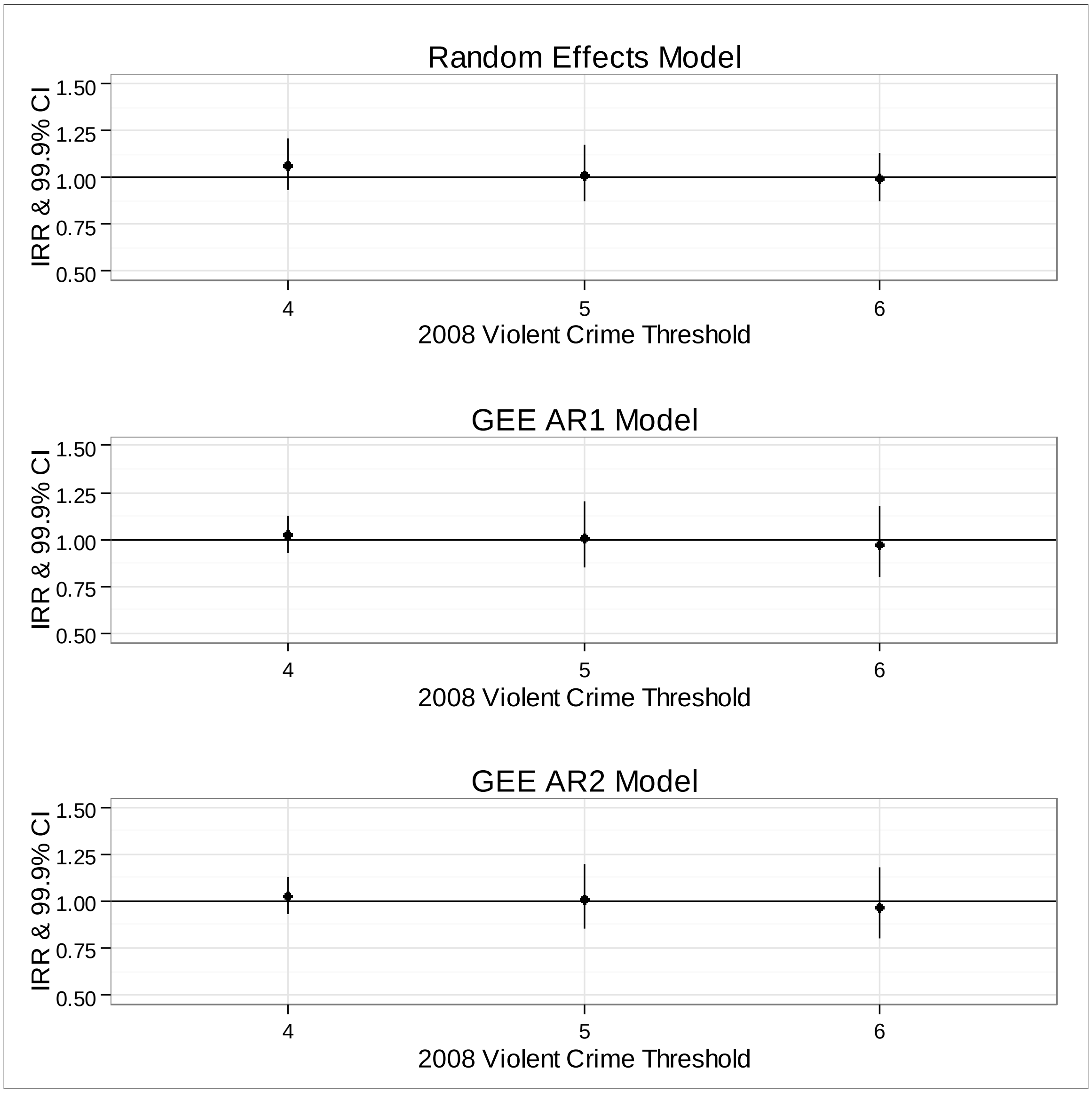
Figure D16. Incident rate ratios for lagged hot spot mean centered monthly quality of life arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

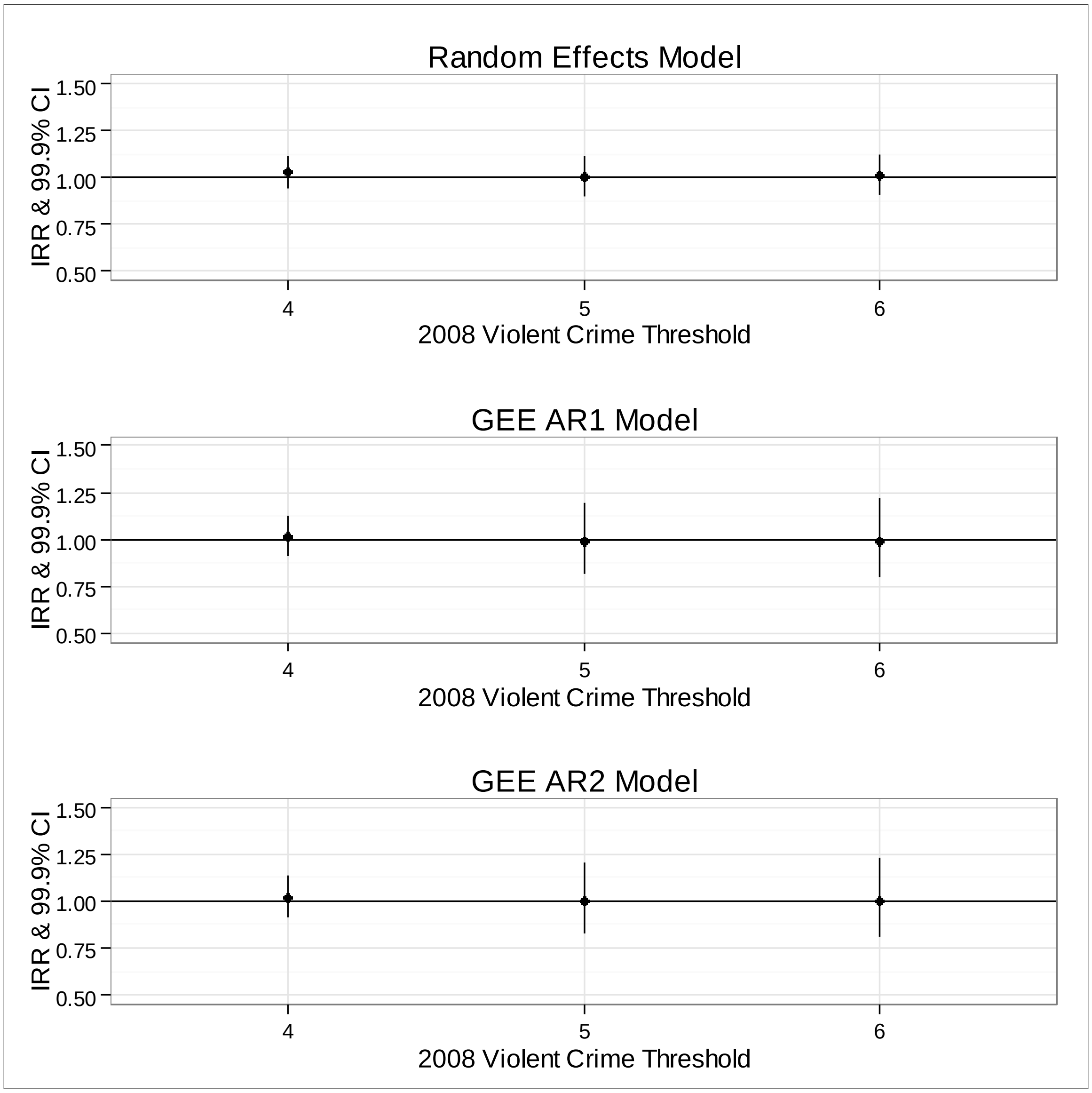
Figure D17. Incident rate ratios for contemporaneous raw monthly felony arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

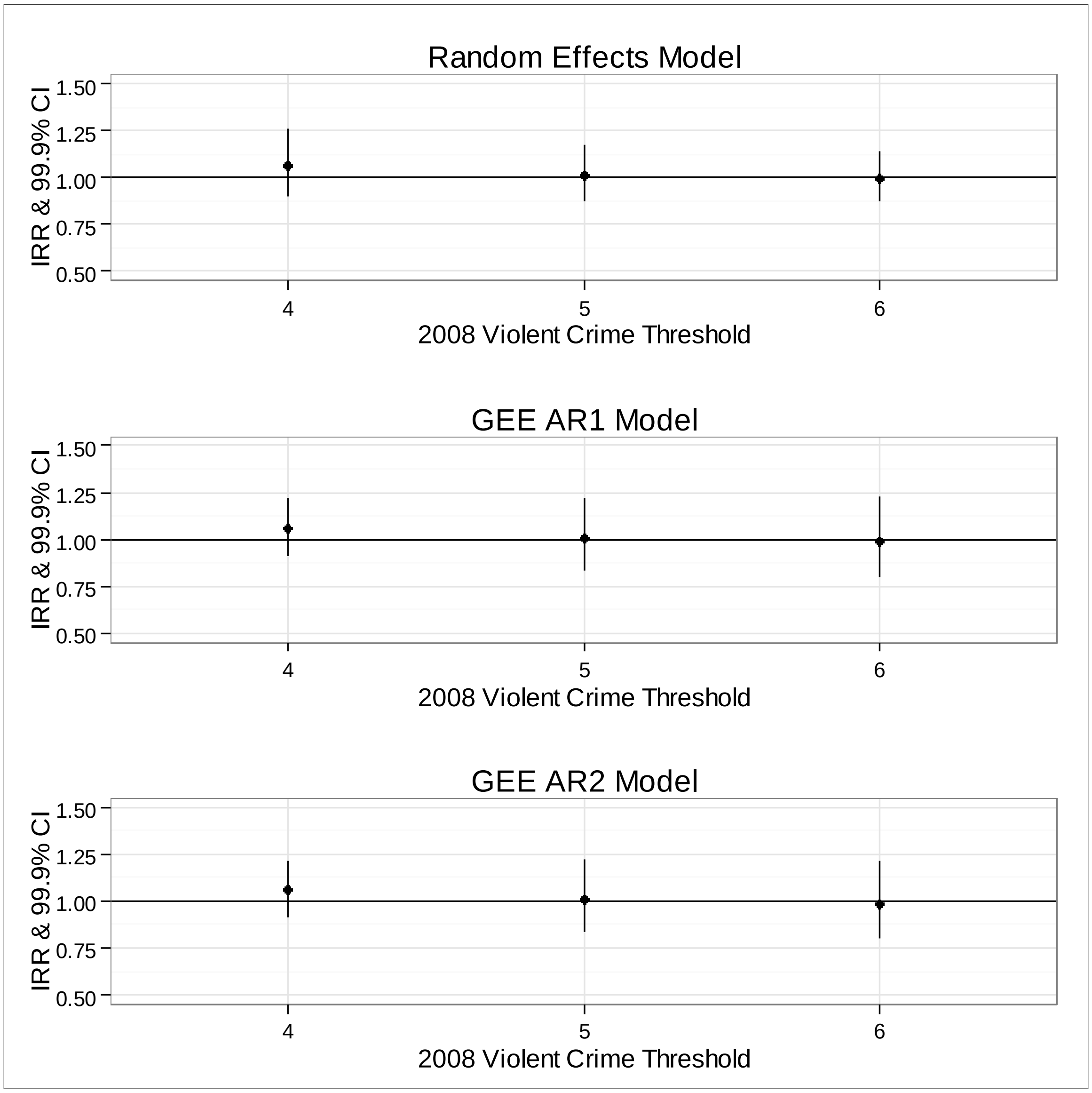
Figure D18. Incident rate ratios for lagged raw monthly felony arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

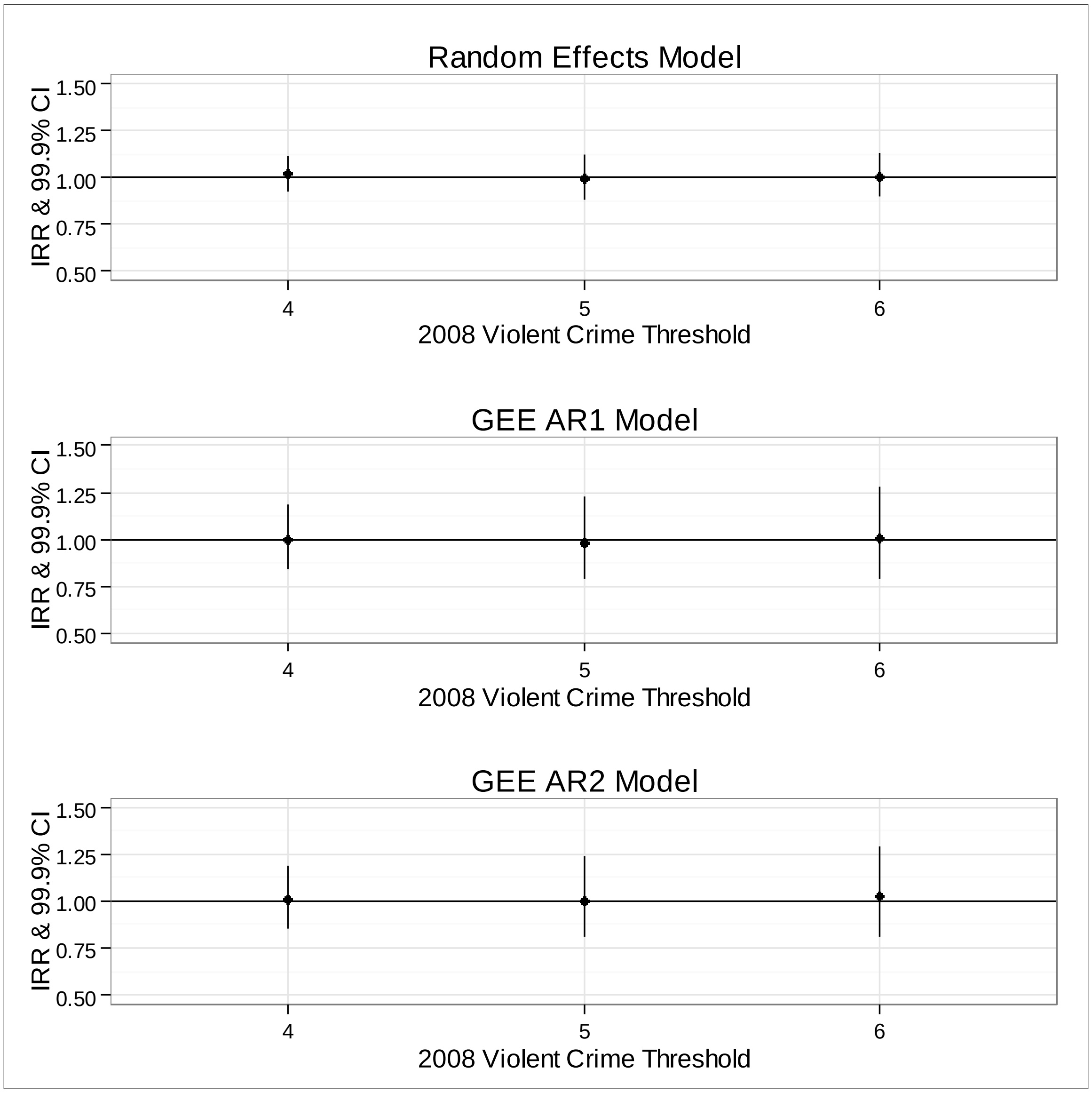
Figure D19. Incident rate ratios for contemporaneous hot spot mean centered monthly felony arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

