UNDERSTANDING EVERYDAY POLICE PROACTIVE ACTIVITY AND ITS RELATIONSHIP WITH CRIME

by

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**Abstract**

UNDERSTANDING EVERYDAY POLICE PROACTIVE ACTIVITY AND ITS RELATIONSHIP WITH CRIME

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Research evidence suggests that proactive policing, when employed in a targeted fashion, can be effective in preventing crime without triggering the displacement of crime to nearby locations. For example, by targeting specific crime hot spots during high risk hours with intermittent and intensified patrol activities, police can effectively manage the risk of criminal and disorderly events. Our knowledge, however, is much more limited with regards to the realities of police proactivity in the everyday context (i.e., how officers are actually practicing proactive activities daily) and its relationship with crime. The scarcity of evidence is conditioned by difficulties in measuring daily proactive activities as well as methodological challenges of drawing inferences using correlational data that records police proactivity as it naturally occurs.

The current study contributes to the literature by answering two exploratory questions. First, what do proactive police patrol patterns and activities look like in

practice, and how does officer proactivity respond to changes in crime at the micro geographic-temporal level? Second, how do changes in proactive patrol then affect crime at those levels, and more specifically, how is the deterrent effect conditioned by the characteristics and the measurement of proactive patrol activities? The study uses calls for service data and police location data generated by automated vehicle locator devices from a large suburban jurisdiction to present a more complete picture of everyday proactivity. Fixed effects models and the Generalized Methods of Moments techniques with time series panel data are employed to tease out the endogenous relationship between crime and police proactivity at micro spatio-temporal levels. In this process, issues related to the optimal practice of proactive patrol are explored.

# Chapter 1. Introduction

Theoretical and research evidence suggests that police proactivity, when employed in a targeted fashion, effectively increases apprehension risk and interrupts opportunities for crime to occur (Clarke & Cornish, 1985; Durlauf & Nagin, 2011; Nagin, 2013; National Academy of Sciences [NAS], 2018). In its most simple yet effective form, proactivity includes patrolling high crime places through the deployment of uncommitted police patrol resources across locations and times. By targeting specific crime hot spots during “hot” hours (times when crime is most frequent) with intermittent and intensified patrol activities, police can effectively manage the risk of criminal and disorderly events (National Research Council [NRC] 2004; Sherman & Weisburd, 1995). Studies have subsequently explored the optimal specification (e.g., dosage and frequency) of proactive patrol that might maximize its residual deterrence, but there remain a few important gaps in the literature that limit our understanding about the realities and effect of police proactive activities.

The challenge is that proactive policing strategies advocated by research evidence may appear very different from those carried out in the everyday operational context. Existing evidence on police proactive strategies has been generated mostly in controlled and regimented environments through experimental testing of interventions (i.e., allowing pre-determined treatment levels to vary across randomly selected or manually matched groups while holding equivalent everything else). However, our knowledge remains scant with regards to the realities of police proactivity in a non-programmatic setting (i.e., how officers are currently practicing proactive policing daily) and its relationship with crime (Lum, Koper, Wu, et al., 2018). The scarcity of evidence is further challenged by difficulties in measuring daily proactive activities, modeling that proactivity against particular outcomes (such as crime), and doing so within appropriate spatial and time units. While experimental and quasi-experimental methods are rightfully regarded as the better vehicle for making causal inferences about the effectiveness of specific proactive interventions, studies of everyday proactive patrol and its relationship with crime can benefit from exploratory work using nonexperimental methods.

Capitalizing on recent advances in the standardization and availability of, and analytic tools for, police data that records the daily movement and activities of patrol officers, the current study attempts to address some of the limitations in the proactivity literature by answering two exploratory questions. First, what do proactive police patrol patterns and activities look like in practice, and how does officer proactivity respond to changes in crime at the micro geographic-temporal level? Second, how do changes in proactive patrol then affect crime at those levels (i.e., is a deterrent effect observed), and, more specifically, how is that deterrent effect conditioned by the characteristics and the measurement of proactive visits? The current study contributes to the literature by exploring the potential causal (and recursive) relationship between everyday police proactivity and crime using holistic measurements of daily proactive work, refined temporal and geographic units of analysis, and improved statistical controls for potential bias. Specifically, I use police vehicle location data generated by GPS devices along with calls for service events data to present a more comprehensive picture of everyday proactivity. Fixed effects models and the Generalized Methods of Moments (GMM) techniques with time series panel data are employed to tease out the endogenous relationship between crime and police proactivity at micro spatio-temporal levels. In this process, issues related to the optimal practice of proactive patrol are explored.

# Chapter 2. Literature Review

To begin, this section reviews the research evidence on the relationship between proactive patrol activities and crime, as well as how proactive work is practiced in the everyday operational context. Studies of routine proactive patrol take a different approach from those evaluating proactive policing interventions. Evaluations of proactive interventions tend to adopt a top-down approach by imposing a set of carefully designed and delineated strategies that often are exceptional to everyday practice. However, the study of the daily practice of proactive patrol is characterized by a bottom-up approach using field observations of police actions or decision-making. Both areas of research are important to understanding and refining proactive patrol deployment to achieve crime prevention gains. Contrasting these two domains of proactive work also sheds light on the discrepancies between proactive policing ideals and the daily practice of proactive work.

Furthermore, the study of routine police proactive patrol across locations and time prompts additional areas of inquiry that are also reviewed in this section and which are important to this dissertation. These include how daily practices of proactivity are operationalized and measured; the development of nonexperimental methods that are best suited to gauge the unique effects proactivity and crime have upon one another; and which units of analysis are most appropriate in developing this line of research. Given that the interactive relationship between crime and proactive patrol is a complex process, this study seeks to lay the foundation for future studies by reviewing and addressing each of these issues in turn.

**Evaluation Research on Proactive Policing and its Impact on Crime**

Reiss and colleagues (Bordua & Reiss, 1966; Reiss, 1973) were some of the earliest policing scholars to use the word “proactive.” Specifically, they made an important distinction between the reactive and proactive mobilization of police action, with reactive action referring to activities in which officers are directed to tasks generated by citizens and proactive action being those initiated by police officers for purposes of detecting crime and controlling vice. Significant theoretical and empirical developments surrounding proactive police activity have been made thereafter, leading to renewed and refined understanding of what exactly constitutes proactive work by the police. In the contemporary context, the definition of proactivity has become more prevention-oriented. It focuses less, as Reiss did, on detecting crime occurrence, and more on the public sentinel aspect of the police in preventing crime before it actually occurs (Nagin, Solow, & Lum, 2015). For instance, the National Academy of Sciences 2018 report on proactive policing defined police proactivity as “[a]ll policing strategies that have as one of their goals the prevention or reduction of crime and disorder and that are not reactive in terms of focusing primarily on uncovering ongoing crime or on investigating or responding to crimes once they have occurred.” (NAS, 2018, p. 1).

Over the last few decades, there have been increasing demands for the police to be more preventative. This shift to proactive policing has in part been propelled by research evidence that debunked the efficacy of traditional policing strategies (Kelling, Pate, Dieckman, & Brown, 1974; Lum & Koper 2017; NRC, 2004; NAS 2018; Sherman & Eck, 2002). The standard or professional model of policing, which Lum and Koper (2017) argue continues to remain the most prevalent police approach in practice today, encompasses three essential strategies: random preventive patrol, rapid response to citizen calls, and reactive investigation of existing crime (Sherman, 2013, calls these strategies the "triple-R"). Under such a model, the police are prescribed as the "thin blue line" that stands between the good citizens and the outlaws. Police engage in crime fighting primarily through enforcing laws and apprehending offenders and are discouraged from taking on "social work" (e.g., problem solving, community outreach) and other preventative activities (Kelling & Moore, 1988). While successful at shielding the police from political influence, these strategies have been generally viewed as ineffective in reducing crime (Kelling et al., 1974; NRC, 2004; Weisburd & Eck, 2004).

On the other hand, ample evidence suggests that police proactivity, when applied properly, reduces crime without generating negative reactions from communities (NAS, 2018; see also reviews by Braga, Welsh, & Schnell, 2015; Lum & Koper, 2017; Lum, Koper, & Telep, 2011; Sherman & Eck, 2002; Weisburd & Eck, 2004). Such proactivity has included a wide range of activities, including place-based patrol, community engagement, problem-solving, and focused deterrence. After reviewing existing evidence, the NAS report concluded that "there is sufficient scientific evidence to support the adoption of some proactive policing practices, certainly if the primary policy goal is to reduce crime" (NAS, 2018, p. 12). Similarly, Sherman (2013) suggested that the triple-R model described above is gradually being replaced in the 21st century by a "Triple-T" model of targeting, testing, and tracking where “proactive management of police resources”, achieved through active monitoring of police activities and the evaluation and feedback mechanisms, is encouraged to facilitate data-driven crime prevention (see also Weisburd & Braga, 2006).

Research has indicated that place-based proactive policing can potentially be an effective proactive approach. For example, research on hot spots policing suggests that proactive patrol, when targeting small and specific (or “micro”) locations that are at high risk for crime and disorder, can effectively prevent crime through mechanisms of deterrence, the blockage of crime opportunities, and incapacitation (Braga, Papachristos, & Hureau, 2012; NRC, 2004), and it does so generally without triggering the displacement of crime to nearby locations (Ratcliffe & Breen, 2011; Weisburd et al., 2006). By redeploying underutilized police resources to places with crime problems during patrol officers’ “non-committed time” (when they are not handling calls for service), hot spots policing capitalizes on the existing patrol function that has long been a core aspect of policing to propel more effective crime prevention. The simplistic, rational, and practical appeal of hot spots policing (along with its demonstrated effectiveness) may account for its popularity among law enforcement agencies. According to the Law Enforcement Management and Administrative Statistics (LEMAS) survey, 13% of local police departments in the United States used computers to identify crime hotspot in 2007 (Reave, 2010). This figure ranged from 56% to 100% for agencies serving a population of 50,000 or more and has likely increased over time. A subsequent study based on a convenience sample of 191 large police agencies suggests that 89% of the responding agencies engaged in violence reduction efforts on hot spots, although the definition of hot spots varied widely across agencies (Koper, 2014).

At the most basic level, place-based proactivity can be carried out through directed or targeted patrol, usually by uniformed officers. In their landmark experiment testing hot spots policing, Sherman and Weisburd (1995) examined intensified but intermittent patrol visits to high risk places during high risk times. In this study, officers had discretion as to what they might do while patrolling a crime hot spot. Discretionary hot spots patrol likely reflects real-life practices considering the lack of direction and guidance from supervisors regarding proactive work in practice (e.g., Famega, Frank, & Mazerolle, 2005). Sherman and Weisburd found that while the timing and length of visits as well as the types of activities varied widely by officers, noticeable reductions in crime and disorder were associated with enhanced dosages of directed patrol. Later, Kochel, Burruss, and Weisburd (2015) instructed officers not to perform specific activities but just to remain visible for short periods of time during each target hot hour at a hot spot. They found that such patrols reduced calls for service and did not result in long term detrimental effects on citizen trust and legitimacy in police. Further, Hegarty and colleagues (2014) explicitly compared heightened intermittent police visibility at crime hot spots during high crime hours with visibility combined with extensive officer activities (e.g., public contact and order maintenance activities). They observed significant reductions in crime and calls for service that were not systematically different across the two groups, demonstrating the crime prevention efficacy of increased police presence itself (see also Koper, 1995; Telep, Mitchell, & Weisburd, 2014. For contradictory evidence, see Rosenfeld, Deckard, & Blackburn, 2014; Taylor, Koper, & Woods, 2011).

Dosage—or the amount of time officers patrol crime hot spots—matters in terms of the deterrent effect of a hot spot visit. To be most efficacious, police patrol should generate enough presence but be limited in duration and rotated across sites to create a sense of uncertainty (Sherman, 1990). In particular, Koper (1995) examined police hot spot visits of different lengths and found a minimum threshold dosage of about 10 minutes that police must reach to generate significantly longer residual deterrence than that generated by simply driving through a location. The optimal dosage with which a proactive presence generates the longest crime deterring effect occurs between 11 to 15 minutes, after which continued police presence brings diminished returns. This strategy, known as the "Koper curve", remained largely untested until fairly recently. In their randomized experiment carried out in Sacramento, Telep and colleagues (2014) confirmed the crime deterring efficacy of random rotational patrol at hot spots that last about 15 minutes each. Subsequent experimental studies provided further support to the effectiveness of brief and intermittent proactive patrol by noting consistent post-program crime reductions (Hegarty et al., 2014; Kochel et al., 2015). More importantly, this proactive strategy can be carried out through redeployment and more efficient use of existing patrol resources without increased demand for external funding (Telep et al., 2014). This has significant practical implications in an environment riddled with resource constraints in which most existing adoptions of evidence-based policing practices still occur in isolated, standalone projects funded by federal or local grants through overtime schemes or specialized unit operations (Lum, 2009).

In addition to increasing their presence at crime hot spots, police officers could potentially strengthen their crime reduction efficacy by engaging in a wide range of proactive activities at those hot spots. Studies suggest that hot spots policing interventions that use problem-solving approaches have shown particularly successful results (see Baker & Wolfer, 2003; Bichler, Schmerler, & Enriquez, 2013; Braga et al., 1999; Braga, Hureau, & Papachristos ,2012; White & Katz, 2013). For example, in a randomized experiment testing a problem-solving approach at hot stops, officers conducted proactive activities tailored to the problems identified at those places (Braga & Bond, 2008). These included situational interventions, order maintenance activities, and social services. This approach resulted in substantial reductions of crime and disorder in the treatment areas, with stronger effect associated with situational and order maintenance proactive activities. Similarly, Taylor, Koper, and Woods (2011) compared a problem-solving approach with a saturated directed patrol strategy at hot spots. Officers varied their proactivity at the problem-solving locations and engaged in a range of activities such as code enforcement and nuisance abatement, situational prevention, and community outreach. Results indicated a stronger and more lasting effect on violence from the problem-solving approach as compared with the saturated patrol strategy.

Other studies, particularly those dealing with specific types of crime problems (e.g., firearm related violence), have further stressed the importance of increasing self-initiated police activities at the hot spots targeting specific suspicious activities and individuals (Cohen & Ludwig, 2003; McGarrell, Chermak, Weiss, & Wilson, 2001; Rosenfeld, Deckard, & Blackburn, 2014; Sherman, Shaw, & Rogan, 1995). Koper and Mayor-Wilson (2012) reviewed existing studies that target gun violence with directed patrol strategies and found that increased patrol coupled with intensified proactive activities effectively reduces firearm violence. These proactive activities include mainly traffic enforcement, proactive interrogations and investigations, and offender-targeted arrest. Community surveys indicate that such enhanced patrol and enforcement activities, given their targeted nature, were generally supported by residents (Sherman et al., 1995). Likewise, Rosenfeld et al., (2014) observed reduced firearm violence in gun crime hot spots following a directed patrol treatment but only when combined with increased self-initiated activities that increased the certainty of apprehension, or the likelihood of seizing illegal guns (Sherman et al., 1995). On the other hand, Groff and colleagues compared multiple approaches targeting crime hot spots and found the strongest success associated with strategies that focus on high-risk individuals (Groff et al., 2015). In short, increased police visibility alone at hot spots during hot hours could be effective in preventing crime and disorder, although the addition of certain types of proactive activities could strengthen its effect on specific crime problems.

**Understanding the Realities of Police Proactivity and Its Effects on Crime**

Overall, research suggests—and the NAS summarized—that place-based proactive policing offers a feasible approach to managing crime risk at places. This is accompanied by research findings that officers' time during their patrol shift is sometimes underutilized. For example, Kelling et al. (1974), in testing the crime prevention efficacy of enhanced routine and random preventative patrol in their Kansas City Patrol Experiment, found that about 60 percent of a police officer's time is typically uncommitted to calls for service and could potentially be utilized for crime reduction purposes. Later, Mastrofski et al. (1998) observed how officers from two police departments spent their time and noted that the amount of time "free[d] from tasks given by the dispatchers or supervisors" ranged from 71% to 86%. More recently, Famega et al. (2005) discovered that officers not only had a substantial amount of time uncommitted to calls for service (81%), but they received very little direction from supervisors on how to spend that period of time more constructively. As a result, officers primarily engaged in routine patrol or back-up activities during their down time, often leading to an inefficient use of resources. Further, Lum et al. (2018), in their national survey on police proactivity, asked whether agencies track the level of time uncommitted to calls for service or administrative duties, and if so, what it is. In the 42 agencies who provided an answer (23% of all the responding agencies), officers' down time ranged from 15% to 75% with an average of 37% per shift. Weisburd et al. (2015), using GPS data that records officer uses of time, found this figure to be about 75%. Several factors may affect these estimates, but overall, police in the United States appear to have a substantial portion of their shifts that is uncommitted to calls for service or administrative work and could be directed for hot spots patrol purposes.

Despite this solid body of evidence on the opportunities for, and the effectiveness of, place-based police proactivity, research gaps continue to exist as to the realities of proactive policing. Indeed, most of our knowledge about proactive policing has been derived from studies like those discussed above that test given interventions in a programmatic setting. However, as Lum et al. (2018) point out, we know much less about whether and how police proactive activities are carried out in the day to day operational setting by patrol officers, and how their activities affect crime on a daily basis. In fact, proactive patrol manifested through everyday routines might look very different from the proactive policing ideal as the motivation to rigorously test for a program is removed. Examining everyday practices of proactivity and their interaction with crime is important given this implied discrepancy. In particular, it allows us to understand what is actually being delivered daily without constraining officers to a set of programmatic conditions, which might be incompatible with other aspects of their work and thereby unsustainable. It also offers insights into the gap between everyday routines and research-informed practices, as well as directions to propel systematic and sustainable changes toward more effective patrol practices.

The very few empirical studies that examined agency use and tracking of proactive activities revealed that such practices are very limited in reality across the landscape of American policing. For example, Lum et al. (2018) conducted a national survey on a representative sample of police agencies with 100 or more sworn officers gauging various aspects of proactivity as utilized and tracked by agencies. Agencies in general had difficulties detecting and measuring their proactive activities, resulting in a low response rate to the survey (27%). Of those who provided answers to the survey, most recorded the number of CAD events, but many fewer separated events generated by citizens (reactive events) from those generated by officers (proactive events) or those that are administrative and therefore non-crime in nature. When further probed, agencies revealed limited uses of proactive activities in terms of both quantity (with great variability) and scope, with traffic enforcement activities, business and property checks, and directed patrols making up the majority of proactive work carried out by patrol officers. These common proactive activities, however, are less commonly tracked, with only 34% of responding agencies tracking directed patrol activities, 51% measuring business check activities, and more prevalently, 81% recording traffic stops with citation. Proactive activities that require a more strategic plan and target more sophisticated problems, such as community collaboration, CPTED, and problem-solving, are even less frequently conducted or tracked. Inadequate practices of proactive activities at the officer level are in tandem with a lack of direction and systematic planning of proactive policing at the organizational level. A majority of responding agencies had no formal policy in place to define or guide proactive activities, nor did they evaluate officer performance on proactivity with a detailed rubric that went beyond rustic or subjective measurements.