Figure D20. Incident rate ratios for lagged hot spot mean centered monthly felony arrests on monthly violent crime counts by hot spot threshold for each statistical technique



Notes: All models were specified with a negative binomial probability distribution and include the month indicators, year indicators, Philadelphia Foot Patrol Experiment, Philadelphia Policing Tactics Experiment, and the unit length control variables. The number of hot spot by month observations for the contemporaneous models included: (1) four threshold (n = 20,880), (2) five threshold (n = 10,149), and (3) six threshold (n = 5,760).

Abbreviations: IRR = Incident rate ratio, CI = Confidence interval, GEE AR1 = Generalized estimating equations with a first-order autoregressive error structure, GEE AR2 = Generalized estimating equations with a second-order autoregressive error structure.

E. Sensitivity Analysis: Dependent Variable Operationalization

Different crime types may be impacted by crime reduction and prevention tactics differently (Clarke, 1980, 2008; Clarke & Cornish, 1985; Clarke & Eck, 2003), so all analyses described in Chapter 4 were repeated after disaggregating the all violent crime dependent variable into: (1) personal violence (homicides and aggravated assaults) and (2) street robberies. The personal violence dependent variable ranged from 0 to 5 with a mean of 0.079 and a standard deviation of 0.323. The street robbery dependent variable ranged from 0 to 6 with a mean of 0.163 and a standard deviation of 0.465. The results for the personal violence and stress robbery outcomes can be found in Table E1 through Table E30. The reader should keep in mind, however, that the hot spots were identified using the all violent crime dependent variable operationalization, and different hot spots may have been identified if the disaggregated dependent variables were used. Nonetheless, the directions, relative magnitudes, and statistical significance of the IRR's were consistent across the models for the total violence, personal violence, and street robbery dependent variables.

Table E1. Personal violence and total police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-3.1552	0.0087	0.0426	0.0218	0.0834	-2.8134	0.0144	0.0600	0.0273	0.1320
Total enforcement	0.0172***	0.0029	1.0174	1.0078	1.0270	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0151***	0.0029	1.0152	1.0057	1.0248
Month – February	0.0627	0.2229	1.0647	0.5347	2.1202	-0.2414	0.1880	0.7855	0.3574	1.7263
Month – March	0.2589	0.2832	1.2954	0.6310	2.6597	0.0035	0.2308	1.0035	0.4708	2.1386
Month – April	0.3910	0.3033	1.4784	0.7527	2.9035	0.0901	0.2436	1.0943	0.5260	2.2765
Month – May	0.4647	0.3484	1.5916	0.7745	3.2708	0.1762	0.2871	1.1927	0.5401	2.6338
Month – June	0.2787	0.2751	1.3213	0.6660	2.6214	-0.0171	0.2246	0.9831	0.4636	2.0847
Month – July	0.5844	0.3846	1.7939	0.8860	3.6324	0.2842	0.3121	1.3287	0.6134	2.8777
Month – August	0.3305	0.3012	1.3917	0.6827	2.8371	-0.0027	0.2342	0.9973	0.4605	2.1596
Month – September	0.4584	0.3239	1.5815	0.8061	3.1028	0.1011	0.2467	1.1064	0.5313	2.3042
Month – October	0.2972	0.2946	1.3461	0.6552	2.7656	-0.0163	0.2353	0.9839	0.4479	2.1611
Month – November	0.2557	0.2920	1.2914	0.6136	2.7178	-0.0639	0.2390	0.9381	0.4057	2.1692
Month – December	-0.6369	0.1501	0.5290	0.2079	1.3456	-1.0870***	0.0982	0.3372	0.1294	0.8790
Year – 2010	-0.0049	0.1223	0.9951	0.6641	1.4910	0.0011	0.1277	1.0011	0.6580	1.5232
Year – 2011	-0.2075	0.1134	0.8126	0.5134	1.2861	-0.2323	0.1138	0.7927	0.4942	1.2714
Year – 2012	-0.6299***	0.0835	0.5327	0.3179	0.8925	-0.6722***	0.0808	0.5106	0.3034	0.8593
Year – 2013	-0.7127***	0.0837	0.4903	0.2796	0.8600	-0.7305***	0.0831	0.4817	0.2731	0.8496

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E1. Personal violence and total police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
PFPE Foot patrol	-0.2797	0.1823	0.7560	0.3420	1.6715	-0.2124	0.1886	0.8086	0.3754	1.7421
PPTE Foot patrol	-0.2707	0.3412	0.7629	0.1751	3.3232	-0.2318	0.3545	0.7931	0.1822	3.4521
PPTE Offender-focused	0.5357	0.4444	1.7086	0.7260	4.0214	0.5235	0.4487	1.6880	0.7038	4.0483
PPTE Problem solving	0.5449	0.6454	1.7244	0.5033	5.9088	0.5179	0.6440	1.6785	0.4750	5.9318
Unit length	0.0003***	0.0001	1.0003	1.0000	1.0006	0.0003***	0.0001	1.0003	1.0000	1.0006
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.4507	0.1025	-----	0.2886	0.7040	0.4681	0.1052	-----	0.3013	0.7272
lnalpha	0.3585	0.2530	-----	-0.1373	0.8543	0.3542	0.2492	-----	-0.1341	0.8426

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E2. Personal violence and hot spot mean centered total police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.9545	0.0105	0.0521	0.0269	0.1008	-2.7102	0.0162	0.0665	0.0299	0.1480
MC total enforcement	0.0123***	0.0035	1.0124	1.0009	1.0240	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0090	0.0034	1.0090	0.9980	1.0202
Month – February	0.0656	0.2223	1.0678	0.5382	2.1183	-0.1560	0.2060	0.8556	0.3875	1.8891
Month – March	0.2766	0.2865	1.3187	0.6451	2.6956	0.0881	0.2526	1.0921	0.5102	2.3376
Month – April	0.3912	0.3006	1.4788	0.7576	2.8864	0.1738	0.2656	1.1898	0.5708	2.4801
Month – May	0.4733	0.3501	1.6053	0.7832	3.2902	0.2643	0.3182	1.3025	0.5831	2.9097
Month – June	0.2860	0.2753	1.3311	0.6740	2.6288	0.0724	0.2486	1.0751	0.5023	2.3011
Month – July	0.5880	0.3831	1.8003	0.8939	3.6260	0.3711	0.3412	1.4493	0.6679	3.1446
Month – August	0.3244	0.2967	1.3832	0.6829	2.8016	0.0841	0.2618	1.0877	0.4927	2.4016
Month – September	0.4422	0.3154	1.5562	0.7988	3.0318	0.1832	0.2716	1.2010	0.5707	2.5275
Month – October	0.2821	0.2881	1.3259	0.6486	2.7106	0.0503	0.2531	1.0516	0.4764	2.3214
Month – November	0.2384	0.2847	1.2692	0.6068	2.6549	0.0005	0.2571	1.0005	0.4295	2.3305
Month – December	-0.6939	0.1408	0.4996	0.1977	1.2626	-1.0268***	0.1046	0.3582	0.1371	0.9359
Year – 2010	0.0110	0.1227	1.0111	0.6781	1.5076	0.0042	0.1272	1.0042	0.6620	1.5233
Year – 2011	-0.2061	0.1108	0.8137	0.5198	1.2738	-0.2361	0.1109	0.7897	0.4975	1.2537
Year – 2012	-0.6686***	0.0796	0.5124	0.3073	0.8546	-0.7241***	0.0761	0.4848	0.2892	0.8125
Year – 2013	-0.7451***	0.0816	0.4747	0.2697	0.8355	-0.7847***	0.0795	0.4563	0.2571	0.8098

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E2. Personal violence and hot spot mean centered total police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
PFPE Foot patrol	-0.1559	0.2057	0.8556	0.3879	1.8875	-0.0845	0.2123	0.9190	0.4298	1.9651
PPTE Foot patrol	-0.2644	0.3425	0.7677	0.1769	3.3317	-0.2259	0.3541	0.7978	0.1852	3.4368
PPTE Offender-focused	0.5350	0.4539	1.7074	0.7119	4.0950	0.5255	0.4561	1.6913	0.6963	4.1080
PPTE Problem solving	0.4959	0.6063	1.6420	0.4872	5.5336	0.4803	0.6109	1.6166	0.4662	5.6056
Unit length	0.0003	0.0001	1.0003	0.9999	1.0006	0.0003	0.0001	1.0003	0.9999	1.0006
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.6986	0.1259	-----	0.4907	0.9945	0.7112	0.1250	-----	0.5040	1.0037
lnalpha	0.3163	0.2522	-----	-0.1780	0.8105	0.3207	0.2479	-----	-0.1652	0.8066

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E3. Personal violence and individual police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-3.1477	0.0088	0.0430	0.0219	0.0841	-2.8139	0.0144	0.0600	0.0272	0.1323
Pedestrian stops	0.0223***	0.0049	1.0225	1.0065	1.0388	-----	-----	-----	-----	-----
Traffic stops	0.0126**	0.0045	1.0127	0.9980	1.0276	-----	-----	-----	-----	-----
QOL arrests	0.0206	0.0180	1.0208	0.9633	1.0818	-----	-----	-----	-----	-----
Felony arrests	0.0436	0.0588	1.0446	0.8681	1.2570	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0195***	0.0035	1.0197	1.0083	1.0312
Traffic stops lag	-----	-----	-----	-----	-----	0.0130	0.0056	1.0131	0.9947	1.0319
QOL arrests lag	-----	-----	-----	-----	-----	-0.0148	0.0265	0.9853	0.9019	1.0765
Felony arrest lags	-----	-----	-----	-----	-----	-0.0657	0.0938	0.9365	0.6736	1.3018
Month – February	0.0690	0.2245	1.0714	0.5376	2.1352	-0.2368	0.1888	0.7891	0.3590	1.7343
Month – March	0.2630	0.2854	1.3008	0.6320	2.6773	0.0040	0.2317	1.0040	0.4698	2.1453
Month – April	0.3906	0.3045	1.4778	0.7501	2.9115	0.0995	0.2457	1.1046	0.5313	2.2968
Month – May	0.4633	0.3481	1.5892	0.7730	3.2672	0.1795	0.2875	1.1967	0.5428	2.6381
Month – June	0.2749	0.2744	1.3165	0.6631	2.6137	-0.0167	0.2245	0.9834	0.4641	2.0840
Month – July	0.5770	0.3843	1.7807	0.8753	3.6228	0.2838	0.3114	1.3281	0.6141	2.8726
Month – August	0.3234	0.3013	1.3819	0.6744	2.8315	-0.0070	0.2331	0.9930	0.4586	2.1502
Month – September	0.4495	0.3236	1.5676	0.7948	3.0918	0.0953	0.2461	1.1000	0.5268	2.2969
Month – October	0.2937	0.2943	1.3414	0.6517	2.7608	-0.0217	0.2347	0.9786	0.4444	2.1546
Month – November	0.2549	0.2920	1.2904	0.6128	2.7172	-0.0626	0.2396	0.9393	0.4057	2.1744
Month – December	-0.6365	0.1499	0.5291	0.2083	1.3439	-1.0820***	0.0984	0.3389	0.1304	0.8809

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E3. Personal violence and individual police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	-0.0130	0.1209	0.9871	0.6597	1.4769	0.0063	0.1291	1.0063	0.6597	1.5348
Year – 2011	-0.2074	0.1125	0.8127	0.5153	1.2815	-0.2182	0.1151	0.8040	0.5019	1.2880
Year – 2012	-0.6322***	0.0830	0.5314	0.3179	0.8885	-0.6558***	0.0823	0.5190	0.3080	0.8747
Year – 2013	-0.7224***	0.0822	0.4856	0.2783	0.8473	-0.7263***	0.0830	0.4837	0.2750	0.8509
PFPE Foot patrol	-0.3613	0.1753	0.6967	0.3045	1.5943	-0.2540	0.1861	0.7757	0.3522	1.7083
PPTE Foot patrol	-0.2947	0.3413	0.7448	0.1649	3.3642	-0.2261	0.3615	0.7976	0.1796	3.5433
PPTE Offender-focused	0.5288	0.4374	1.6969	0.7266	3.9626	0.5208	0.4477	1.6834	0.7017	4.0388
PPTE Problem solving	0.5402	0.6374	1.7163	0.5057	5.8251	0.5103	0.6379	1.6659	0.4725	5.8733
Unit length	0.0003***	0.0001	1.0003	1.0000	1.0006	0.0003***	0.0001	1.0003	1.0000	1.0006
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.4515	0.1016	-----	0.2904	0.7018	0.4668	0.1056	-----	0.2996	0.7273
lnalpha	0.3554	0.2543	-----	-0.1429	0.8537	0.3458	0.2528	-----	-0.1496	0.8413