These results are largely consistent with Lum et al.'s (2018) systematic observations and interviews of more than 80 officers in two agencies. They found great variability in officers' definition or perception of what proactivity means to them. Many described proactivity as traffic enforcement, location patrols, looking for drugs and suspicious events, community engagement, or other activities. When observed in practice, however, officers carried out proactivity in a much more limited fashion. Lum et al. found that two types of activities, traffic enforcement and place-based patrol, made up the majority of the proactive work observed by researchers in both agencies. Multiagency analyses of computer-assisted dispatch (CAD) data also confirmed the most frequent types of officer-initiated activities as being vehicle stops, parking violations, and other traffic-related events (see also Wu & Lum, forthcoming). Overall, these studies revealed a consistent picture about the realities of proactive activities—police proactive work in practice is fairly limited in scope. As Lum and Koper (2017) and Lum et al. (2018) have extensively discussed, this limited scope is likely due to the lack of internal systems that guide, train, track, and reward (or correct) officers on effective proactive crime prevention techniques.

In sum, there appears to be a gap between the types of police proactivity that are the subject of evaluation research and the daily proactive work actually carried out by the police. While the study of programmatic interventions is needed to direct police to adjust their deployment in new ways, it is useful to assess the effectiveness of police proactivity as currently practiced as discussed above. Understanding proactivity as it naturally occurs, however, requires a different set of methodologies than experiments or quasi-experiments, which have been used to generate most of the evidence on proactivity reviewed above. For example, Nagin and Sampson, in their presentation at the 2018 American Society of Criminology conference in Atlanta, pointed out that the most important policy issue is to figure out the difference "between counterfactual worlds that emerge as a consequence of their being subjected to different universal treatment regimes over a sustained period of time." (Nagin & Sampson, 2018, abstract). Their argument suggests that by focusing on a subset of geographic space and often over a short period of time in a regimented environment, experiments are limited in producing a universal counterfactual world or understanding what effect everyday police activities have on crime across various locations and times. Also, while experiments can test exogenous changes in the predicting variable (e.g., police proactive patrol), police activities in real life are often endogenous and affected by crime levels in various ways. The issue of endogeneity will be revisited shortly, but experimental methods are not a panacea particularly in studying system-wide variations and effects.

Before experiments became widely accepted as the norm of establishing causality, correlational data were commonly utilized to investigate the relationship between police activities and crime. This group of studies was largely attacked on the ground that the vast majority of them were poorly specified and suffered from a variety of issues limiting their ability to draw causal inferences (see discussion in Greenberg et al., 1979; Kubrin et al., 2010; Nagin, 1998). While we can never be perfectly certain about the causal inference derived from correlational data, some longitudinal and panel studies have used advanced statistical techniques and controls to eliminate some of the threats to internal validity. These techniques included the use of instrumental variables and two stage least square analysis, fixed effects modeling and better control of unobserved heterogeneity, better measurements of police proactivity, and other procedures that tease out the endogeneity between crime and police activity (Greenberg et al., 1979; Kubrin et al., 2010; MacDonald, 2002; Marvell & Moody, 1996; Sampson & Cohen, 1988; Tittle & Rowe, 1974; Wilson & Boland, 1978). Newer procedures have also been developed in the econometrics literature to accommodate the growing use of comprehensive panel data with large numbers of cross sections and time periods to overcome some of the specification limitations in previous studies (Dumitrescu & Hurlin, 2012; Roodman, 2009). Such methods might be particularly suited for the study of everyday proactivity and its interaction with crime given the exploratory nature of this inquiry. Also, correlational studies can detect patterns that may be tested in future experiments, as happened with the "Koper curve" study which suggested that 10-15 minutes stops at hot spots are particularly effective (Koper, 1995).

The study of everyday proactivity and its relationship with crime, however, directly hinges on the tracking and measurement of routine proactive patrol activities. The police often do a diligent job in recording incidents related to crime and their specific details, but much less effort has been devoted to the recording of police proactive patrol or officers' use of uncommitted time. It is especially concerning to compare how much evidence has been generated on effective proactive policing versus how little we know about what officers actually do to be proactive. A refined mobilization of proactive deployment (what most proactive policing strategies strive to achieve) cannot be achieved without some systematic ways of measuring officers' patrol activities. The next section reviews research and developments on tracking and measuring police work.

**Measuring Police Proactivity**

Further strengthening our understanding of everyday proactivity and its relationship to crime requires being able to measure police proactivity. The proactive strategies discussed above all require the police to anticipate problems through systematic data collection and analysis and to adjust their deployment and activities accordingly to prevent crime. The feasibility and effectiveness of these proactive tactics is therefore contingent on the tracking of agency resource allocation and officer proactive activities (Wain & Ariel, 2014). Without knowing officers' whereabouts and activities during their noncommitted time, any efforts to implement and institutionalize research-supported proactive policing strategies will likely be impaired. As Sherman (2013) suggested, tracking and measurement of police patrol and activities is an essential step towards the shift to greater emphases on crime prevention through proactive strategies.

Despite the importance of recording and tracking proactive activities, efforts to develop routine and systematic proactivity measures have been limited. In some of the hot spots studies, agencies and researchers have tracked patrol activities through activity logs and patrol logs filled out manually by officers of what they did throughout a shift. For example, Sherman and Weisburd (1995), in their Minneapolis hot spot experiment, relied on both researchers' independent observations as well as logs filled out by patrol officers to keep track of proactive patrols. In the Operation Beck hot spot experiment (Ariel & Sherman, 2012, cited in de Brito & Ariel, 2017), officers called in through the radio to report their hot spot visits, which were then manually tracked by their sergeants. De Brito and Ariel (2017) relied on the patrol cards filled out regularly by British Transport Police that recorded the arrival and departure time of the police visits to measure program delivery. Similarly, Piza (2018) used after-action reports submitted by foot-patrol officers to differentiate between enforcement and guardian actions. In a more systematic and large-scaled effort to link police patrol deployment to the demand and cost effectiveness of patrolling, the UK police tried adopting the Activity Based Costing (ABC) surveys which required officers to manually fill out a form every 15 minutes recording what they did during that time (Wain & Ariel, 2014). The surveys were then used to gauge how much time officers spent across beats in their patrol function. Unfortunately, the data was not rigorously utilized and the practice was abolished a few years after. Depending on the agency, manual recording of officer proactive activities can lack enough details to be analyzed in any meaningful way (Famega et al., 2005).

Outside of planned evaluations and experiments, officers sometimes report what they do proactively through over-the-radio conversations, which may or may not get recorded into the system, given that this is done mostly for management or officer safety purposes. For example, officers may ask dispatchers to mark their status as “busy” when they engage in a stationary posting so that they will not be dispatched for calls. Special codes may sometimes be created to capture specific types of proactive activities. When testing the efficacy of intermittent hot spot patrol using the Koper curve strategy (Koper, 1995), Telep and colleagues (2014) created a special call sign “D1HOT” for officers to call in whenever they showed up at a hot spot. Similar codes are used in other agencies that apply hot spot policing and other evidence-supported proactive policing, and different codes may be created to capture the variation in the types of proactive activities. This approach is helpful in increasing the reporting rate of proactive activities carried out by officers, especially those that involved no interactions with citizens.

Previous nonexperimental studies have relied on specific proxies or activities to understand the relationship between proactive police activities and crime. Early studies used the number of officers per capita to examine the general deterrence of police and police activities (Marvell & Moody, 1996; Wilson & Boland, 1978). Other studies turned to police arrest data as an indicator of police activity (Greenberg et al., 1979; Tittle & Rowe, 1974). Sampson and Cohen (1988) operationalized proactive policing as the ratio of arrests for disorderly conduct and driving under the influence to the number of police officers in the jurisdiction. The assumption is that agencies with a higher arrest ratio are likely more aggressive in carrying out proactive crime prevention activities. This measure was replicated by subsequent studies, consistently pointing to a negative relationship between police activity and violent crime (MacDonald, 2002; Kubrin et al., 2010). Despite the advanced statistical analysis performed in these studies, however, those measures of proactivity suffer from a variety of issues that limit the validity of their inferences (Nagin, 1998). None of them (except for perhaps policing aggressiveness) is a direct measurement of proactive police work conducted by officers, and these measures are often affected by various other factors unrelated to policing (e.g., crime levels, political factors, funding, and institutional capacity). Proactive enforcement activity (such as misdemeanor arrests) on specific violations is but a partial manifestation of proactivity in general and is dependent on where the police go and the opportunity structures for enforcement and arrest.

More recently, police proactivity has been measured using computer-aided dispatch (CAD) system data, examining those calls that were initiated by officers themselves, as opposed to citizens calling 911. The 911 CAD system commonly employed by law enforcement agencies records detailed information on officers' handling of calls for service. While the system was primarily designed to be used by citizens to make complaints and report criminal incidents, police officers can generate self-initiated calls through the system, often for safety and management concerns. Wu and Lum (2017) examined the spatial correlation between crime and police proactive activities using citizen-initiated and officer-initiated calls, respectively. While citizen-initiated calls consisted primarily of disorderly events, suspicious incidents, and property and violent crime, the majority of officer-initiated calls were for proactive investigation, service, and traffic enforcement. Similarly, Wallace et al. (2018) used officer-initiated calls to measure levels of police activity and to understand the de-policing impact of body-worn cameras (see also Grossmith et al., 2015; Headley, Guerette, & Shariati, 2017; Peterson, Yu, La Vigne, & Lawrence, 2018; White, Todak, & Gaub, 2018) . Officer-initiated calls have also been used to measure different types of police activities (Simpson & Hipp, 2017) and as a proxy for police proactive work (Lum et al., 2018). In addition to the greater details and breadth of activities recorded, CAD also has the advantage of being more common than manual log systems.