Notes: ***p < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E4. Personal violence and hot spot mean centered individual police enforcement actions random effects models

	Model A					**Model B**				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.9419	0.0106	0.0528	0.0272	0.1024	-2.7255	0.0159	0.0655	0.0295	0.1457
MC pedestrian stops	0.0180***	0.0053	1.0181	1.0010	1.0356	-----	-----	-----	----	----
MC traffic stops	0.0057	0.0047	1.0057	0.9902	1.0214	-----	-----	-----	----	----
MC QOL arrests	0.0294	0.0235	1.0299	0.9554	1.1101	-----	-----	-----	----	----
MC felony arrests	0.0341	0.0597	1.0347	0.8558	1.2509	-----	-----	-----	----	----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0142***	0.0033	1.0144	1.0035	1.0253
MC traffic stops lag	-----	-----	-----	-----	-----	0.0056	0.0068	1.0056	0.9835	1.0283
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0284	0.0333	0.9720	0.8682	1.0881
MC felony arrests lag	-----	-----	-----	-----	-----	-0.0949	0.1040	0.9094	0.6242	1.3250
Month – February	0.0736	0.2245	1.0764	0.5419	2.1383	-0.1453	0.2085	0.8648	0.3912	1.9115
Month – March	0.2793	0.2890	1.3222	0.6441	2.7145	0.0952	0.2563	1.0999	0.5110	2.3675
Month – April	0.3898	0.3008	1.4766	0.7554	2.8864	0.1909	0.2716	1.2103	0.5784	2.5326
Month – May	0.4714	0.3498	1.6023	0.7813	3.2862	0.2749	0.3216	1.3164	0.5893	2.9408
Month – June	0.2819	0.2743	1.3256	0.6710	2.6191	0.0792	0.2509	1.0825	0.5049	2.3207
Month – July	0.5777	0.3820	1.7820	0.8801	3.6079	0.3763	0.3420	1.4569	0.6728	3.1545
Month – August	0.3132	0.2956	1.3678	0.6718	2.7853	0.0856	0.2618	1.0893	0.4940	2.4020
Month – September	0.4273	0.3133	1.5331	0.7826	3.0035	0.1829	0.2714	1.2007	0.5707	2.5262
Month – October	0.2755	0.2872	1.3172	0.6428	2.6992	0.0483	0.2528	1.0495	0.4750	2.3187
Month – November	0.2336	0.2835	1.2631	0.6034	2.6439	0.0064	0.2588	1.0064	0.4318	2.3456
Month – December	-0.7008	0.1397	0.4962	0.1965	1.2532	-1.0171***	0.1053	0.3616	0.1387	0.9429

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E4. Personal violence and hot spot mean centered individual police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0020	0.1208	1.0020	0.6738	1.4901	0.0093	0.1285	1.0094	0.6640	1.5344
Year – 2011	-0.2103	0.1096	0.8103	0.5193	1.2643	-0.2207	0.1122	0.8020	0.5061	1.2710
Year – 2012	-0.6797***	0.0784	0.5067	0.3045	0.8434	-0.7069***	0.0776	0.4931	0.2938	0.8278
Year – 2013	-0.7642***	0.0796	0.4657	0.2654	0.8173	-0.7840***	0.0797	0.4566	0.2571	0.8107
PFPE Foot patrol	-0.2389	0.1970	0.7875	0.3457	1.7939	-0.1236	0.2082	0.8837	0.4071	1.9185
PPTE Foot patrol	-0.2868	0.3427	0.7506	0.1671	3.3718	-0.2264	0.3573	0.7974	0.1825	3.4837
PPTE Offender-focused	0.5264	0.4443	1.6929	0.7138	4.0150	0.5254	0.4555	1.6912	0.6970	4.1031
PPTE Problem solving	0.4934	0.5987	1.6379	0.4919	5.4534	0.4733	0.6035	1.6053	0.4660	5.5307
Unit length	0.0003	0.0001	1.0003	0.9999	1.0006	0.0003	0.0001	1.0003	0.9999	1.0006
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.7000	0.1257	-----	0.4923	0.9951	0.7086	0.1246	-----	0.5021	1.0001
lnalpha	0.3110	0.2542	-----	-0.1873	0.8093	0.3101	0.2512	-----	-0.1823	0.8025

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E5. Personal violence random effects models equality of coefficients Wald tests

	Contemporaneous Model	**Lagged Model**
	χ^2 (*df*)	**χ^2 (*df*)**
Table 21: Individual count predictors model		
Omnibus test	2.28(3)	3.49(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----
Table 22: Individual hot spot mean centered predictors model		
Omnibus test	4.01(3)	3.49(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table E6. Personal violence and total police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.9640	0.0085	0.0516	0.0301	0.0885	-2.6191	0.0137	0.0729	0.0393	0.1352
Total enforcement	0.0192***	0.0013	1.0194	1.0151	1.0236	-----	-----	-----	---	---
Total enforcement lag	-----	-----	-----	-----	-----	0.0185***	0.0013	1.0186	1.0143	1.0229
Month – February	0.0564	0.2094	1.0580	0.5517	2.0291	-0.2749	0.1614	0.7596	0.3776	1.5283
Month – March	0.2374	0.2450	1.2679	0.6714	2.3944	-0.0393	0.1996	0.9614	0.4855	1.9039
Month – April	0.3742	0.2754	1.4538	0.7794	2.7117	0.0460	0.2136	1.0471	0.5351	2.0490
Month – May	0.4650	0.2968	1.5920	0.8619	2.9403	0.1513	0.2338	1.1634	0.6006	2.2535
Month – June	0.2703	0.2530	1.3103	0.6941	2.4736	-0.0492	0.1975	0.9520	0.4810	1.8840
Month – July	0.5924***	0.3316	1.8083	0.9891	3.3061	0.2641	0.2577	1.3023	0.6790	2.4977
Month – August	0.3273	0.2675	1.3873	0.7355	2.6167	-0.0312	0.2007	0.9693	0.4905	1.9155
Month – September	0.4723	0.3020	1.6036	0.8630	2.9798	0.0889	0.2219	1.0929	0.5603	2.1319
Month – October	0.2995	0.2622	1.3492	0.7118	2.5575	-0.0310	0.2020	0.9695	0.4885	1.9242
Month – November	0.2664	0.2554	1.3052	0.6855	2.4852	-0.0779	0.1937	0.9251	0.4644	1.8427
Month – December	-0.6381	0.1364	0.5283	0.2259	1.2354	-1.1109***	0.0878	0.3293	0.1369	0.7921
Year – 2010	0.0130	0.1142	1.0131	0.6991	1.4682	0.0234	0.1179	1.0237	0.7008	1.4952
Year – 2011	-0.1757	0.0977	0.8389	0.5717	1.2308	-0.1966	0.0981	0.8216	0.5547	1.2168
Year – 2012	-0.5855***	0.0755	0.5568	0.3564	0.8701	-0.6168***	0.0746	0.5397	0.3424	0.8506
Year – 2013	-0.6519***	0.0722	0.5211	0.3303	0.8220	-0.6601***	0.0729	0.5168	0.3248	0.8223
PFPE Foot patrol	-0.2748	0.1702	0.7598	0.3636	1.5876	-0.2291	0.1786	0.7952	0.3798	1.6650
PPTE Foot patrol	-0.2096	0.3048	0.8109	0.2354	2.7936	-0.1900	0.3087	0.8270	0.2421	2.8247
PPTE Offender-focused	0.2957	0.5279	1.3440	0.3691	4.8944	0.2864	0.5217	1.3317	0.3670	4.8328
PPTE Problem solving	0.8077	0.9736	2.2427	0.5376	9.3567	0.7786	0.9439	2.1783	0.5235	9.0648
Unit length	0.0003***	0.0001	1.0003	1.0001	1.0005	0.0003***	0.0001	1.0003	1.0001	1.0005

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E7. Personal violence and total police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.9631	0.0085	0.0517	0.0300	0.0889	-2.6166	0.0138	0.0731	0.0393	0.1359
Total enforcement	0.0190***	0.0013	1.0192	1.0149	1.0236	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0183***	0.0013	1.0184	1.0141	1.0229
Month – February	0.0569	0.2096	1.0586	0.5518	2.0310	-0.2741	0.1615	0.7603	0.3779	1.5297
Month – March	0.2394	0.2420	1.2705	0.6789	2.3777	-0.0382	0.1975	0.9625	0.4899	1.8910
Month – April	0.3754	0.2756	1.4555	0.7806	2.7141	0.0470	0.2137	1.0482	0.5359	2.0502
Month – May	0.4663	0.2972	1.5941	0.8631	2.9442	0.1530	0.2341	1.1653	0.6017	2.2567
Month – June	0.2713	0.2534	1.3117	0.6946	2.4769	-0.0476	0.1978	0.9535	0.4818	1.8871
Month – July	0.5939***	0.3323	1.8111	0.9903	3.3122	0.2661	0.2583	1.3049	0.6803	2.5028
Month – August	0.3292	0.2681	1.3898	0.7366	2.6222	-0.0282	0.2012	0.9722	0.4920	1.9212
Month – September	0.4740	0.3025	1.6064	0.8645	2.9849	0.0896	0.2220	1.0938	0.5608	2.1332
Month – October	0.3003	0.2624	1.3503	0.7125	2.5592	-0.0298	0.2020	0.9706	0.4893	1.9252
Month – November	0.2635	0.2520	1.3015	0.6882	2.4614	-0.0783	0.1912	0.9247	0.4683	1.8259
Month – December	-0.6416	0.1361	0.5264	0.2249	1.2323	-1.1139***	0.0877	0.3283	0.1363	0.7909
Year – 2010	0.0168	0.1170	1.0170	0.6964	1.4852	0.0262	0.1205	1.0266	0.6977	1.5105
Year – 2011	-0.1787	0.0999	0.8363	0.5645	1.2390	-0.1999	0.1001	0.8188	0.5477	1.2241
Year – 2012	-0.5849***	0.0774	0.5572	0.3527	0.8801	-0.6178***	0.0763	0.5392	0.3384	0.8589
Year – 2013	-0.6500***	0.0741	0.5220	0.3273	0.8326	-0.6616***	0.0746	0.5160	0.3208	0.8301
PFPE Foot patrol	-0.2764	0.1723	0.7585	0.3593	1.6014	-0.2253	0.1813	0.7983	0.3781	1.6856
PPTE Foot patrol	-0.2339	0.3036	0.7914	0.2240	2.7963	-0.2144	0.3075	0.8070	0.2303	2.8274
PPTE Offender-focused	0.3076	0.5414	1.3601	0.3670	5.0403	0.2977	0.5344	1.3468	0.3650	4.9695
PPTE Problem solving	0.7857	0.9754	2.1938	0.5079	9.4753	0.7570	0.9452	2.1319	0.4957	9.1692
Unit length	0.0003***	0.0001	1.0003	1.0000	1.0005	0.0003***	0.0001	1.0003	1.0000	1.0006

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E8. Personal violence and hot spot mean centered total police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Intercept	-2.6758	0.0111	0.0688	0.0404	0.1172	-2.4220	0.0166	0.0887	0.0479	0.1643
MC total enforcement	0.0177***	0.0029	1.0179	1.0083	1.0276	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	----	----	0.0143***	0.0030	1.0144	1.0044	1.0244
Month – February	0.0714	0.2094	1.0740	0.5654	2.0402	-0.1660	0.1783	0.8471	0.4237	1.6933
Month – March	0.2638	0.2492	1.3018	0.6935	2.4438	0.0745	0.2224	1.0773	0.5462	2.1249
Month – April	0.3643	0.2713	1.4395	0.7742	2.6766	0.1387	0.2343	1.1487	0.5871	2.2477
Month – May	0.4607	0.2935	1.5852	0.8620	2.9151	0.2517	0.2580	1.2863	0.6648	2.4886
Month – June	0.2704	0.2515	1.3104	0.6969	2.4642	0.0481	0.2174	1.0493	0.5306	2.0750
Month – July	0.5906***	0.3283	1.8050	0.9921	3.2841	0.3672	0.2849	1.4436	0.7540	2.7639
Month – August	0.3142	0.2624	1.3692	0.7288	2.5723	0.0661	0.2207	1.0683	0.5414	2.1080
Month – September	0.4569	0.2955	1.5792	0.8532	2.9229	0.1908	0.2449	1.2103	0.6218	2.3554
Month – October	0.2752	0.2551	1.3167	0.6961	2.4906	0.0397	0.2165	1.0405	0.5248	2.0633
Month – November	0.2506	0.2499	1.2848	0.6774	2.4368	0.0032	0.2093	1.0032	0.5050	1.9929
Month – December	-0.6971	0.1276	0.4981	0.2144	1.1569	-1.0391***	0.0935	0.3538	0.1482	0.8443

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E8. Personal violence and hot spot mean centered total police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0724	0.1217	1.0750	0.7408	1.5602	0.0709	0.1242	1.0735	0.7337	1.5707
Year – 2011	-0.1347	0.1027	0.8740	0.5937	1.2866	-0.1608	0.1023	0.8515	0.5734	1.2644
Year – 2012	-0.5852***	0.0773	0.5570	0.3529	0.8792	-0.6377***	0.0746	0.5285	0.3320	0.8412
Year – 2013	-0.6474***	0.0739	0.5234	0.3290	0.8327	-0.6870***	0.0724	0.5031	0.3132	0.8080
PFPE Foot patrol	-0.0766	0.2132	0.9262	0.4343	1.9756	0.0050	0.2303	1.0051	0.4728	2.1363
PPTE Foot patrol	-0.1729	0.3154	0.8413	0.2450	2.8882	-0.1482	0.3218	0.8623	0.2526	2.9438
PPTE Offender-focused	0.1361	0.4542	1.1458	0.3108	4.2233	0.1318	0.4513	1.1409	0.3104	4.1933
PPTE Problem solving	0.6570	0.8411	1.9291	0.4595	8.0984	0.6420	0.8269	1.9003	0.4539	7.9560
Unit length	0.0002***	0.0001	1.0002	1.0000	1.0005	0.0002	0.0001	1.0002	1.0000	1.0005

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E9. Personal violence and hot spot mean centered total police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.6734	0.0113	0.0690	0.0403	0.1182	-2.4165	0.0168	0.0892	0.0480	0.1659
MC total enforcement	0.0172***	0.0030	1.0174	1.0075	1.0274	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0137***	0.0031	1.0138	1.0035	1.0241
Month – February	0.0710	0.2095	1.0736	0.5649	2.0404	-0.1657	0.1782	0.8473	0.4241	1.6931
Month – March	0.2662	0.2429	1.3050	0.7073	2.4079	0.0738	0.2173	1.0766	0.5542	2.0915
Month – April	0.3663	0.2713	1.4424	0.7767	2.6784	0.1394	0.2339	1.1495	0.5886	2.2451
Month – May	0.4636	0.2939	1.5897	0.8652	2.9210	0.2534	0.2579	1.2884	0.6668	2.4892
Month – June	0.2718	0.2519	1.3123	0.6977	2.4682	0.0500	0.2176	1.0512	0.5319	2.0775
Month – July	0.5929***	0.3292	1.8092	0.9941	3.2926	0.3692	0.2853	1.4466	0.7560	2.7680
Month – August	0.3173	0.2633	1.3735	0.7310	2.5808	0.0699	0.2213	1.0724	0.5439	2.1145
Month – September	0.4597	0.2959	1.5835	0.8562	2.9288	0.1909	0.2444	1.2104	0.6227	2.3525
Month – October	0.2755	0.2547	1.3172	0.6971	2.4889	0.0402	0.2158	1.0410	0.5262	2.0595
Month – November	0.2447	0.2433	1.2772	0.6825	2.3902	-0.0001	0.2035	0.9999	0.5119	1.9535
Month – December	-0.7023	0.1270	0.4954	0.2131	1.1517	-1.0460***	0.0931	0.3513	0.1470	0.8399

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E9. Personal violence and hot spot mean centered total police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0765	0.1269	1.0795	0.7333	1.5891	0.0725	0.1287	1.0752	0.7251	1.5944
Year – 2011	-0.1435	0.1066	0.8663	0.5779	1.2986	-0.1711	0.1057	0.8428	0.5578	1.2733
Year – 2012	-0.5889***	0.0804	0.5549	0.3444	0.8941	-0.6445***	0.0773	0.5249	0.3234	0.8521
Year – 2013	-0.6478***	0.0771	0.5232	0.3222	0.8497	-0.6944***	0.0750	0.4994	0.3046	0.8186
PFPE Foot patrol	-0.0882	0.2165	0.9155	0.4205	1.9932	0.0018	0.2346	1.0018	0.4637	2.1647
PPTE Foot patrol	-0.2211	0.3122	0.8017	0.2226	2.8876	-0.1979	0.3182	0.8204	0.2289	2.9399
PPTE Offender-focused	0.1655	0.4781	1.1800	0.3111	4.4756	0.1602	0.4738	1.1737	0.3109	4.4303
PPTE Problem solving	0.6236	0.8477	1.8657	0.4183	8.3212	0.6105	0.8330	1.8413	0.4156	8.1586
Unit length	0.0002	0.0001	1.0002	0.9999	1.0005	0.0002	0.0001	1.0002	0.9999	1.0005

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E10. Personal violence and individual police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.9698	0.0084	0.0513	0.0299	0.0880	-2.6237	0.0136	0.0725	0.0391	0.1346
Pedestrian stops	0.0251***	0.0034	1.0254	1.0141	1.0368	-----	-----	-----	-----	-----
Traffic stops	0.0157***	0.0024	1.0158	1.0079	1.0238	-----	-----	-----	-----	-----
QOL arrests	0.0000	0.0205	1.0000	0.9347	1.0698	-----	-----	-----	-----	-----
Felony arrests	0.0550	0.0822	1.0565	0.8178	1.3650	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0235***	0.0035	1.0238	1.0125	1.0353
Traffic stops lag	-----	-----	-----	-----	-----	0.0164***	0.0024	1.0165	1.0086	1.0245
QOL arrests lag	-----	-----	-----	-----	-----	-0.0141	0.0227	0.9860	0.9140	1.0636
Felony arrest lags	-----	-----	-----	-----	-----	-0.0351	0.0917	0.9655	0.7064	1.3196
Month – February	0.0616	0.2110	1.0635	0.5537	2.0430	-0.2722	0.1619	0.7617	0.3784	1.5329
Month – March	0.2460	0.2475	1.2789	0.6765	2.4176	-0.0419	0.1992	0.9590	0.4841	1.8998
Month – April	0.3768	0.2766	1.4577	0.7807	2.7215	0.0574	0.2161	1.0590	0.5412	2.0725
Month – May	0.4646	0.2971	1.5913	0.8609	2.9416	0.1526	0.2341	1.1649	0.6014	2.2566
Month – June	0.2655	0.2521	1.3040	0.6903	2.4635	-0.0508	0.1972	0.9505	0.4802	1.8813
Month – July	0.5876***	0.3306	1.7997	0.9833	3.2938	0.2620	0.2573	1.2995	0.6774	2.4930
Month – August	0.3242	0.2670	1.3829	0.7327	2.6102	-0.0394	0.1992	0.9614	0.4862	1.9011
Month – September	0.4682	0.3013	1.5972	0.8586	2.9712	0.0757	0.2194	1.0787	0.5523	2.1066
Month – October	0.2987	0.2623	1.3481	0.7107	2.5571	-0.0394	0.2004	0.9614	0.4842	1.9088
Month – November	0.2708	0.2568	1.3111	0.6882	2.4978	-0.0786	0.1936	0.9244	0.4641	1.8412
Month – December	-0.6304	0.1376	0.5324	0.2274	1.2464	-1.1083***	0.0880	0.3301	0.1372	0.7940

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E10. Personal violence and individual police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0052	0.1133	1.0052	0.6937	1.4567	0.0259	0.1181	1.0263	0.7027	1.4988
Year – 2011	-0.1677	0.0986	0.8456	0.5761	1.2412	-0.1799	0.0999	0.8354	0.5635	1.2383
Year – 2012	-0.5728***	0.0765	0.5640	0.3608	0.8815	-0.5979***	0.0762	0.5500	0.3486	0.8678
Year – 2013	-0.6498***	0.0723	0.5222	0.3311	0.8236	-0.6526***	0.0735	0.5207	0.3271	0.8287
PFPE Foot patrol	-0.3873	0.1583	0.6789	0.3152	1.4621	-0.3013	0.1713	0.7398	0.3453	1.5850
PPTE Foot patrol	-0.2231	0.3017	0.8000	0.2313	2.7672	-0.1628	0.3174	0.8498	0.2486	2.9051
PPTE Offender-focused	0.2902	0.5249	1.3367	0.3672	4.8666	0.2846	0.5204	1.3293	0.3666	4.8204
PPTE Problem solving	0.8039	0.9704	2.2342	0.5351	9.3285	0.7723	0.9380	2.1648	0.5202	9.0080
Unit length	0.0003***	0.0001	1.0003	1.0001	1.0005	0.0003***	0.0001	1.0003	1.0001	1.0005

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E11. Personal violence and individual police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.9686	0.0085	0.0514	0.0298	0.0884	-2.6215	0.0137	0.0727	0.0391	0.1353
Pedestrian stops	0.0247***	0.0035	1.0250	1.0136	1.0366	-----	-----	-----	-----	-----
Traffic stops	0.0157***	0.0025	1.0159	1.0078	1.0240	-----	-----	-----	-----	-----
QOL arrests	0.0014	0.0207	1.0014	0.9357	1.0718	-----	-----	-----	-----	-----
Felony arrests	0.0488	0.0820	1.0500	0.8121	1.3576	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0233***	0.0035	1.0235	1.0120	1.0352
Traffic stops lag	-----	-----	-----	-----	-----	0.0163***	0.0025	1.0164	1.0083	1.0246
QOL arrests lag	-----	-----	-----	-----	-----	-0.0144	0.0231	0.9857	0.9126	1.0646
Felony arrest lags	-----	-----	-----	-----	-----	-0.0391	0.0921	0.9617	0.7017	1.3179
Month – February	0.0615	0.2111	1.0634	0.5534	2.0436	-0.2708	0.1621	0.7627	0.3790	1.5351
Month – March	0.2475	0.2444	1.2808	0.6835	2.3998	-0.0409	0.1971	0.9600	0.4885	1.8866
Month – April	0.3774	0.2766	1.4585	0.7813	2.7224	0.0584	0.2162	1.0602	0.5420	2.0739
Month – May	0.4659	0.2975	1.5935	0.8620	2.9455	0.1545	0.2344	1.1671	0.6026	2.2604
Month – June	0.2665	0.2525	1.3055	0.6908	2.4669	-0.0489	0.1976	0.9523	0.4811	1.8848
Month – July	0.5892***	0.3313	1.8026	0.9846	3.3002	0.2643	0.2579	1.3025	0.6789	2.4989
Month – August	0.3261	0.2676	1.3855	0.7339	2.6158	-0.0358	0.1999	0.9648	0.4880	1.9077
Month – September	0.4698	0.3018	1.5997	0.8599	2.9758	0.0773	0.2197	1.0803	0.5533	2.1094
Month – October	0.2994	0.2624	1.3490	0.7113	2.5586	-0.0381	0.2005	0.9626	0.4851	1.9101
Month – November	0.2680	0.2534	1.3073	0.6908	2.4741	-0.0787	0.1910	0.9243	0.4682	1.8247
Month – December	-0.6342	0.1373	0.5304	0.2263	1.2428	-1.1107***	0.0880	0.3293	0.1367	0.7932

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E11. Personal violence and individual police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Year – 2010	0.0097	0.1161	1.0097	0.6916	1.4742	0.0292	0.1209	1.0296	0.6997	1.5151
Year – 2011	-0.1707	0.1007	0.8431	0.5690	1.2492	-0.1828	0.1021	0.8329	0.5566	1.2465
Year – 2012	-0.5728***	0.0784	0.5640	0.3570	0.8910	-0.5986***	0.0780	0.5496	0.3446	0.8767
Year – 2013	-0.6477***	0.0742	0.5233	0.3282	0.8342	-0.6539***	0.0752	0.5200	0.3231	0.8371
PFPE Foot patrol	-0.3837	0.1609	0.6813	0.3132	1.4819	-0.2938	0.1744	0.7454	0.3451	1.6098
PPTE Foot patrol	-0.2471	0.3004	0.7810	0.2203	2.7686	-0.1883	0.3161	0.8284	0.2360	2.9081
PPTE Offender-focused	0.3023	0.5383	1.3530	0.3653	5.0107	0.2966	0.5335	1.3453	0.3648	4.9604
PPTE Problem solving	0.7823	0.9722	2.1864	0.5062	9.4440	0.7502	0.9391	2.1174	0.4920	9.1115
Unit length	0.0003***	0.0001	1.0003	1.0001	1.0006	0.0003***	0.0001	1.0003	1.0000	1.0006

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E12. Personal violence and hot spot mean centered individual police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.6670	0.0113	0.0695	0.0408	0.1184	-2.4402	0.0163	0.0871	0.0470	0.1615
MC pedestrian stops	0.0215***	0.0050	1.0218	1.0055	1.0384	-----	-----	-----	-----	-----
MC traffic stops	0.0124	0.0057	1.0125	0.9940	1.0313	-----	-----	-----	-----	-----
MC QOL arrests	0.0322	0.0290	1.0327	0.9417	1.1326	-----	-----	-----	-----	-----
MC felony arrests	0.0209	0.0909	1.0211	0.7618	1.3687	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0177***	0.0051	1.0178	1.0013	1.0347
MC traffic stops lag	-----	-----	-----	-----	-----	0.0130	0.0057	1.0131	0.9947	1.0319
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0322	0.0360	0.9683	0.8567	1.0945
MC felony arrest lags	-----	-----	-----	-----	-----	-0.1458	0.1059	0.8643	0.5777	1.2933
Month – February	0.0756	0.2107	1.0786	0.5672	2.0510	-0.1560	0.1802	0.8556	0.4278	1.7111
Month – March	0.2664	0.2502	1.3052	0.6946	2.4528	0.0773	0.2234	1.0804	0.5471	2.1336
Month – April	0.3623	0.2711	1.4367	0.7721	2.6733	0.1535	0.2385	1.1659	0.5948	2.2854
Month – May	0.4598	0.2934	1.5837	0.8608	2.9136	0.2606	0.2606	1.2977	0.6703	2.5125
Month – June	0.2671	0.2508	1.3062	0.6943	2.4573	0.0557	0.2193	1.0573	0.5342	2.0924
Month – July	0.5835***	0.3267	1.7923	0.9839	3.2650	0.3737	0.2871	1.4530	0.7585	2.7837
Month – August	0.3086	0.2612	1.3615	0.7242	2.5596	0.0719	0.2221	1.0745	0.5444	2.1211
Month – September	0.4499	0.2940	1.5682	0.8463	2.9059	0.1953	0.2463	1.2156	0.6241	2.3676
Month – October	0.2727	0.2546	1.3135	0.6941	2.4857	0.0413	0.2169	1.0421	0.5255	2.0668
Month – November	0.2481	0.2495	1.2816	0.6753	2.4323	0.0114	0.2111	1.0114	0.5090	2.0098
Month – December	-0.7028	0.1270	0.4952	0.2129	1.1516	-1.0306***	0.0943	0.3568	0.1495	0.8516