The challenge with these types of measures, however, is that they only capture recorded or reported activities. For example, if an officer sat at a high-crime intersection but did not pull over a vehicle or initiate a pedestrian stop, that highly visible, directed patrol activity might never be reported into the CAD system. In turn, if the increased visibility led to a deterrent effect, it would be difficult to attribute the deterrence to that activity had we only used CAD data to measure police proactivity. Indeed, Lum et al. (2018) found that between 50% and 60% of proactive activities went unreported to CAD. While most of these unmeasured proactive activities are generalized place-based patrols, they can also include activities such as community engagement, location checks, and pedestrian stops. CAD data alone, therefore, can be insufficient for purposes of understanding the full scope of everyday proactivity and its effect on important outcomes.

In addition to using CAD data to detect and measure proactivity, another innovative and alternative way to measure proactive activity by patrol officers is through data collected by automated vehicle locators (AVLs). AVLs are GPS devices installed in patrol vehicles that track the real-time location of a patrol car. Law enforcement agencies in the United States began using AVL technology early in the 1960s, mostly to provide rapid and accurate car location information to dispatchers (Law Enforcement Assistance Administration, 1969). AVLs were seen as a technology to guide the dispatching of officers and reduce response time, facilitate tactical and administrative control, ensure officer safety (by knowing where officers' vehicles are at all times), and promote patrol effectiveness (Hansen & Leflang, 1976). While research remained scarce over the years on the effectiveness of AVL technology in achieving its intended goals, recent studies have started examining the utility of AVL or similar GPS data in a variety of applications.

In terms of measuring police proactivity, AVL data has the unique advantage of tracking where and for how long officers patrol when they are not answering calls for service, thereby allowing us to directly measure the dosage of proactive patrol across locations. For example, studies have used AVL data (or similar GPS data generated by body-worn radio devices in the UK) to measure the amount of time officers spend in preventative patrol in given areas, using it to corroborate the intended intervention in a program setting (Ariel, Weinborn, & Sherman, 2016; Hutt, Bowers, Johnson, & Davies, 2018; Telep et al., 2014; Williams & Coupe, 2017). Often, studies examining proactive hot spot patrols do not know the extent to which officers are adhering to the intended operation. As Mitchell (2017) suggested, “the lack of precision in most hot spot studies stems largely from the lack of measurement of policing itself”, including how much time officers spent in the hot spots and the types of activities carried out during the patrols. Factors that may contribute to inadequate program fidelity include inadequate resources due to high citizen call volume, officer deviations, or a lack of tracking that allows officers or supervisors to assess the amount of proactivity delivered. Studies have therefore used AVL location data to assess the actual amount of time officers stayed in designated areas to more accurately evaluate program delivery and the crime-deterring effect of proactive presence. From a managerial perspective, access by police managers to information on the actual patrol dosage and unassigned time generated from AVL appears to lead to increased amounts of proactive patrol at crime hot spots, helping to achieve greater efficiency in the deployment of police patrol resources (Weisburd et al., 2015).

Information on the actual dosage of police proactive patrol across very specific locations generated from AVL data can also be used to understand the distribution of routine proactive police presence and its relationship with crime. As aforementioned, most of our knowledge about the impact of proactive policing was generated through experimental testing of interventions. When measuring and examining proactivity in the everyday routine context, prior studies used various proxies that indirectly or partially measured police proactive work, and they often did so at relatively macro levels (e.g., jurisdiction-level and yearly data). Compared with CAD data, AVL data provides a direct and more complete measurement of how much time officers stayed proactively at specific locations. This could allow us to refine our understanding of proactive patrol and its relationship with crime. For example, our knowledge about the optimization of police patrol has not advanced much since the discovery of the “Koper curve” in 1995, which was made possible by the precise measurement of proactive police presence recorded by trained observers in the original Minneapolis hot spot experiment by Sherman and Weisburd (1995). The spatio-temporal data generated by AVLs and other GPS devices that record officers’ movements may allow us to potentially revisit the issue on the optimization of police deployment.

Scholars have used GPS data to try and investigate some of these questions related to proactivity. For example, Hutt et al., (2018) evaluated the specific characteristics of a hot-spots intervention as implemented, and its impact on crime. In particular, the study measured the length of each proactive presence officers made to high-risk prospective boxes (250 * 250 meters) of crime using GPS location data. In addition to observing a large discrepancy between the intended and delivered treatment, they also found that foot patrols are most effective when they last between 10 and 20 mins. The GPS data have also been used to examine the comparative efficacy between shorter, more frequent and longer but fewer proactive police visits. While they have yet to reach a consensus on the optimal configuration of proactive patrol (Ariel et al., 2016; Mitchell, 2017; Williams & Coupe, 2017), scholars have recognized AVL and similar location trackers as useful sources to measure and understand police proactive patrol. With that said, AVL data is severely limited in measuring some aspects of proactive work. Most importantly, AVL location data does not provide information on what officers are doing at those locations when they are proactively present. In other words, any added benefits of specific proactive activities officers carried out at places cannot be probed with just AVL data.

Police proactive patrols as recorded through AVL have also demonstrated different patterns from those recorded by CAD, raising questions about any systematic differences between recorded proactive activities (by CAD) and unrecorded ones. For example, Mitchell (2017) examined the impact of the Sacramento hot spots intervention on crime, comparing AVL and CAD measures of proactive visits to hot spots. Using AVL data, the study found a significant negative relationship between longer proactive visits and Part I crime. However, when using CAD data, patrol frequencies, instead of lengthier visits, mattered more in generating a deterrent effect on crime. While evidence is inconclusive regarding the practice of proactive patrol, the location data from AVL might provide a useful supplemental source to measure patrol dosages.

Overall, AVL and CAD data may both be useful in measuring officer proactive behavior, thereby allowing us to more accurately determine the relationship between everyday proactivity and crime. As aforementioned, an important limitation of AVL lies in the lack of information about the types of proactive activities officers engaged in. This might be alleviated by combining CAD and AVL data, since the more significant proactive interactions with citizens are more likely to be reported into the CAD system.

At the same time, Lum et al. (2018) found that officers often did not record substantive proactive activities, including traffic stops, preventative patrol, and community engagements, to name a few. With that said, AVL coupled with CAD offer the best available sources of information on officers' patrol activities, which can then be aggregated across locations and time periods.

**Temporal and Spatial Scales of Analysis in Studying Proactivity and Crime**

CAD and AVL data record raw information on incidents of officers' self-initiated calls and spatial points that correspond to officers' movement across space, respectively. At what location and time units, then, should we measure and examine the practice of police proactive patrol and its relationship with crime? The level of time and place to which we aggregate these incidents and points has direct implications to the results and the policy recommendations we want to make. Such considerations should therefore be based on our theoretical and empirical understanding about the concentration and interaction between crime and police patrol.

Place-based studies have revealed a tremendous variability of crime and the opportunity structures for crime at the micro geographic level (Groff, Weisburd, & Yang, 2010; Sherman & Weisburd, 1995; Weisburd, Groff, & Yang, 2012; Weisburd et al., 2004). As a result, one of the most fruitful areas of inquiry on proactive policing has come from studies of interventions targeting micro geographic locations, or hot spots. Researchers have generally defined hot spots in a variety of ways, such as clusters of addresses, intersections, or street blocks, as well as small areas like a census block or a grid cell, but they have generally focused on areas smaller than community-level units

(Lum , Koper, & Telep, 2010; Weisburd, Bernasco, & Bruinsma, 2009). Experimental studies, over time, have capitalized on the theoretical advancement of crime concentrations at micro locations (see various micro-location interventions reviewed in Braga, 2007; Lum et al., 2011; Lum & Koper, 2017). Police interventions of various sort have incorporated components of a micro geographic focus (e.g., problem-oriented policing, disorder policing, and focused deterrence). Nonexperimental studies of police proactive work have also caught up on this trend. While the early studies on everyday police patrol focused largely on the relationship between crime and proactive police work at ecological levels using city- or even state-level data (e.g., Kubrin et al., 2010; MacDonald, 2002; Sampson & Cohen, 1988; Tittle & Rowe, 1974; Wilson & Boland, 1978), recent examinations of everyday police work have more commonly examined the micro spatial level dynamics (e.g., Simpson & Hipp, 2017; Wu & Lum, 2017).

Fewer studies of police proactivity, however, have combined micro spatial units with small temporal scales. The appropriate temporal scale for proactivity analysis is likely subject to debate. Sherman and Rogan (1995), in their randomized controlled experiment on proactive drug raids, observed initial reductions in calls for service and offense reports on the immediate street block which decayed in a matter of 12 days. Likewise, when testing the crime deterring efficacy of hot spots patrols with license plate readers, Koper, Taylor, and Woods (2013) found some significant effects from these patrols (notably, reductions in person crimes and auto theft calls) that did not last beyond two weeks post intervention. In this sense, weekly or even daily scales would be appropriate given that the deterrence of a proactive visit by a single (sometimes two) officer(s) is likely smaller and shorter-lasting than that of a crackdown. Simpson and Hipp (2017), on the other hand, argue that larger temporal units (e.g., months) over long periods of time should be employed given the low counts of proactive police activities at each block, meaning that it may take longer for would-be offenders to notice changes in the opportunity structures and apprehension risk. Larger temporal units were preferred also because they were interested in the long-term accumulative effect of police proactivity on crime.