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E12. Personal violence and hot spot mean centered individual police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0674	0.1210	1.0698	0.7372	1.5524	0.0756	0.1249	1.0785	0.7369	1.5786
Year – 2011	-0.1367	0.1026	0.8723	0.5922	1.2846	-0.1460	0.1041	0.8642	0.5815	1.2843
Year – 2012	-0.5933***	0.0768	0.5525	0.3498	0.8728	-0.6223***	0.0760	0.5367	0.3369	0.8551
Year – 2013	-0.6576***	0.0732	0.5181	0.3254	0.8248	-0.6789***	0.0732	0.5072	0.3154	0.8156
PFPE Foot patrol	-0.1269	0.2081	0.8809	0.4048	1.9168	-0.0100	0.2307	0.9901	0.4599	2.1316
PPTE Foot patrol	-0.1923	0.3097	0.8250	0.2399	2.8372	-0.1421	0.3240	0.8676	0.2539	2.9643
PPTE Offender-focused	0.1317	0.4522	1.1408	0.3095	4.2045	0.1362	0.4535	1.1459	0.3116	4.2141
PPTE Problem solving	0.6544	0.8392	1.9240	0.4580	8.0818	0.6389	0.8251	1.8945	0.4519	7.9414
Unit length	0.0002	0.0001	1.0002	1.0000	1.0005	0.0002	0.0001	1.0002	1.0000	1.0005

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E13. Personal violence and hot spot mean centered individual police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					**Model B**				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.6652	0.0114	0.0696	0.0406	0.1193	-2.4344	0.0165	0.0876	0.0471	0.1631
MC pedestrian stops	0.0207***	0.0051	1.0209	1.0042	1.0379	-----	-----	-----	-----	-----
MC traffic stops	0.0123	0.0058	1.0123	0.9935	1.0316	-----	-----	-----	-----	-----
MC QOL arrests	0.0335	0.0292	1.0340	0.9424	1.1345	-----	-----	-----	-----	-----
MC felony arrests	0.0130	0.0906	1.0131	0.7549	1.3597	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0173***	0.0052	1.0174	1.0005	1.0346
MC traffic stops lag	-----	-----	-----	-----	-----	0.0123	0.0058	1.0123	0.9935	1.0316
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0317	0.0362	0.9688	0.8567	1.0955
MC felony arrest lags	-----	-----	-----	-----	-----	-0.1416	0.1057	0.8680	0.5814	1.2959
Month – February	0.0746	0.2106	1.0775	0.5663	2.0499	-0.1551	0.1803	0.8563	0.4284	1.7118
Month – March	0.2681	0.2441	1.3075	0.7073	2.4171	0.0766	0.2183	1.0797	0.5550	2.1002
Month – April	0.3637	0.2710	1.4387	0.7741	2.6738	0.1532	0.2378	1.1656	0.5956	2.2810
Month – May	0.4627	0.2939	1.5884	0.8640	2.9200	0.2620	0.2604	1.2995	0.6721	2.5126
Month – June	0.2689	0.2514	1.3086	0.6954	2.4624	0.0568	0.2194	1.0584	0.5351	2.0935
Month – July	0.5867***	0.3279	1.7981	0.9868	3.2763	0.3753	0.2873	1.4554	0.7601	2.7868
Month – August	0.3119	0.2622	1.3661	0.7265	2.5688	0.0750	0.2225	1.0779	0.5464	2.1263
Month – September	0.4529	0.2946	1.5729	0.8494	2.9129	0.1952	0.2457	1.2155	0.6250	2.3642
Month – October	0.2732	0.2544	1.3141	0.6951	2.4846	0.0404	0.2160	1.0412	0.5261	2.0606
Month – November	0.2426	0.2432	1.2746	0.6802	2.3882	0.0081	0.2052	1.0082	0.5159	1.9700
Month – December	-0.7079	0.1265	0.4927	0.2117	1.1466	-1.0368***	0.0939	0.3546	0.1483	0.8477

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E13. Personal violence and hot spot mean centered individual police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0719	0.1260	1.0746	0.7305	1.5807	0.0765	0.1294	1.0795	0.7277	1.6014
Year – 2011	-0.1451	0.1063	0.8649	0.5772	1.2962	-0.1557	0.1075	0.8558	0.5660	1.2940
Year – 2012	-0.5965***	0.0798	0.5507	0.3419	0.8871	-0.6280***	0.0787	0.5337	0.3285	0.8670
Year – 2013	-0.6573***	0.0763	0.5183	0.3192	0.8414	-0.6859***	0.0758	0.5036	0.3069	0.8266
PFPE Foot patrol	-0.1342	0.2118	0.8744	0.3941	1.9403	-0.0151	0.2344	0.9850	0.4502	2.1549
PPTE Foot patrol	-0.2388	0.3067	0.7876	0.2187	2.8362	-0.1952	0.3198	0.8227	0.2290	2.9559
PPTE Offender-focused	0.1607	0.4753	1.1743	0.3100	4.4477	0.1666	0.4766	1.1813	0.3131	4.4561
PPTE Problem solving	0.6225	0.8456	1.8635	0.4187	8.2949	0.6069	0.8307	1.8347	0.4135	8.1398
Unit length	0.0002	0.0001	1.0002	0.9999	1.0005	0.0002	0.0001	1.0002	0.9999	1.0005

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E14. Personal violence generalized estimating equations first-order autoregressive error models equality of coefficients Wald tests

	Contemporaneous Model	**Lagged Model**
	χ^2 (*df*)	**χ^2 (*df*)**
Table 28**: Individual count predictors model**		
Omnibus test	3.62(3)	4.83(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----
Table 30**: Individual hot spot mean centered predictors model**		
Omnibus test	1.57(3)	4.41(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table E15. Personal violence generalized estimating equations second-order autoregressive error models equality of coefficients Wald tests

	Contemporaneous Model	**Lagged Model**
	χ^2 (*df*)	**χ^2 (*df*)**
Table 29**: Individual count predictors model**		
Omnibus test	3.20(3)	4.69(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----
Table 31**: Individual hot spot mean centered predictors model**		
Omnibus test	1.40(3)	4.20(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table E16. Street robbery and total police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-2.0291	0.0171	0.1315	0.0856	0.2018	-1.9426	0.0208	0.1433	0.0889	0.2312
Total enforcement	0.0090***	0.0019	1.0090	1.0027	1.0154	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0079***	0.0019	1.0079	1.0017	1.0142
Month – February	-0.3366	0.0973	0.7142	0.4561	1.1182	-0.4333	0.0929	0.6484	0.4047	1.0388
Month – March	-0.2068	0.0870	0.8132	0.5719	1.1563	-0.2720	0.0934	0.7619	0.5089	1.1406
Month – April	-0.0775	0.1188	0.9254	0.6065	1.4120	-0.1599	0.1192	0.8522	0.5379	1.3501
Month – May	0.0611	0.1190	1.0630	0.7355	1.5365	-0.0296	0.1220	0.9709	0.6420	1.4682
Month – June	-0.1152	0.1049	0.8912	0.6049	1.3128	-0.1979	0.1017	0.8205	0.5457	1.2335
Month – July	0.0805	0.1236	1.0838	0.7448	1.5771	-0.0181	0.1248	0.9820	0.6463	1.4920
Month – August	0.2413	0.1494	1.2729	0.8650	1.8731	0.1309	0.1492	1.1398	0.7409	1.7535
Month – September	0.1724	0.1297	1.1881	0.8295	1.7018	0.0457	0.1305	1.0468	0.6946	1.5777
Month – October	0.2022	0.1364	1.2241	0.8484	1.7664	0.1095	0.1448	1.1157	0.7279	1.7100
Month – November	-0.2094	0.1105	0.8110	0.5179	1.2700	-0.3144	0.1018	0.7302	0.4615	1.1554
Month – December	-0.8584***	0.0704	0.4238	0.2454	0.7318	-1.0528***	0.0643	0.3490	0.1903	0.6400
Year – 2010	0.0508	0.0772	1.0521	0.8265	1.3393	0.0894	0.0820	1.0936	0.8544	1.3997
Year – 2011	-0.0454	0.0669	0.9557	0.7591	1.2031	-0.0272	0.0699	0.9732	0.7683	1.2327
Year – 2012	-0.8243***	0.0481	0.4386	0.3057	0.6291	-0.8169***	0.0497	0.4418	0.3050	0.6399
Year – 2013	-0.9092***	0.0466	0.4028	0.2754	0.5893	-0.8903***	0.0509	0.4105	0.2731	0.6172

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E16. Street robbery and total police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
PFPE Foot patrol	-0.2158	0.1381	0.8059	0.4585	1.4166	-0.1582	0.1394	0.8537	0.4987	1.4613
PPTE Foot patrol	0.1821	0.2029	1.1997	0.6876	2.0930	0.1767	0.2087	1.1932	0.6711	2.1214
PPTE Offender-focused	0.0745	0.2922	1.0774	0.4414	2.6299	0.0790	0.3056	1.0822	0.4274	2.7403
PPTE Problem solving	-0.4837	0.2011	0.6165	0.2107	1.8034	-0.4867	0.2037	0.6146	0.2065	1.8295
Unit length	-0.0006***	0.0002	0.9994	0.9989	1.0000	-0.0006***	0.0002	0.9994	0.9988	1.0000
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.7878	0.1350	----	0.5631	1.1021	0.8137	0.1368	----	0.5853	1.1312
lnalpha	-2.1255	0.5907	----	-3.2832	-0.9678	-2.0950	0.5692	----	-3.2106	-0.9794

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E17. Street robbery and hot spot mean centered total police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.9133	0.0194	0.1476	0.0958	0.2274	-1.8939	0.0227	0.1505	0.0917	0.2470
MC total enforcement	0.0056	0.0019	1.0056	0.9995	1.0118	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0045**	0.0018	1.0046	0.9987	1.0105
Month – February	-0.3382	0.0966	0.7131	0.4567	1.1135	-0.3737**	0.0977	0.6882	0.4313	1.0979
Month – March	-0.2002	0.0869	0.8185	0.5772	1.1607	-0.2164	0.0983	0.8054	0.5391	1.2034
Month – April	-0.0730	0.1184	0.9296	0.6113	1.4138	-0.0998	0.1258	0.9051	0.5728	1.4300
Month – May	0.0653	0.1185	1.0675	0.7408	1.5382	0.0335	0.1289	1.0341	0.6862	1.5584
Month – June	-0.1093	0.1043	0.8965	0.6113	1.3147	-0.1362	0.1077	0.8727	0.5815	1.3098
Month – July	0.0817	0.1231	1.0851	0.7470	1.5762	0.0447	0.1314	1.0457	0.6915	1.5812
Month – August	0.2343	0.1478	1.2640	0.8604	1.8571	0.1894	0.1588	1.2085	0.7843	1.8623
Month – September	0.1558	0.1270	1.1686	0.8172	1.6710	0.1013	0.1384	1.1066	0.7333	1.6698
Month – October	0.1869	0.1334	1.2055	0.8376	1.7350	0.1524	0.1512	1.1646	0.7598	1.7850
Month – November	-0.2292	0.1078	0.7952	0.5090	1.2422	-0.2719	0.1065	0.7620	0.4811	1.2069
Month – December	-0.9137***	0.0670	0.4010	0.2313	0.6952	-1.0146***	0.0671	0.3625	0.1972	0.6665
Year – 2010	0.0515	0.0757	1.0528	0.8309	1.3341	0.0833	0.0806	1.0869	0.8515	1.3873
Year – 2011	-0.0552	0.0650	0.9463	0.7548	1.1863	-0.0373	0.0683	0.9634	0.7629	1.2166
Year – 2012	-0.8694***	0.0455	0.4192	0.2932	0.5993	-0.8626***	0.0473	0.4220	0.2919	0.6103
Year – 2013	-0.9504***	0.0448	0.3866	0.2641	0.5658	-0.9371***	0.0487	0.3917	0.2603	0.5895

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E17. Street robbery and hot spot mean centered total police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
PFPE Foot patrol	-0.1484	0.1454	0.8621	0.4950	1.5014	-0.0944	0.1463	0.9099	0.5362	1.5442
PPTE Foot patrol	0.1926	0.2014	1.2124	0.7019	2.0941	0.1898	0.2050	1.2090	0.6920	2.1124
PPTE Offender-focused	0.0725	0.2894	1.0752	0.4435	2.6070	0.0778	0.3024	1.0809	0.4306	2.7135
PPTE Problem solving	-0.4863	0.2030	0.6149	0.2075	1.8223	-0.4809	0.2090	0.6183	0.2033	1.8805
Unit length	-0.0006***	0.0002	0.9994	0.9988	1.0000	-0.0006	0.0002	0.9994	0.9987	1.0000
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	1.0041	0.1450	-----	0.7566	1.3325	1.0097	0.1461	-----	0.7603	1.3408
lnalpha	-2.2814	0.6553	-----	-3.5658	-0.9970	-2.2096	0.6139	-----	-3.4128	-1.0065

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E18. Street robbery and individual police enforcement actions random effects models

	Model A					Model B				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Intercept	-2.0163	0.0176	0.1331	0.0861	0.2059	-1.9432	0.0210	0.1432	0.0885	0.2318
Pedestrian stops	0.0109***	0.0028	1.0110	1.0019	1.0201	-----	-----	-----	-----	-----
Traffic stops	0.0063	0.0037	1.0063	0.9942	1.0186	-----	-----	-----	-----	-----
QOL arrests	0.0201	0.0104	1.0203	0.9865	1.0552	-----	-----	-----	-----	-----
Felony arrests	0.0048	0.0510	1.0048	0.8503	1.1875	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0125***	0.0029	1.0126	1.0032	1.0221
Traffic stops lag	-----	-----	-----	-----	-----	0.0039	0.0032	1.0039	0.9933	1.0146
QOL arrests lag	-----	-----	-----	-----	-----	-0.0227	0.0170	0.9775	0.9232	1.0351
Felony arrest lags	-----	-----	-----	-----	-----	0.0349	0.0294	1.0356	0.9433	1.1369
Month – February	-0.3336	0.0974	0.7163	0.4579	1.1206	-0.4175	0.0945	0.6587	0.4109	1.0560
Month – March	-0.2085	0.0869	0.8118	0.5708	1.1545	-0.2582	0.0951	0.7724	0.5152	1.1580
Month – April	-0.0825	0.1203	0.9208	0.5991	1.4152	-0.1364	0.1218	0.8725	0.5511	1.3812
Month – May	0.0594	0.1196	1.0612	0.7325	1.5375	-0.0177	0.1230	0.9825	0.6507	1.4834
Month – June	-0.1203	0.1060	0.8867	0.5982	1.3142	-0.1888	0.1026	0.8280	0.5506	1.2450
Month – July	0.0715	0.1241	1.0741	0.7345	1.5708	-0.0122	0.1256	0.9878	0.6501	1.5011
Month – August	0.2359	0.1504	1.2661	0.8564	1.8718	0.1374	0.1495	1.1473	0.7473	1.7614
Month – September	0.1661	0.1313	1.1807	0.8189	1.7024	0.0445	0.1304	1.0455	0.6937	1.5759
Month – October	0.1982	0.1361	1.2192	0.8445	1.7601	0.1079	0.1450	1.1140	0.7260	1.7093
Month – November	-0.2127	0.1105	0.8084	0.5156	1.2674	-0.3081	0.1027	0.7349	0.4641	1.1637
Month – December	-0.8652***	0.0705	0.4210	0.2427	0.7303	-1.0416***	0.0649	0.3529	0.1927	0.6462

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E18. Street robbery and individual police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0442	0.0764	1.0451	0.8216	1.3295	0.0826	0.0814	1.0861	0.8486	1.3900
Year – 2011	-0.0492	0.0669	0.9520	0.7553	1.1999	-0.0149	0.0705	0.9852	0.7785	1.2469
Year – 2012	-0.8319***	0.0482	0.4352	0.3024	0.6264	-0.7980***	0.0509	0.4502	0.3105	0.6529
Year – 2013	-0.9175***	0.0454	0.3995	0.2748	0.5807	-0.8886***	0.0508	0.4112	0.2739	0.6173
PFPE Foot patrol	-0.2528	0.1416	0.7766	0.4262	1.4150	-0.2075	0.1352	0.8126	0.4701	1.4047
PPTE Foot patrol	0.1669	0.2039	1.1816	0.6698	2.0846	0.1869	0.2154	1.2055	0.6696	2.1702
PPTE Offender-focused	0.0735	0.2913	1.0763	0.4417	2.6223	0.0802	0.3031	1.0835	0.4316	2.7202
PPTE Problem solving	-0.4831	0.2015	0.6169	0.2105	1.8074	-0.4909	0.2025	0.6121	0.2061	1.8181
Unit length	-0.0006***	0.0002	0.9994	0.9989	1.0000	-0.0006	0.0002	0.9994	0.9988	1.0000
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	0.7945	0.1377	-----	0.5657	1.1159	0.8309	0.1393	-----	0.5982	1.1541
lnalpha	-2.1249	0.5967	-----	-3.2944	-0.9553	-2.0972	0.5608	-----	-3.1963	-0.9982

Notes: ***$p < 0.001$. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E19. Street robbery and hot spot mean centered individual police enforcement actions random effects models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.8989	0.0199	0.1497	0.0968	0.2317	-1.9109	0.0223	0.1479	0.0900	0.2431
MC pedestrian stops	0.0088***	0.0027	1.0089	1.0000	1.0178	-----	-----	-----	-----	-----
MC traffic stops	0.0014	0.0040	1.0014	0.9884	1.0146	-----	-----	-----	-----	-----
MC QOL arrests	0.0156	0.0105	1.0158	0.9817	1.0510	-----	-----	-----	-----	-----
MC felony arrests	0.0035	0.0521	1.0036	0.8459	1.1907	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0107***	0.0028	1.0107	1.0015	1.0200
MC traffic stops lag	-----	-----	-----	-----	-----	-0.0013	0.0032	0.9987	0.9883	1.0092
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0310	0.0174	0.9695	0.9139	1.0284
MC felony arrests lag	-----	-----	-----	-----	-----	0.0320	0.0311	1.0325	0.9352	1.1399
Month – February	-0.3352	0.0968	0.7152	0.4582	1.1164	-0.3482	0.1001	0.7059	0.4428	1.1254
Month – March	-0.2017	0.0871	0.8173	0.5755	1.1608	-0.1932	0.1013	0.8243	0.5501	1.2352
Month – April	-0.0799	0.1199	0.9232	0.6021	1.4154	-0.0661	0.1290	0.9360	0.5947	1.4733
Month – May	0.0619	0.1190	1.0638	0.7361	1.5374	0.0532	0.1308	1.0547	0.7013	1.5860
Month – June	-0.1178	0.1053	0.8889	0.6020	1.3124	-0.1192	0.1104	0.8876	0.5896	1.3363
Month – July	0.0685	0.1236	1.0709	0.7325	1.5657	0.0573	0.1330	1.0590	0.7006	1.6006
Month – August	0.2249	0.1487	1.2522	0.8472	1.8508	0.2015	0.1598	1.2232	0.7957	1.8804
Month – September	0.1442	0.1282	1.1551	0.8016	1.6645	0.1036	0.1385	1.1092	0.7355	1.6727
Month – October	0.1791	0.1324	1.1962	0.8310	1.7219	0.1531	0.1515	1.1655	0.7599	1.7876
Month – November	-0.2350	0.1075	0.7906	0.5055	1.2365	-0.2602	0.1083	0.7709	0.4855	1.2239
Month – December	-0.9264***	0.0670	0.3960	0.2269	0.6911	-0.9971***	0.0680	0.3689	0.2012	0.6767

Notes: ****p* < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E19. Street robbery and hot spot mean centered individual police enforcement actions random effects models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0418	0.0749	1.0427	0.8232	1.3206	0.0736	0.0799	1.0763	0.8430	1.3743
Year – 2011	-0.0587	0.0656	0.9430	0.7499	1.1857	-0.0236	0.0698	0.9766	0.7719	1.2357
Year – 2012	-0.8779***	0.0458	0.4157	0.2893	0.5972	-0.8415***	0.0488	0.4310	0.2970	0.6256
Year – 2013	-0.9624***	0.0434	0.3820	0.2628	0.5552	-0.9387***	0.0485	0.3911	0.2602	0.5880
PFPE Foot patrol	-0.2038	0.1464	0.8156	0.4518	1.4725	-0.1583	0.1399	0.8536	0.4979	1.4635
PPTE Foot patrol	0.1756	0.2024	1.1919	0.6817	2.0839	0.1994	0.2123	1.2206	0.6887	2.1633
PPTE Offender-focused	0.0704	0.2872	1.0730	0.4448	2.5885	0.0805	0.2987	1.0838	0.4376	2.6845
PPTE Problem solving	-0.4853	0.2038	0.6155	0.2071	1.8298	-0.4850	0.2078	0.6157	0.2028	1.8694
Unit length	-0.0006***	0.0002	0.9994	0.9988	1.0000	-0.0006	0.0002	0.9994	0.9987	1.0000
Global parameters	**Est.**	**S.E.**		**95% CI**		**Est.**	**S.E.**		**95% CI**	
Variance component	1.0051	0.1450	-----	0.7576	1.3334	1.0044	0.1460	-----	0.7554	1.3355
lnalpha	-2.2830	0.6719	-----	-3.5998	-0.9661	-2.2093	0.6029	-----	-3.3909	-1.0277

Notes: ***p < 0.001. Level-one units are monthly observations (n = 60). Level-two units are hot spot street blocks and intersections (n = 169). Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, CI = Confidence interval, MC = Mean centered, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E20. Street robbery random effects models equality of coefficients Wald tests

	Contemporaneous Model	Lagged Model
	χ^2 (*df*)	χ^2 (*df*)
Table 36: Individual count predictors model		
Omnibus test	2.27(3)	7.37(3)
Pedestrian stops vs. Traffic stops	-----	-----
Pedestrian stops vs. Misdemeanor arrests	-----	-----
Pedestrian stops vs. Felony arrests	-----	-----
Traffic stops vs. Misdemeanor arrests	-----	-----
Traffic stops vs. Felony arrests	-----	-----
Misdemeanor arrests vs. Felony arrests	-----	-----
Table 37: Individual hot spot mean centered predictors model		
Omnibus test	2.63(3)	11.09(3)**
Pedestrian stops vs. Traffic stops	-----	5.61(1)*
Pedestrian stops vs. Misdemeanor arrests	-----	5.28(1)*
Pedestrian stops vs. Felony arrests	-----	n.s.
Traffic stops vs. Misdemeanor arrests	-----	n.s.
Traffic stops vs. Felony arrests	-----	n.s.
Misdemeanor arrests vs. Felony arrests	-----	n.s.

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table E21. Street robbery and total police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Intercept	-1.9348	0.0162	0.1445	0.0999	0.2089	-1.6951	0.0245	0.1836	0.1184	0.2847
Total enforcement	0.0228	0.0010	1.0230	1.0196	1.0264	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	-----	-----	0.0220***	0.0010	1.0222	1.0188	1.0257
Month – February	-0.3343	0.0971	0.7158	0.4581	1.1185	-0.6230***	0.0801	0.5363	0.3282	0.8766
Month – March	-0.2267	0.1093	0.7971	0.5078	1.2514	-0.4394	0.0962	0.6444	0.3943	1.0534
Month – April	-0.0903	0.1229	0.9136	0.5870	1.4221	-0.3329	0.1048	0.7169	0.4430	1.1599
Month – May	0.0296	0.1352	1.0300	0.6686	1.5867	-0.2309	0.1142	0.7939	0.4945	1.2745
Month – June	-0.1601	0.1162	0.8520	0.5439	1.3348	-0.4041	0.0989	0.6676	0.4100	1.0871
Month – July	0.0570	0.1390	1.0586	0.6872	1.6307	-0.2212	0.1153	0.8016	0.4993	1.2869
Month – August	0.2345	0.1615	1.2642	0.8303	1.9249	-0.0596	0.1322	0.9421	0.5938	1.4947
Month – September	0.1841	0.1551	1.2022	0.7862	1.8382	-0.1375	0.1237	0.8716	0.5464	1.3902
Month – October	0.2160	0.1590	1.2411	0.8141	1.8920	-0.0288	0.1361	0.9716	0.6127	1.5407
Month – November	-0.1567	0.1186	0.8549	0.5416	1.3496	-0.4413	0.0967	0.6432	0.3922	1.0549
Month – December	-0.7014***	0.0818	0.4959	0.2881	0.8535	-1.1662***	0.0542	0.3115	0.1758	0.5522
Year – 2010	0.0649	0.0944	1.0671	0.7976	1.4275	0.1330	0.1047	1.1422	0.8449	1.5441
Year – 2011	-0.0056	0.0887	0.9944	0.7414	1.3336	0.0288	0.0953	1.0292	0.7588	1.3959
Year – 2012	-0.6985***	0.0548	0.4973	0.3460	0.7149	-0.6798***	0.0573	0.5067	0.3493	0.7352
Year – 2013	-0.7569***	0.0527	0.4691	0.3242	0.6789	-0.7126***	0.0565	0.4904	0.3357	0.7163
PFPE Foot patrol	-0.2997	0.1291	0.7410	0.4177	1.3145	-0.2391	0.1386	0.7873	0.4412	1.4051
PPTE Foot patrol	0.4070	0.3333	1.5023	0.7239	3.1178	0.4044	0.3305	1.4984	0.7252	3.0962
PPTE Offender-focused	-0.0142	0.3248	0.9859	0.3335	2.9149	-0.0432	0.3155	0.9577	0.3240	2.8311
PPTE Problem solving	-0.4125	0.3493	0.6620	0.1166	3.7575	-0.4374	0.3381	0.6457	0.1153	3.6167
Unit length	-0.0006***	0.0001	0.9994	0.9990	0.9998	-0.0006***	0.0001	0.9994	0.9989	0.9998

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E22. Street robbery and total police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Intercept	-1.9192	0.0167	0.1467	0.1009	0.2134	-1.6875	0.0250	0.1850	0.1186	0.2886
Total enforcement	0.0221***	0.0011	1.0224	1.0188	1.0259	-----	-----	-----	-----	-----
Total enforcement lag	-----	-----	-----	----	----	0.0212***	0.0011	1.0214	1.0178	1.0251
Month – February	-0.3231	0.0980	0.7239	0.4637	1.1302	-0.5977***	0.0819	0.5501	0.3370	0.8979
Month – March	-0.2226	0.1063	0.8005	0.5170	1.2393	-0.4307	0.0946	0.6500	0.4027	1.0493
Month – April	-0.0860	0.1228	0.9176	0.5908	1.4252	-0.3190	0.1059	0.7268	0.4500	1.1740
Month – May	0.0329	0.1354	1.0335	0.6714	1.5906	-0.2167	0.1157	0.8052	0.5019	1.2918
Month – June	-0.1564	0.1167	0.8552	0.5459	1.3398	-0.3898	0.1004	0.6772	0.4158	1.1029
Month – July	0.0612	0.1396	1.0631	0.6901	1.6379	-0.2055	0.1172	0.8142	0.5071	1.3074
Month – August	0.2388	0.1623	1.2698	0.8339	1.9335	-0.0446	0.1342	0.9563	0.6027	1.5175
Month – September	0.1871	0.1554	1.2058	0.7891	1.8425	-0.1241	0.1251	0.8833	0.5542	1.4077
Month – October	0.2189	0.1589	1.2448	0.8179	1.8945	-0.0179	0.1371	0.9822	0.6206	1.5546
Month – November	-0.1534	0.1160	0.8578	0.5497	1.3386	-0.4339	0.0947	0.6480	0.4006	1.0480
Month – December	-0.7032***	0.0816	0.4950	0.2878	0.8514	-1.1585***	0.0547	0.3139	0.1769	0.5571
Year – 2010	0.0641	0.0980	1.0662	0.7879	1.4428	0.1337	0.1090	1.1430	0.8351	1.5645
Year – 2011	-0.0151	0.0921	0.9850	0.7240	1.3400	0.0219	0.0995	1.0221	0.7421	1.4079
Year – 2012	-0.7137***	0.0568	0.4898	0.3345	0.7173	-0.6909***	0.0596	0.5011	0.3388	0.7413
Year – 2013	-0.7601***	0.0550	0.4676	0.3175	0.6887	-0.7153***	0.0591	0.4891	0.3285	0.7281
PFPE Foot patrol	-0.3047	0.1316	0.7373	0.4098	1.3265	-0.2401	0.1418	0.7865	0.4347	1.4233
PPTE Foot patrol	0.3902	0.3357	1.4773	0.6995	3.1201	0.3904	0.3338	1.4776	0.7026	3.1075
PPTE Offender-focused	-0.0495	0.3294	0.9517	0.3047	2.9726	-0.0818	0.3197	0.9215	0.2942	2.8858
PPTE Problem solving	-0.3754	0.3653	0.6870	0.1194	3.9518	-0.3915	0.3557	0.6760	0.1197	3.8187
Unit length	-0.0006***	0.0001	0.9994	0.9989	0.9999	-0.0007***	0.0001	0.9993	0.9989	0.9998