With that said, policing studies have increasingly emphasized the value of utilizing micro-temporal units. By focusing on time periods within a week following a police stop, question, and frisk (SQF), Weisburd and colleagues (2016) investigated the immediate impacts of SQF on crime. According to them, smaller time units have the benefit of alleviating threats of an endogenous process whereby SQF and crime affect one another over longer periods of time. In addition, Santos and Santos (2015) pointed out the temporal nature of crime hot spots and the practical value of focusing on smaller temporal units such as several days to weeks. By responding to the “flare ups” of crime at hot spots, the police might suppress greater spikes of crime and disorder over short periods of time. Focusing on a short timeframe is perhaps also justified on an empirical ground given that commanders and supervisors often monitor crime patterns on a weekly or multi-week basis and make adjustments. Nevertheless, the micro-temporal dynamic relationship between police patrol work and crime remains underexplored.

### Crime as a Determinant of Proactivity

While most of the above discussion has focused on how everyday police proactivity might affect crime, police are also constantly responding to crime problems that arise, which may pull them to certain places. In other words, crime might also prompt proactivity. A crime spree in a neighborhood (for example, theft from multiple vehicles on a street block) may prompt police to increase patrols in that area. It has long been recognized that the relationship between crime and police work is a dynamic one, following a long-term equilibrium (Weisburd et al., 2016). Yet, few studies have examined the impact that crime exerts over police decisions on where to focus their proactive patrols. Empirical evidence, while limited, supports to some extent that police officers visit more frequently and spend more time at places where crime is most concentrated. Wu and Lum (2017) noted a positive correlation between crime and proactivity that is consistent across spatial scales. For each crime call received at a street block, they observed 0.7 police self-initiated proactive activities and 28 minutes in time spent on conducting those proactive works. That study, however, focused on the cross-sectional relationship between crime and proactive activities and spoke little to the potential causal relationship between the two variables over time. Simpson and Hipp (2018), using longitudinal data and temporally lagged variables, found the existence of a reciprocal relationship between crime and proactivity at the micro-geographic level. For example, police stops (both traffic and pedestrian) in a block went up following an increase in burglary incidents. The risk for future burglaries, in turn, went down in reaction to heightened police stops.

There are, however, several reasons to suspect that on average police proactivity may not align so well with crime at micro locations. Police officers may have a general sense of where crime occurs and concentrates, but their perceptions could be inaccurate or not tuned to the micro level emphasized in research. Koper (2014) conducted a survey on a national convenience sample consisting primarily of large municipal police agencies, in which 89% of the respondents indicated that they focused their violence reduction efforts on hot spots. While the majority of respondents identified hot spots as addresses or clusters of addresses, substantial proportions also identified “hot spots” as neighborhoods or patrol beats. Similarly, Ratcliffe and McCullagh (2001) compared police perceptions of crime patterns with empirical data and found a variable result depending on crime type. Officers provided a more accurate assessment of the geographic concentration for crime that they assigned a higher priority than those that they perceived as less important. Further, hot spot and data-driven policing requires more active intervention from supervisors, but in practice patrol officers often received little direction from supervisors on where and how to be proactive (Famega et a., 2005). These results resonate well with the previous field observations of the author. Overall, police seem to hold a very informal understanding of hot spot locations. This misalignment, coupled with inadequate tracking and feedback processes, likely contributes to a gap on the spatial alignment between proactive patrol activities and crime. Without an accurate knowledge of where crime locates and concentrates, officers might fail to act proactively in places where police intervention is needed, leading to a reduced impact of crime on proactivity.

**Summary**

Overall, gaps remain in our knowledge about police proactivity that hinder our ability to fully translate the evidence-base on proactive interventions to the police. Most importantly, while we know a great deal about the effectiveness of planned, regimented proactive interventions on crime, we know much less about the relationship between actual police proactivity—as daily practiced—and crime. Part of the difficulty in building our understanding in this area is related to measuring everyday proactivity. Without the ability to measure proactivity, we cannot accurately understand how it both affects and is shaped by crime. Part of the challenge is also methodological. Correlational methods need to be carefully designed and executed to avoid the many pitfalls that could invalidate any attempt for causal inferences. In this process, choices of the time and place unit of analysis should be mindfully made in accordance with the recent theoretical and empirical developments on the practice and effect of police proactive patrol.

To contribute to this knowledge area, this study focuses on two questions. First, what does police proactive activity look like in practice and to what extent does it respond to concentration and changes in crime at the micro spatio-temporal level? Second, how does police proactivity carried out in the everyday operational setting, then, affect crime in the near future? Causal, or sequential, relationships between these two are explored with statistical controls and techniques described below. With the use of two separate data sources of police activity, the study sheds light on potential limitations of the CAD system for tracking proactivity and ways to adequately measure proactive police patrol. In addition, understanding the effect (or lack thereof) that police dosage in week $t$

has on crime in a given micro location over the course of subsequent weeks ($t$+1, $t$+2, etc.) will be helpful to police commanders engaged in dynamic planning and adjustment of patrol strategies on a continuous basis. Patterns discovered in the current study could also point to directions for future changes in refining police patrol strategies and operations. Indeed, important limitations exist in the current body of evidence on place-based patrol, precisely because we lack an established formula for the best way to implement hot spots policing with regard to patrol dosage or activities. The field studies have contributed greatly to this knowledge base, but do not often allow for direct comparisons since the treatment regimens vary a great deal from one study to another. The present study provides another angle to understand this issue by capitalizing on everyday variability in proactive patrol as practiced and illuminating the effects of week-to-week variation in patrol dosage and activities.

# Chapter 3. Data and Methods

To examine how crime prompts proactivity and then how proactivity, in turn, affects crime in the daily context, this study examines both in a suburban jurisdiction. Specifically, this study uses the panel Granger Causality test and the Generalized Methods of Moment framework applied to correlational data to examine this proactivity-crime nexus. Police calls for service data and officer GPS location data are each used to measure police proactive visibility across micro locations and time periods. A direct comparison between these two measures is attempted by focusing on the dosage of proactive presence and its relationship to crime events (as derived from citizen-initiated calls for service data).

## Study Location

Police calls for service from computer-aided dispatch (CAD) data and vehicle location data generated by automatic vehicle locator systems (AVLs) throughout 2016 were provided for this study by a county police department located in a large suburban area in the Mid–Atlantic region. The agency has between 1,000 and 1,500 sworn officers, and serves a suburban/urban population of over 1 million inhabitants with a 5-7% population growth between 2010 and 2017. According to the American Community Survey demographic and housing estimates from the U.S. Census in 2016, the agency's jurisdiction has a diverse population, with approximately 40% racial and ethnic minorities. The rates of violent and property crime in this jurisdiction in 2017, according to the Federal Bureau of Investigation's Uniform Crime Reporting Program, were lower than average for similar populations, averaging approximately 100 violent crimes per 100,000 inhabitants, and between 1,000 and 1,500 property crimes per 100,000 inhabitants.

The agency did not systematically implement hot spot policing or data-driven crime prevention activities as of 2016, although it publicly announced plans to increase community outreach positions for responding to hot spot areas during the time period of this study. In the agency's 2017 annual report, community policing officers responsible for crime prevention activities in each district are described as charged with community engagement responsibilities such as elementary school education and liaison with businesses. Targeted crime prevention is not listed among officers' major responsibilities in the report and does not appear to be incorporated into daily patrol activities. Survey data reported by the agency also revealed very limited tracking of police proactive work.[1] Common proactive activities such as directed patrol were not recorded in the administrative system at the time of the data collection, and the agency did not routinely track officers' use of time during patrol (except through the CAD system). As alluded to in the previous chapter, the limited tracking and practice of proactive crime prevention activities by this agency is common in law enforcement. As such, examining this agency offers a fair opportunity to understand the realities of police proactivity and the

[1] Information retrieved from the national survey on proactivity conducted by Lum et al. (2018).

relationship between proactivity and crime. Among the total 523 census blocks examined in the final sample, 456 share a boundary with at least one other hot spot.

**Spatial and Temporal Units of Analysis**

In line with previous micro-geographic studies of police proactive work and crime (e.g., Carter & Piza, 2017; Simpson & Hipp, 2017), the census block is chosen as the spatial unit of analysis for the current study. According to the U.S. Census Bureau, a census block is a small area bounded by visible features, such as roads, or invisible boundaries, such as property lines. In cities, a census block typically consists of a city block bounded on all sides by streets, whereas in suburban areas, a census block might appear more irregular. A census block is usually much smaller than spatial units such as census tracts, police beats, or neighborhoods. The size of a census block is comparable with the sizes of places that are often used in hot spot policing studies. In the jurisdiction examined, the average size of a census block is less than 0.04 square miles.