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E23. Street robbery and hot spot mean centered total police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.4828	0.0247	0.2270	0.1586	0.3249	-1.4091	0.0323	0.2444	0.1582	0.3774
MC total enforcement	0.0136***	0.0024	1.0137	1.0060	1.0216	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0105***	0.0024	1.0106	1.0027	1.0186
Month – February	-0.3401	0.0911	0.7117	0.4670	1.0847	-0.4353***	0.0922	0.6471	0.4049	1.0342
Month – March	-0.2204	0.1064	0.8022	0.5186	1.2411	-0.2747	0.1108	0.7598	0.4703	1.2276
Month – April	-0.1157	0.1168	0.8908	0.5787	1.3711	-0.1829	0.1201	0.8329	0.5183	1.3384
Month – May	0.0104	0.1292	1.0104	0.6635	1.5388	-0.0656	0.1326	0.9365	0.5877	1.4923
Month – June	-0.1636	0.1126	0.8491	0.5488	1.3137	-0.2314	0.1156	0.7934	0.4912	1.2817
Month – July	0.0318	0.1320	1.0323	0.6778	1.5723	-0.0552	0.1338	0.9463	0.5942	1.5070
Month – August	0.1936	0.1511	1.2136	0.8056	1.8283	0.0928	0.1517	1.0973	0.6962	1.7295
Month – September	0.1302	0.1435	1.1391	0.7525	1.7243	0.0132	0.1416	1.0133	0.6398	1.6047
Month – October	0.1826	0.1495	1.2003	0.7966	1.8086	0.1036	0.1526	1.1091	0.7052	1.7444
Month – November	-0.2239	0.1081	0.7994	0.5123	1.2475	-0.3266	0.1062	0.7214	0.4445	1.1708
Month – December	-0.8477***	0.0680	0.4284	0.2541	0.7221	-1.0537***	0.0580	0.3486	0.2017	0.6027

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E23. Street robbery and hot spot mean centered total police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1125	0.1011	1.1191	0.8314	1.5064	0.1569	0.1100	1.1699	0.8585	1.5943
Year – 2011	0.0052	0.0924	1.0052	0.7429	1.3601	0.0289	0.0985	1.0293	0.7514	1.4101
Year – 2012	-0.7813***	0.0530	0.4578	0.3127	0.6702	-0.7825***	0.0543	0.4573	0.3093	0.6760
Year – 2013	-0.8302***	0.0512	0.4360	0.2962	0.6417	-0.8244***	0.0530	0.4385	0.2946	0.6528
PFPE Foot patrol	0.0592	0.1878	1.0609	0.5926	1.8995	0.1489	0.2053	1.1606	0.6485	2.0771
PPTE Foot patrol	0.4303	0.3448	1.5377	0.7353	3.2158	0.4424	0.3469	1.5565	0.7476	3.2407
PPTE Offender-focused	-0.2343	0.2735	0.7911	0.2536	2.4681	-0.2511	0.2697	0.7780	0.2486	2.4341
PPTE Problem solving	-0.6162	0.2954	0.5400	0.0892	3.2674	-0.6126	0.2945	0.5420	0.0907	3.2397
Unit length	-0.0009***	0.0002	0.9991	0.9986	0.9996	-0.0009***	0.0002	0.9991	0.9986	0.9996

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E24. Street robbery and hot spot mean centered total police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.4619	0.0259	0.2318	0.1605	0.3348	-1.4102	0.0330	0.2441	0.1565	0.3808
MC total enforcement	0.0116***	0.0025	1.0116	1.0035	1.0199	-----	-----	-----	-----	-----
MC total enforcement lag	-----	-----	-----	-----	-----	0.0083***	0.0025	1.0084	1.0001	1.0167
Month – February	-0.3213	0.0926	0.7252	0.4765	1.1037	-0.3880	0.0964	0.6784	0.4251	1.0828
Month – March	-0.2118	0.1013	0.8091	0.5359	1.2218	-0.2492	0.1087	0.7794	0.4926	1.2333
Month – April	-0.1038	0.1163	0.9014	0.5895	1.3784	-0.1503	0.1228	0.8605	0.5380	1.3762
Month – May	0.0207	0.1293	1.0209	0.6729	1.5489	-0.0325	0.1364	0.9680	0.6089	1.5389
Month – June	-0.1539	0.1134	0.8574	0.5549	1.3249	-0.1993	0.1194	0.8193	0.5073	1.3232
Month – July	0.0438	0.1333	1.0448	0.6866	1.5900	-0.0175	0.1389	0.9827	0.6171	1.5648
Month – August	0.2042	0.1524	1.2266	0.8150	1.8460	0.1284	0.1572	1.1370	0.7215	1.7918
Month – September	0.1352	0.1432	1.1448	0.7585	1.7280	0.0439	0.1452	1.0449	0.6614	1.6506
Month – October	0.1870	0.1484	1.2057	0.8041	1.8077	0.1264	0.1545	1.1348	0.7250	1.7763
Month – November	-0.2190	0.1036	0.8033	0.5255	1.2281	-0.3042	0.1034	0.7377	0.4652	1.1701
Month – December	-0.8567***	0.0673	0.4246	0.2520	0.7153	-1.0317***	0.0594	0.3564	0.2059	0.6169

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E24. Street robbery and hot spot mean centered total police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1030	0.1064	1.1085	0.8082	1.5205	0.1466	0.1157	1.1579	0.8335	1.6087
Year – 2011	-0.0245	0.0971	0.9758	0.7034	1.3537	0.0020	0.1037	1.0020	0.7129	1.4083
Year – 2012	-0.8224***	0.0552	0.4394	0.2906	0.6644	-0.8199***	0.0567	0.4405	0.2884	0.6727
Year – 2013	-0.8532***	0.0541	0.4260	0.2805	0.6471	-0.8488***	0.0559	0.4279	0.2784	0.6579
PFPE Foot patrol	0.0235	0.1878	1.0238	0.5598	1.8724	0.1118	0.2047	1.1183	0.6123	2.0425
PPTE Foot patrol	0.3875	0.3422	1.4734	0.6861	3.1641	0.3973	0.3441	1.4878	0.6951	3.1844
PPTE Offender-focused	-0.2752	0.2824	0.7594	0.2234	2.5820	-0.2903	0.2787	0.7481	0.2195	2.5494
PPTE Problem solving	-0.5063	0.3261	0.6027	0.1016	3.5760	-0.4997	0.3260	0.6067	0.1035	3.5555
Unit length	-0.0009***	0.0002	0.9991	0.9985	0.9997	-0.0009***	0.0002	0.9991	0.9985	0.9996

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, MC = Mean centered, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E25. Street robbery and individual police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.9294	0.0163	0.1452	0.1005	0.2100	-1.6988	0.0244	0.1829	0.1179	0.2837
Pedestrian stops	0.0304***	0.0027	1.0309	1.0220	1.0398	-----	-----	-----	-----	-----
Traffic stops	0.0174***	0.0019	1.0175	1.0111	1.0239	-----	-----	-----	-----	-----
QOL arrests	0.0191	0.0148	1.0193	0.9717	1.0693	-----	-----	-----	-----	-----
Felony arrests	-0.0197	0.0582	0.9805	0.8065	1.1921	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0312***	0.0027	1.0317	1.0229	1.0406
Traffic stops lag	-----	-----	-----	-----	-----	0.0164***	0.0020	1.0166	1.0101	1.0231
QOL arrests lag	-----	-----	-----	-----	-----	-0.0123	0.0159	0.9878	0.9367	1.0416
Felony arrest lags	-----	-----	-----	-----	-----	0.0082	0.0638	1.0083	0.8188	1.2415
Month – February	-0.3309	0.0977	0.7183	0.4590	1.1239	-0.6183***	0.0806	0.5388	0.3294	0.8815
Month – March	-0.2251	0.1096	0.7984	0.5082	1.2544	-0.4326	0.0970	0.6488	0.3968	1.0610
Month – April	-0.0951	0.1225	0.9093	0.5837	1.4163	-0.3192	0.1063	0.7267	0.4490	1.1762
Month – May	0.0203	0.1343	1.0205	0.6619	1.5733	-0.2367	0.1137	0.7892	0.4911	1.2681
Month – June	-0.1713	0.1151	0.8426	0.5374	1.3210	-0.4123	0.0983	0.6621	0.4062	1.0791
Month – July	0.0440	0.1375	1.0450	0.6778	1.6111	-0.2273	0.1148	0.7967	0.4959	1.2799
Month – August	0.2264	0.1604	1.2541	0.8233	1.9102	-0.0662	0.1314	0.9360	0.5897	1.4855
Month – September	0.1706	0.1533	1.1860	0.7751	1.8148	-0.1580	0.1215	0.8538	0.5347	1.3635
Month – October	0.2100	0.1582	1.2336	0.8089	1.8814	-0.0440	0.1343	0.9570	0.6030	1.5187
Month – November	-0.1587	0.1185	0.8532	0.5403	1.3475	-0.4460***	0.0963	0.6402	0.3902	1.0504
Month – December	-0.6975***	0.0823	0.4978	0.2890	0.8575	-1.1611***	0.0545	0.3131	0.1765	0.5554

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E25. Street robbery and individual police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0554	0.0934	1.0569	0.7903	1.4135	0.1275	0.1041	1.1359	0.8403	1.5355
Year – 2011	-0.0011	0.0891	0.9989	0.7448	1.3397	0.0434	0.0969	1.0444	0.7695	1.4174
Year – 2012	-0.6811***	0.0558	0.5061	0.3522	0.7273	-0.6464***	0.0593	0.5239	0.3610	0.7603
Year – 2013	-0.7556***	0.0527	0.4697	0.3248	0.6793	-0.7031***	0.0570	0.4950	0.3389	0.7231
PFPE Foot patrol	-0.4527	0.1156	0.6359	0.3496	1.1567	-0.3710	0.1252	0.6900	0.3799	1.2533
PPTE Foot patrol	0.3520	0.3188	1.4219	0.6800	2.9732	0.3975	0.3293	1.4880	0.7184	3.0824
PPTE Offender-focused	-0.0072	0.3257	0.9928	0.3373	2.9220	-0.0390	0.3156	0.9618	0.3267	2.8315
PPTE Problem solving	-0.4096	0.3488	0.6639	0.1178	3.7402	-0.4510	0.3337	0.6370	0.1136	3.5717
Unit length	-0.0006***	0.0001	0.9994	0.9990	0.9998	-0.0006***	0.0001	0.9994	0.9989	0.9998

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E26. Street robbery and individual police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Intercept	-1.9152	0.0168	0.1473	0.1013	0.2142	-1.6929	0.0249	0.1840	0.1179	0.2871
Pedestrian stops	0.0286***	0.0028	1.0290	1.0198	1.0382	-----	-----	-----	-----	-----
Traffic stops	0.0175***	0.0020	1.0176	1.0110	1.0243	-----	-----	-----	-----	-----
QOL arrests	0.0197	0.0151	1.0199	0.9713	1.0710	-----	-----	-----	-----	-----
Felony arrests	-0.0103	0.0582	0.9897	0.8157	1.2008	-----	-----	-----	-----	-----
Pedestrian stops lag	-----	-----	-----	-----	-----	0.0296***	0.0028	1.0301	1.0210	1.0393
Traffic stops lag	-----	-----	-----	-----	-----	0.0162***	0.0021	1.0163	1.0095	1.0231
QOL arrests lag	-----	-----	-----	-----	-----	-0.0146	0.0164	0.9855	0.9329	1.0411
Felony arrest lags	-----	-----	-----	-----	-----	0.0237	0.0641	1.0240	0.8334	1.2582
Month – February	-0.3209	0.0985	0.7255	0.4640	1.1343	-0.5932***	0.0824	0.5526	0.3382	0.9027
Month – March	-0.2221	0.1067	0.8009	0.5165	1.2417	-0.4243	0.0953	0.6542	0.4050	1.0568
Month – April	-0.0905	0.1225	0.9135	0.5877	1.4200	-0.3064	0.1074	0.7361	0.4555	1.1894
Month – May	0.0245	0.1346	1.0248	0.6653	1.5787	-0.2214	0.1153	0.8014	0.4991	1.2868
Month – June	-0.1667	0.1157	0.8464	0.5399	1.3271	-0.3969	0.0998	0.6724	0.4125	1.0959
Month – July	0.0496	0.1383	1.0508	0.6815	1.6203	-0.2120	0.1166	0.8089	0.5035	1.2998
Month – August	0.2314	0.1612	1.2603	0.8273	1.9198	-0.0505	0.1335	0.9507	0.5989	1.5091
Month – September	0.1753	0.1538	1.1916	0.7792	1.8221	-0.1428	0.1231	0.8669	0.5433	1.3833
Month – October	0.2132	0.1582	1.2376	0.8128	1.8846	-0.0317	0.1354	0.9688	0.6116	1.5346
Month – November	-0.1552	0.1160	0.8562	0.5482	1.3373	-0.4384***	0.0944	0.6450	0.3985	1.0441
Month – December	-0.7000***	0.0820	0.4966	0.2885	0.8548	-1.1530***	0.0551	0.3157	0.1778	0.5606