Other micro spatial units such as street segments are plausible, but census blocks are chosen for this study given the following reasons. First, as will be shown below, the jurisdiction has a relatively modest baseline crime level even in the hottest areas. The number of events that could be joined to the street segment level is likely very low. Census blocks are larger areas that could capture a meaningful amount of events for analysis at the micro geographic and temporal level. Second, crime and police events frequently occurred within the neighborhood or at specific places such as a park or a parking lot that might not be attached to a specific street. Census blocks connect a small group of streets and alleys and reasonably account for the connection among events that occurred within proximity to each other.[2]

Instead of conducting a county-level analysis, this study focuses on understanding the proactivity-crime relationship only in the top 5% of census blocks with the most crime, often referred to as crime "hot spots." Similar to methods done by Sherman et al. (1989) and Weisburd (2015), census blocks are ranked based on the total number of crime and disorderly events occurred at those places, after which the top 5% (523 out of 10,471) of census blocks are selected for the study. A few reasons support this approach only to look at crime hot spots. First, proactive policing is often interested in the dynamics between officer activity and crime in places that are most crime- or disorder-ridden. However, officers may also carry out proactive activities for many reasons in other, non-hot spots, places. Focusing on crime hot spots is aligned with the assumption in this study that officers carry out proactive activities either in response to, or to proactively prevent, crime and disorder challenges. Secondly, selecting census blocks with the highest crime and disorder also ensures meaningful variation in the data given the small spatial and time units employed. By the law of crime concentration (Weisburd, 2015), lower risk census blocks typically experience too few crime or disorderly events particularly at the weekly level that could be meaningfully analyzed over time. Third, as will be described below, this study uses officer location data as one way to measure proactive activities for purposes of crime response or prevention. Focusing on high crime

[2] One of the consequences of using census blocks is that we might underestimate proactive events that might have impacts on crime and disorder in one census block but were joined to another. For example, when a proactive event occurred across the street, it might affect crime on the other side. Such deterrent effects will not be captured in the subsequent models. Despite the potential downward bias however, the study observed evidence of an effect in both directions, as will be discussed below.

places hypothetically reduces the error of coincidence in which officers visit a place for non-proactive reasons (given that the GPS data does not tell us *why* an officer visits a location).

Geocoding of the CAD and AVL data is performed in ArcGIS so as to assign each crime, disorder, or officer location event to a particular census block. Both crime and proactivity are then aggregated within each census block weekly, to estimate the effect of police dosage on crime over time while controlling for the effect that crime has on police dosage. The weekly time unit is chosen for the study given the interest of the current study in the mechanism between crime and proactivity at the micro temporal level. Using weekly time units is also consistent with the typically short-term adjustment police managers and commanders make to their deployment on a weekly or multi-week basis. In essence, the data is constructed into a panel format, with a large N (hot spots) and relatively large T (weeks). Because of the length of the time series (N=52 weeks), issues with mean stationarity are relevant in the current analysis.

**Measurement of Crime and Proactive Police Presence**

As mentioned above, two variables are measured in this study using CAD and AVL data: crime and proactivity. Because the goal is to investigate the reciprocal relationship between these two variables, each will serve as the dependent variable in one set of models with the other as the predicting variable. Crime and disorder is measured weekly and at the census block level, first using all citizen-initiated calls for violent and property crime, suspicious incidents, and disorderly events and second using a subset of citizen-initiated calls that capture the more serious forms of offenses including violence, crimes with weapons, and property crimes. Specific types of calls included in each measure are listed as Appendix A. Citizen calls for service (CFS) data has been frequently employed to measure crime and hot spots (e.g., Braga & Bond, 2008; Sherman et al., 1989; Simpson & Hipp, 2017; Weisburd & Sherman, 1995; Wu & Lum, 2017). Compared with officer official reports of crime incidents, CFS data that is collected by CAD systems has the advantage of being more complete, given that officers do not always write reports on all crime and disorderly events called into by citizens to the police. Furthermore, the criticism that CFS data may result in double-counting of crime incidents or inaccurate recording (see Klinger & Bridges, 1997) has been greatly alleviated over time through advancement of CAD systems. With that said, CFS data includes a wide range of calls that might not be criminal in nature. To address this, the current study carefully screens the types of calls and excludes anything that is not criminal or disorderly in nature.

This study primarily measures the *dosage* of police proactivity to determine the effect of proactivity on crime. Specifically, this study uses CAD and AVL data, separately, to measure two dimensions of proactive police dosage: the amount of time officers stayed at the hot spots when they were potentially being proactive, and the number of visits they made to those locations when they were not involved in answering calls for service at these locations. This is done to estimate both the frequency of proactive visits and the length of time officers spent at these places, which may have different implications for crime (Ariel et al., 2016; Mitchell, 2017; Williams & Coupe, 2017).

To measure these proactive dosage dimensions using CAD data, only officer-initiated CAD events are used. These include officer initiated events related to traffic related activities, community and preventative patrol, school-related proactive activities, proactive investigation, officer-initiated public service, and proactive events related to crime, drugs, and disorders (see Appendix A). The number of proactive visits to the hot spots identified (i.e., the top 5% of places with the most crime) is calculated by aggregating the number of officer-initiated events that fall within the boundary of each location for each week. The length of stay for each officer-initiated event is calculated as the time between officer arrival of the event[3] and completion of the call for each event, summed up weekly for each hot spot.

However, as discussed in Chapter 2, there are many challenges to using CAD data to measure police proactivity. In particular, we now know from Lum et al. (2018) that police might not record as much as 50% of their proactive activity while in patrol. Thus, this study also employs the use of AVL data to estimate police proactivity. Measuring proactive dosage dimensions using AVL data also has its challenges. In the agency examined, AVL generates a ping every 300 meters when the vehicle is moving and every 10 minutes when stationary. This point-based data records the time when the ping was generated, the latitude-longitude ("x-y") coordinates of the vehicle, the unique vehicle identification, the speed of the vehicle at the time of recording, and a unique event number if the ping was generated while officers were handling a call event, either citizen initiated or officer initiated. AVL data is linked to CAD data, thereby allowing pings to

[3] When the arrival time is missing (about 4% of cases), it is replaced with the time dispatched.

be flagged with a CAD event number when officer movement is associated with either an officer- or citizen-initiated call. If the ping was generated during a non-committed time, the event number will be empty. By removing any AVL record associated with a valid event number that is linked to a citizen-initiated call, the remaining records are theoretically associated with officer movements when they were not committed to CAD-related reactive events (citizen calls). In other words, by capturing AVL records generated when officers were handling self-initiated CAD events or were uncommitted to a call event, AVL could provide a more complete picture of officers' proactive presence. A proactive visit is defined as the totality of continuous, undisrupted points that were generated when officers were within the boundary of the hot block. If an officer entered an area, left and came back later, that will be counted as two separate visits. The length of stay is calculated by computing the time difference between the first point after an officer entered the location and the last point before the officer crossed the boundary.

Several complexities emerged in this step. Census blocks are typically divided from the middle of the street, such that each side of the street belongs to a different census block. This, coupled with the micro nature of census blocks, raises several issues with regards to the measurement of proactive visits using AVL data and of events that occurred at intersections. First, AVL points are projected onto the map and spatially joined to a census block within which the point was generated, based on their longitude-latitude information. The accuracy of AVL coordinates is therefore crucial to ensure correct measurement of proactive visits to their corresponding census blocks. A visual examination of the AVL points suggests that they are in general projected to the right side of the road, but they also frequently cluster in the middle of two roads, which allows for a single visit to be counted as several shorter visits associated with adjacent census blocks. For example, more than 60% of AVL visits in the top 5% of hot spots lasted for under one minute. To account for this potential inflation, AVL visits that lasted for particularly short periods of time are examined separately from the longer and more consistent visits, which will be further discussed below.

In terms of where the intersection points (of either crime or proactive events) get assigned, it depends on the specific boundaries of the adjacent census blocks at individual intersections. While generally census blocks are divided by the middle line, this is not always the case. Intersection points are typically joined to the corresponding census block depending on their relative locations at the intersection.[4] For example, events pinged down on the left bottom of the intersection would be joined to the left bottom census block dividing that intersection. But in occasions with irregular or uneven divisions of census blocks at the intersection, the left bottom event might not be joined to the left bottom census block. In other words, a systematic rule is absent that dictates which census block an intersection point will necessarily be joined to, which introduces certain levels of inconsistencies particularly for events that occurred at the intersection. That being said, the same issue exists for any other spatial unit of analysis and is mostly inherent to the process of spatial analyses.

It is important to note a particular limitation of AVL data in measuring officer proactive activity. AVL systems record the *de facto* visits made by police officers to

[4] Due to the high number of decimal place stored in the coordinate information, points do not fall right on the boundary.

specific locations, not the motivations of those officers. Thus, unlike CAD officer-initiated data, AVL information cannot tell us *why* an officer is visiting a hot spots. For example, officers could be backing up other officers on citizen calls for service without notifying the dispatcher of their movements. This is not a proactive visit to the hot spots, but rather might normally be interpreted as part of visit related to a citizen call for service. Officer could also be making random visits (or drive-throughs) to crime hot spots for reasons unrelated to proactively attending to crime. In this jurisdiction, dispatchers often record whether officers are officially assigned to back-up other officers for specific citizen-initiated calls, thereby allowing these specific types of officer visits to be screened from the AVL data used to estimate police proactive visits to hot spots. This still leaves the problem of researchers not knowing if the remaining AVL-recorded visits to hot spots are intended for proactive activity, which cannot be resolved here. However, by reducing the location of analyses to only crime hot spots, this assumption is strengthened (compared to if all census blocks in the county were analyzed).

By using these two dimensions of police proactivity, this study focuses primarily on patrol dosage (frequency and length of visits) rather than the impact that specific proactive activities may have on crime. The reason for doing this is to enable the comparison between CAD and AVL measures of proactivity. However, given the limitations of CAD and AVL data mentioned above, caution is exercised in this comparison in this study.

In addition to comparing CAD and AVL data, this study also examines CAD data to explore the types of proactive activities officers carried out during their proactive presence. The CAD data allows proactive activities to be categorized into five groups: traffic enforcement activities; preventative patrol and community outreach; service-related activities and follow-up investigations; miscellaneous proactive activities (activities for which the specific nature or the goal was not specified in the CAD system); and proactive activities related to crime and disorder (those in which officers proactively spotted and dealt with a criminal or disorderly event). Traffic-related proactive activities are examined specifically because they are often the predominant way through which officers act proactively (Lum et al., 2018; Wu & Lum, forthcoming), and they tend to be enforcement-oriented. Other types of proactive activities are also explored in terms of their relationship with crime and disorder events using subgroup analysis.

## Methods

### *Descriptive analysis of proactivity*

First, I perform descriptive analyses of the dosage and types of proactivity to understand the profile of proactivity and any systematic differences in the pattern of police proactive work across hot spots. This part focuses primarily on CAD-recorded proactivity as it captures both the dosage and types of those activities. The top 5% of census blocks with most crime are categorized into four quartiles based on the number of CAD recorded proactive visits. For each quartile, the study examines the average number of CAD proactive events, crime and disorderly events, serious crimes, and the trend of CAD proactivity over time. In terms of the types of proactivity, each census block is categorized according to the type of proactive activity that is the most predominant in that block. For example, if traffic enforcement activities accounted for most of the CAD proactive activities in a census block, that block will be categorized as one that received primarily “traffic” proactive activities. In addition, the average percent of proactive visits recorded by CAD is calculated for each proactivity quartile. As mentioned earlier, proactive visits recorded by CAD often involve those in which officers initiated a recordable event and interacted with citizens in significant ways (e.g., traffic stops, subject stops, and suspicious persons). The percent of proactive visits captured by CAD is therefore used as a proxy to understand the level of proactive interaction officers engaged in with citizens controlling for the total amount of proactivity recorded by AVL. Subgroup analyses are then conducted to understand the interaction between types of proactivity and the impact of police proactive patrol.

Descriptive information on the quantity and types of proactivity are also examined across police patrol beats. The goal is to understand whether beat level controls are needed for the formal analysis. Officers in the jurisdiction are typically assigned by patrol beats. Depending on individual background, experiences, and outlook for crime control, there could be individual- or beat-level differences in the characteristics of proactive patrol being carried out. Systematic differences at the beat level could mean that the hot spots within each beat are correlated, thus violating the independence assumption. To understand this, the 84 police patrol areas that host all events occurred at the top 5% of census blocks are categorized into four quartiles based on a ranking of the number of CAD proactive calls.[5] For each quartile, the numbers of proactive CAD

[5] The study takes proactive events and crime measured through CAD that fall within the top 5% of the census blocks and rejoined them to patrol beats. This process returned a total of 84 police patrol beats. However, when directly joining the top 5% census blocks to police patrol beats, 78 patrol beats were returned. The discrepancy likely resulted from the fact that the boundaries of census blocks do not always

events, crime and disorder events, and serious offenses are examined, as well as the distribution of the types of proactive calls.

***Using the panel Granger Causality test to examine reciprocal relationships between proactivity and crime***

To disentangle the reciprocal relationships of police proactivity and crime, this study then employs the Granger Causality test. Under the standard definition of Granger (1969) causality, for each individual $i \in [1, N]$, a stationary variable $x_{i,t}$ (a variable whose statistical properties such as mean, variance, and autocorrelation are constant over time) is deemed to be causing another stationary variable $y_{i,t}$, if past values of $x_{i,t}$ increase the predicting power of the model on $y_{i,t}$ compared to using only past values of $y_{i,t}$. The Granger Causality method establishes causality through forecasting, and therefore requires longitudinal data. To apply this in the current context, we say that proactivity causes crime in a Granger sense if we are better at predicting crime at the current moment by incorporating past values of proactivity in the model than by using just past values of crime. The logic is straightforward; if past values of proactivity do not add any additional value to the prediction of crime after controlling for past values of crime, proactivity probably does not cause crime to change.

The original Granger Causality test was spelled out for individual time series data only, but scholars have extended the formula to panel data given the proliferation over time of panel data with large N and large T (Dumitrescu and Hurlin, 2012). The modified

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align with those of patrol beats. Based on results of direct spatial joining, a patrol beat contains an average of 130.5 census blocks and about 6.7 hot spots, ranging from 1 to 17. Most patrol beats include 2 hot census blocks. The average ratio of hot spots over the total census blocks is 6.8%, ranging from 0.5% to 33.3%.

panel Granger Causality test, which is formulated below, will be used in the current analysis. Again, for each individual $i = 1, \dots, N$, at time $t = 1, \dots, T$, the modified test considers the following linear model:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_t^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \epsilon_{i,t}$$

where $x_{i,t}$ and $y_{i,t}$ are the observations of two stationary variables for individual $i$ in period $t$. Variables should be made stationary (e.g., taking the first difference) before fitting the above model. Individual effects $\alpha_i$ are fixed in the time dimension, controlling for the effect on the outcome variable of time-invariant variables such as social disorganization factors. In other words, comparison is made within hot-spots, whereas between-hot-spots variance is discarded from the analysis so as to control for any individual hot spot heterogeneity resulting from time-stable variables (Allison, 2005). Lag orders K are assumed to be identical for all cross-section units of the panel and the panel is balanced with an equal number of time points for each cross-sectional unit.

Previous applications of the Granger test often had difficulties determining the value of K. In the current study, K will be determined based on prior research on the residual deterrence of proactive patrol and by minimizing the average of Akaike, the Bayesian, and the Hannan-Quinn information criterion (Lopez & Weber, 2017). The autoregressive coefficient $\gamma_t^{(k)}$ and the regression coefficient $\beta_i^{(k)}$ are allowed to vary across individuals to accommodate for a heterogeneous panel. Studies using fixed coefficients assume that any effect or lack of effect is homogenous across the panel, which is a rather strong assumption. It is possible that the causal relationship between crime and proactivity exists only in a subset of hot spots or that their relationship may be different across hot spots. The modified test thus allows the coefficients to vary cross-sectionally.[6]

A series of F tests will then be conducted for significance inference. Essentially, the modified test proposes the following procedures: perform the N individual regressions formulated above, run the F-tests on the null hypothesis that $\beta_{i1} = \ldots = \beta_{iK} = 0$, and derive the average Wald statistics based on the previous set of F-tests (Lopez & Weber, 2017). The model therefore tests causality at the panel level and assumes at least two groups of hot spots that have different dynamics between crime and proactivity. The null hypothesis assumes that proactivity and crime do not cause one another, whereas the alternate hypothesis indicates that causality exists between the two in at least one or a subset of hot spots. Therefore, rejecting the null hypothesis does not necessarily suggest a universal causal relationship between proactivity and crime.

While the panel Granger causality approach allows testing the existence and the direction of causality between variables (from A to B or from B to A), it does not provide information on the strength or the direction of the relationship (positive or negative). Previous studies applying the Granger test or the modified test often used it as a preliminary test to determine the existence and direction of the causality, similar to the way the unit root test is used in the time series context to help determine preliminarily the

[6] Note that the model is not a random coefficient model; it is a fixed coefficients model with fixed individual effects (Dumitrescu and Hurlin, 2012). Allison (2005) questioned the necessity of adding the dynamic component, or the lagged term of the outcome variable, in the model when a fixed effect is already present. He tested the models with and without the dynamic term and found the results to be similar.

existence of a unit root. To estimate the average effect, additional models are often fitted, which are next described.

#### ***Using Generalized Methods of Moments to estimate magnitude and direction of effects***

I then use the Generalized Methods of Moments (GMM) dynamic framework to estimate the magnitude and direction of the relationship between crime and proactivity. In the context of time series panel data, fixed effect models are frequently utilized to remove the unobserved individual heterogeneity that may be correlated with the regressors and hence bias the results (Allison, 2009). In this study, a basic fixed effect model encounters several difficulties related to endogeneity. First, previous studies observed evidence of a reciprocal relationship between crime and police proactivity (Simpson & Hipp, 2017; Wu & Lum, 2016). When causality runs in both directions, the predictor becomes endogenous and will likely be correlated with the error term. Second, the concentration of crime (or lack thereof) at places is known to be highly persistent over time (Weisburd, Bushway, Lum, & Yang, 2004), arguing for the inclusion of a dynamic component whereby the current realization of crime is affected by past values. There are also theoretical reasons to believe that previous levels of crime can have impacts on crime at future time points (e.g., retaliatory crimes). Likewise, the day-to-day proactivity embedded in the everyday routine of police work is likely impacted by past patterns. This autocorrelation is especially plausible given police tendencies to follow past experiences and practices (Willis, Mastrofski, & Weisburd, 2007). The presence of lagged dependent variables, however, creates a dynamic panel bias (Nickell, 1981), which cannot be expunged by within-group transformation or first differences typically used in fixed effect models. This is so because the differenced/demeaned lagged dependent variable is still correlated with the differenced/demeaned error term, both containing information on order *t-1*. Panels with small T and large N are particularly susceptible to such biases. Judson and Owen (1999) suggest a 20% downward bias in the coefficient of a lagged dependent variable using within group transformation even when T=30. This may then bias the coefficients of other regressors as well if they are associated with the lagged dependent variable.