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E26. Street robbery and individual police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.0565	0.0970	1.0581	0.7825	1.4309	0.1297	0.1085	1.1385	0.8321	1.5579
Year – 2011	-0.0102	0.0925	0.9899	0.7280	1.3461	0.0375	0.1011	1.0382	0.7535	1.4305
Year – 2012	-0.6981***	0.0576	0.4976	0.3400	0.7280	-0.6585***	0.0616	0.5176	0.3499	0.7657
Year – 2013	-0.7581***	0.0549	0.4685	0.3186	0.6891	-0.7045***	0.0597	0.4943	0.3322	0.7356
PFPE Foot patrol	-0.4297	0.1207	0.6507	0.3534	1.1980	-0.3508	0.1302	0.7041	0.3832	1.2938
PPTE Foot patrol	0.3460	0.3237	1.4133	0.6652	3.0027	0.3924	0.3350	1.4805	0.7032	3.1171
PPTE Offender-focused	-0.0440	0.3296	0.9569	0.3081	2.9725	-0.0790	0.3192	0.9240	0.2965	2.8797
PPTE Problem solving	-0.3735	0.3644	0.6883	0.1206	3.9294	-0.4050	0.3511	0.6670	0.1180	3.7705
Unit length	-0.0006***	0.0001	0.9994	0.9989	0.9999	-0.0007***	0.0001	0.9993	0.9989	0.9998

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E27. Street robbery and hot spot mean centered individual police enforcement actions generalized estimating equations first-order autoregressive error models

	Model A					Model B				
	B	S.E.	IRR	LL	UL	B	S.E.	IRR	LL	UL
Fixed effects										
Intercept	-1.4725	0.0250	0.2293	0.1602	0.3284	-1.4378	0.0315	0.2375	0.1535	0.3673
MC pedestrian stops	0.0181***	0.0040	1.0183	1.0051	1.0315	-----	-----	-----	-----	-----
MC traffic stops	0.0084	0.0045	1.0084	0.9937	1.0233	-----	-----	-----	-----	-----
MC QOL arrests	0.0178	0.0228	1.0180	0.9456	1.0960	-----	-----	-----	-----	-----
MC felony arrests	-0.0020	0.0681	0.9980	0.7973	1.2491	-----	-----	-----	-----	-----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0200***	0.0039	1.0202	1.0073	1.0332
MC traffic stops lag	-----	-----	-----	-----	-----	0.0024	0.0046	1.0024	0.9873	1.0178
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0628	0.0261	0.9391	0.8570	1.0291
MC felony arrest lags	-----	-----	-----	-----	-----	0.0360	0.0785	1.0366	0.8080	1.3299
Month – February	-0.3396	0.0914	0.7120	0.4667	1.0862	-0.4083***	0.0951	0.6648	0.4151	1.0646
Month – March	-0.2196	0.1066	0.8028	0.5187	1.2425	-0.2502	0.1140	0.7786	0.4809	1.2606
Month – April	-0.1216	0.1162	0.8855	0.5751	1.3635	-0.1446	0.1252	0.8654	0.5376	1.3932
Month – May	0.0042	0.1284	1.0042	0.6592	1.5295	-0.0460	0.1357	0.9550	0.5984	1.5241
Month – June	-0.1708	0.1119	0.8430	0.5446	1.3047	-0.2223	0.1172	0.8007	0.4946	1.2963
Month – July	0.0208	0.1308	1.0210	0.6698	1.5564	-0.0403	0.1362	0.9605	0.6023	1.5315
Month – August	0.1845	0.1499	1.2026	0.7979	1.8124	0.1065	0.1541	1.1124	0.7051	1.7550
Month – September	0.1176	0.1420	1.1248	0.7424	1.7042	0.0126	0.1419	1.0127	0.6386	1.6060
Month – October	0.1756	0.1486	1.1919	0.7908	1.7965	0.1007	0.1527	1.1060	0.7022	1.7420
Month – November	-0.2290	0.1076	0.7953	0.5095	1.2415	-0.3144	0.1077	0.7302	0.4493	1.1866
Month – December	-0.8594***	0.0674	0.4234	0.2507	0.7150	-1.0306***	0.0594	0.3568	0.2062	0.6173

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E27. Street robbery and hot spot mean centered individual police enforcement actions generalized estimating equations first-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1076	0.1003	1.1136	0.8278	1.4979	0.1523	0.1097	1.1645	0.8541	1.5876
Year – 2011	0.0065	0.0923	1.0066	0.7443	1.3612	0.0509	0.1008	1.0522	0.7678	1.4419
Year – 2012	-0.7838***	0.0528	0.4566	0.3121	0.6682	-0.7592***	0.0556	0.4680	0.3165	0.6920
Year – 2013	-0.8385***	0.0508	0.4324	0.2938	0.6362	-0.8179***	0.0535	0.4414	0.2962	0.6576
PFPE Foot patrol	0.0020	0.1815	1.0020	0.5522	1.8184	0.0824	0.1954	1.0859	0.6006	1.9633
PPTE Foot patrol	0.4105	0.3388	1.5076	0.7197	3.1580	0.4591	0.3517	1.5826	0.7617	3.2881
PPTE Offender-focused	-0.2359	0.2724	0.7899	0.2539	2.4573	-0.2455	0.2707	0.7823	0.2505	2.4429
PPTE Problem solving	-0.6093	0.2959	0.5437	0.0907	3.2598	-0.6280	0.2919	0.5336	0.0882	3.2286
Unit length	-0.0009***	0.0002	0.9991	0.9986	0.9996	-0.0009***	0.0002	0.9991	0.9986	0.9996

Notes: ****p* < 0.001. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E28. Street robbery and hot spot mean centered individual police enforcement actions generalized estimating equations second-order autoregressive error models

	Model A					Model B				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Intercept	-1.4553	0.0261	0.2333	0.1614	0.3372	-1.4405	0.0321	0.2368	0.1516	0.3700
MC pedestrian stops	0.0143***	0.0042	1.0144	1.0006	1.0283	-----	-----	-----	----	----
MC traffic stops	0.0082	0.0046	1.0083	0.9931	1.0236	-----	-----	-----	----	----
MC QOL arrests	0.0153	0.0233	1.0154	0.9415	1.0952	-----	-----	-----	----	----
MC felony arrests	0.0092	0.0681	1.0092	0.8083	1.2601	-----	-----	-----	----	----
MC pedestrian stops lag	-----	-----	-----	-----	-----	0.0169***	0.0041	1.0171	1.0037	1.0306
MC traffic stops lag	-----	-----	-----	-----	-----	0.0014	0.0048	1.0014	0.9858	1.0173
MC QOL arrests lag	-----	-----	-----	-----	-----	-0.0638	0.0262	0.9382	0.8557	1.0287
MC felony arrest lags	-----	-----	-----	-----	-----	0.0555	0.0783	1.0571	0.8284	1.3488
Month – February	-0.3209	0.0927	0.7255	0.4764	1.1048	-0.3633	0.0993	0.6954	0.4348	1.1123
Month – March	-0.2118	0.1015	0.8092	0.5356	1.2224	-0.2263	0.1118	0.7974	0.5028	1.2647
Month – April	-0.1075	0.1160	0.8981	0.5870	1.3739	-0.1148	0.1278	0.8916	0.5564	1.4287
Month – May	0.0169	0.1289	1.0170	0.6702	1.5435	-0.0149	0.1393	0.9852	0.6187	1.5690
Month – June	-0.1590	0.1129	0.8530	0.5517	1.3187	-0.1905	0.1210	0.8266	0.5106	1.3380
Month – July	0.0371	0.1327	1.0378	0.6814	1.5807	-0.0060	0.1410	0.9940	0.6233	1.5853
Month – August	0.1984	0.1517	1.2194	0.8098	1.8362	0.1421	0.1597	1.1527	0.7307	1.8184
Month – September	0.1274	0.1424	1.1358	0.7518	1.7160	0.0434	0.1456	1.0444	0.6601	1.6522
Month – October	0.1821	0.1478	1.1997	0.7998	1.7995	0.1233	0.1546	1.1312	0.7215	1.7736
Month – November	-0.2222	0.1034	0.8008	0.5236	1.2246	-0.2930	0.1049	0.7460	0.4697	1.1848
Month – December	-0.8646***	0.0669	0.4212	0.2497	0.7106	-1.0094***	0.0609	0.3644	0.2104	0.6314

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E28. Street robbery and hot spot mean centered individual police enforcement actions generalized estimating equations second-order autoregressive error models (cont.)

	Model A cont.					Model B cont.				
	B	**S.E.**	**IRR**	**LL**	**UL**	**B**	**S.E.**	**IRR**	**LL**	**UL**
Fixed effects										
Year – 2010	0.1001	0.1060	1.1053	0.8062	1.5154	0.1450	0.1157	1.1560	0.8316	1.6070
Year – 2011	-0.0234	0.0971	0.9769	0.7043	1.3549	0.0248	0.1062	1.0251	0.7290	1.4416
Year – 2012	-0.8244***	0.0551	0.4385	0.2900	0.6630	-0.7933***	0.0582	0.4523	0.2961	0.6909
Year – 2013	-0.8590***	0.0538	0.4236	0.2789	0.6434	-0.8370***	0.0567	0.4330	0.2814	0.6662
PFPE Foot patrol	-0.0107	0.1852	0.9894	0.5344	1.8319	0.0565	0.1965	1.0581	0.5744	1.9492
PPTE Foot patrol	0.3761	0.3390	1.4566	0.6773	3.1327	0.4264	0.3520	1.5318	0.7191	3.2631
PPTE Offender-focused	-0.2781	0.2813	0.7573	0.2230	2.5711	-0.2857	0.2796	0.7515	0.2209	2.5563
PPTE Problem solving	-0.5027	0.3264	0.6049	0.1025	3.5706	-0.5143	0.3234	0.5979	0.1008	3.5452
Unit length	-0.0009***	0.0002	0.9991	0.9985	0.9997	-0.0009***	0.0002	0.9991	0.9985	0.9996

Notes: ***$p < 0.001$. Total hot spot monthly observations equals 10,140 in the contemporaneous model and 9,971 in the lagged model. All models specified with a negative binomial probability distribution.

Abbreviations: B = Coefficient, S.E. = Standard error, IRR = Incident rate ratio, LL = Lower-level of 99.9% confidence interval, UL = Upper level of 99.9% confidence interval, Est. = Estimate, QOL = Quality of life, PFPE = Philadelphia Foot Patrol Experiment, PPTE = Philadelphia Policing Tactics Experiment

Table E29. Street robbery generalized estimating equations first-order autoregressive error models equality of coefficients Wald tests

	Contemporaneous Model	**Lagged Model**
	χ^2 (*df*)	**χ^2 (*df*)**
Table 43**: Individual count predictors model**		
Omnibus test	11.56(3)**	16.17(3)***
Pedestrian stops vs. Traffic stops	10.79(1)**	13.77(1)***
Pedestrian stops vs. Misdemeanor arrests	n.s.	6.43(1)**
Pedestrian stops vs. Felony arrests	n.s.	n.s.
Traffic stops vs. Misdemeanor arrests	n.s.	n.s.
Traffic stops vs. Felony arrests	n.s.	n.s.
Misdemeanor arrests vs. Felony arrests	n.s.	n.s.
Table 45**: Individual hot spot mean centered predictors model**		
Omnibus test	2.13(3)	13.13(3)**
Pedestrian stops vs. Traffic stops	-----	6.44(1)**
Pedestrian stops vs. Misdemeanor arrests	-----	8.47(1)**
Pedestrian stops vs. Felony arrests	-----	n.s.
Traffic stops vs. Misdemeanor arrests	-----	5.33(1)*
Traffic stops vs. Felony arrests	-----	n.s.
Misdemeanor arrests vs. Felony arrests	-----	n.s.

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom

Table E30. Street robbery generalized estimating equations first-order autoregressive error models equality of coefficients Wald tests

	Contemporaneous Model	**Lagged Model**
	χ^2 (*df*)	**χ^2 (*df*)**
Table 44**: Individual count predictors model**		
Omnibus test	7.72(3)*	12.94(3)**
Pedestrian stops vs. Traffic stops	7.20(1)**	10.60(1)***
Pedestrian stops vs. Misdemeanor arrests	n.s.	6.21(1)**
Pedestrian stops vs. Felony arrests	n.s.	n.s.
Traffic stops vs. Misdemeanor arrests	n.s.	n.s.
Traffic stops vs. Felony arrests	n.s.	n.s.
Misdemeanor arrests vs. Felony arrests	n.s.	n.s.
Table 46**: Individual hot spot mean centered predictors model**		
Omnibus test	0.78(3)	11.01(3)**
Pedestrian stops vs. Traffic stops	-----	4.70(1)*
Pedestrian stops vs. Misdemeanor arrests	-----	7.93(1)**
Pedestrian stops vs. Felony arrests	-----	n.s.
Traffic stops vs. Misdemeanor arrests	-----	5.25(1)*
Traffic stops vs. Felony arrests	-----	n.s.
Misdemeanor arrests vs. Felony arrests	-----	n.s.

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Abbreviations: *df* = degrees of freedom