The Arellano-Bond (1991) difference GMM estimator, and its extension to the system GMM context (Arellano & Bover, 1995; Blundell & Bond, 1998), are specifically designed for situations with dynamic processes and endogenous independent variables. The GMM models remove the dynamic and endogeneity bias by constructing instrumental variables that are highly correlated with the regressors but uncorrelated with the error term, thus enabling one to statistically identify the unique effects that crime and proactivity have on one another under these circumstances. It assumes that the best available instruments are internal and therefore use past values to instrument (see Roodman, 2009 for a detailed explanation). This framework is particularly useful to the analysis of crime and proactivity at the micro time and spatial level, given the lack of common external information at those levels that could serve as better proxies. The major difference between difference and system GMM lies in the methods used to transform data to purge the fixed effect while allowing for unbiased instruments. Difference GMM, as indicated by its name, takes the first-difference transformation of the regressors and uses longer lags as instruments. System GMM, on the other hand, differences the lagged terms to make them orthogonal to the error term. In other words, difference GMM uses past values to predict current changes, whereas system GMM uses past changes to predict current values. Under an additional assumption about the initial condition of the data generating process[7], system GMM introduces additional instruments and greatly improves efficiency (Roodman, 2009). The current study uses system GMM models to estimate the relationship between crime and proactivity, explicitly dealing with issues related to endogeneity and dynamic panel bias that are often unaddressed in nonexperimental studies.[8]

To assess the magnitude and direction of the reciprocal dynamic between crime/serious crime and police proactivity, each serves as the outcome variable in one set of models with the other as the predictor. In addition, both the Granger test and the system GMM model are performed across each measure of proactivity separately, using information recorded by CAD or AVL. A parsimonious specification of the GMM models is adopted by including only lagged terms of the dependent variable and the key independent variable and its lags (when needed) as regressors. Demographic and socioeconomic variables are left out of the models. To the extent that their levels and impacts on crime and proactivity remain relatively stable from week-to-week, they are

[7] System GMM assumes that the correlation between the instrumenting variable and the fixed effect is time-invariant, such that changes in the instrumenting variable are uncorrelated with the fixed effect (Roodman, 2009).

[8] When dynamic components are present, the traditional OLS regression is known to bias the lagged dependent variable's coefficient upward whereas the fixed effects models bias the results downward (Baum, 2013). The true estimate is often expected to lie between these two values. In addition to improved efficiency, system GMM is selected over difference GMM for the current study also for empirical consistency- the coefficients often lie outside of the range of OLS and fixed effects models when difference GMM is employed.

already purged out of the models by construction. Monthly time dummies were considered but not included in the final models given that they do not improve model performance.

Depending on the underlying autocorrelation structure in the outcome series, one or several lagged terms of the dependent variable are included in the GMM models. Two test statistics are conducted specifically to assist with model identification. The Arellano-Bond test for ARs in first differences detects autocorrelation left in the differenced residuals. The test for an AR(1) process in first differences is expected to be significant, since the residuals of the differenced equation should possess serial correlation by construction (e.g., $y_{i,t-1}$ is correlated with $v_{i,t-1}$ in the error term in differences, $\Delta\varepsilon_{it} = v_{it} - v_{i,t-1}$, by construction). The test for an AR(2) process, however, should not reject the null hypothesis because it tests for serial correlation in levels (e.g., when the AR(2) term is significant, $y_{i,t-2}$ would be endogenous to $v_{i,t-1}$ in the error term in differences, $\Delta\varepsilon_{it} = v_{it} - v_{i,t-1}$, and therefore becomes an invalid instrument). Adding higher-order lags of the dependent variable as regressors along with using deeper lags as instruments is a typical solution to a significant AR(2) test and controls for serial correlation. This process is to be repeated until AR(n) becomes insignificant, with n equaling the number of lags included for the dependent variable plus 1. In addition, the Sargan/Hansen test is a standard output following GMM estimation and is typically used to understand whether the instruments as a whole are exogenous and valid. An insignificant test statistic is preferred as it suggests that the instruments overall are valid. Note that given the relatively large T in the current panel, the number of instruments will proliferate without restricting how many lags to include as instruments. The current study avoids instrument proliferation and overidentification by selecting the most parsimonious number of lags that satisfies the Hansen test.

Using the instrumenting methods discussed above, the GMM framework allows us to statistically tease out the contemporaneous effects of crime and proactivity upon one another. Moreover, lags of the key independent variable are included in the GMM models to examine the impact of proactivity and crime on each other that goes beyond the first week. The selection of the lag term of independent variables is commonly informed by theoretical reasoning, which has not been very well developed for crime and proactivity at the micro time level. Evidence is variable with regards to the amount of time that the residual effect of proactivity lasts. Also, little research exists on the timeframe within which the police respond to increases in crime with proactivity. Empirical applications of GMM models have often included the same number of lags for both the dependent and independent variables. The current study uses the number of lags for the dependent variable as the upper bound and incrementally tests out a few lags of the independent variable. This turns out to be effective as the impacts of higher-order lags of the independent variable are often insignificant and then removed from the model for parsimony.

***Robustness checks***

The reason this study aggregates data by week and to each census block is driven by a theoretical interest in the reciprocal dynamic between crime and proactivity at the micro geographic and temporal levels. To test the robustness of the results to these levels of measurement, the study varies the place and time units of analysis within the boundaries of this theoretical interest. Specifically, bi-weekly measures are applied based on prior research showing that specific police actions at micro hot spots can have effects over multiple weeks. Larger time intervals could also reduce excessive variability in the data. With that said, larger intervals may mask day-to-day and week-to-week adjustments that police make in the field. Results using different time units are compared to understand these differences.

In addition to using census blocks as the micro unit of place, the study also employs a grid approach to identify hot spots. Prior studies have defined micro hot spots in a variety of ways (such as street blocks, groups of blocks, address clusters, grid cells, and police beats), but few have examined how the precise way of measuring micro hot spots affects the results regarding the relationship between crime and police proactive work. In this robustness check, the study uses grid cells of the size of 0.1 * 0.1 square miles. These cells are approximately the size of a street block. They are geographically smaller than census blocks but large enough to host meaningful amounts of criminal and police activities. By varying the spatial unit of analysis within the common operationalization of hot spots, the study tests whether and to what extent the interactive dynamic relationship between crime and police proactivity is sensitive to the specific way used to identify hot spots of crime.

Finally, the top 5% of census blocks of crime are divided into two subgroups, one that received predominantly traffic enforcement proactive activities and one that received primarily non-traffic related proactive activities as measured through CAD (see the descriptive analysis of proactivity profiles below). The motivation behind this robustness check is to understand the interaction between crime and proactive activities in census blocks with different profiles of proactivity. Empirical studies pointed out that officers often resort to traffic enforcement activities as the major way to be proactive (Lum et al., 2018; Wu & Lum, forthcoming). Whether this is due to the greater efficacy of traffic stops over other types of proactive interactions in terms of their crime control benefit is less known. The subgroup analysis might offer some preliminary evidence on the interaction between the types of proactive activities most conducted and crime outcomes.

# Chapter 4. Results

## Descriptive analysis of proactivity

Table 1 presents the descriptive statistics on all census blocks in the jurisdiction, and Table 2 focuses specifically on the top 5% of census blocks on the scale of crime and disorder. These include the amount of proactivity and proactive time officers spent at each census block per week and the weekly level of crime and serious crime at those places. Proactivity is measured first by officer-initiated CAD events and then by AVL recorded proactive visits as described in Chapter 3. AVL proactive visits are further divided into three groups: those that lasted between 0 and 5 minutes, those between 5 and 20 minutes, and those over 20 minutes. They are examined separately because the vast majority of proactive visits to an average census block recorded by AVL lasted for very brief periods of time, ranging from a few seconds to a few minutes. These are often associated with officers driving through an area during their uncommitted time or potentially after logging out of a citizen call. Brief proactive visits and officer drive-throughs like these, according to previous research on police deterrence (Koper, 1995), might not have much deterrent value and therefore are considered separately from the more meaningful visits.

*Table 1. Descriptive statistics for all census blocks (excluding those with missing census block identification information)*

| Per census block per week | mean | s.d. |
|---|---|---|
| CAD proactivity | 0.50 | 2.28 |
| CAD proactive time, from arrival to complete (in minutes) | 15.69 | 122.09 |
| CAD crime and disorder | 0.43 | 1.45 |
| CAD serious crime | 0.08 | 0.43 |
| AVL average N of proactive visits | 37.08 | 80.00 |
| AVL average N of proactive visits (between 0 to 5 minutes) | 34.27 | 72.02 |
| AVL average N of proactive visit (between 5 to 20 minutes) | 1.41 | 5.90 |
| AVL average N of proactive visit (more than 20 minutes) | 1.40 | 10.53 |
| AVL average proactive time (in hours) | 2.06 | 14.24 |

N of weeks = 52; N of census blocks =10,471 ; Total N = 544,492

*Table 2. Descriptive statistics for the top 5% of hot spots*

| Per census block per week | mean | s.d. |
|---|---|---|
| CAD proactivity | 5.05 | 8.13 |
| CAD proactive time, from arrival to complete (in minutes) | 174.37 | 460.34 |
| CAD crime and disorder | 4.25 | 14.37 |
| CAD serious crime | .84 | 1.43 |
| AVL average N of proactive visit | 206.51 | 195.32 |

| | | |
|---|---|---|
| AVL average N of proactive visit (between 0 to 5 minutes) | 176.10 | 166.26 |
| AVL average N of proactive visit (between 5 to 20 minutes) | 13.60 | 20.70 |
| AVL average N of proactive visit (more than 20 minutes) | 16.81 | 42.95 |
| AVL average proactive time (in hours) | 22.99 | 58.01 |

N of weeks = 52; N of census blocks = 523; Total N = 27,196

As expected, high risk census blocks (those in Table 2) generally received greater levels of proactive work from the police than all census blocks on average as shown in Table 1. The top 5% of census blocks of crime accounted for about 49% of all crime, 50% of all CAD proactivity and proactive time, 48%-60% of AVL proactive visits that lasted for over 5 minutes, and 56% of all AVL proactive time. Based on AVL estimates, when officers visit a high crime census block, they generally spend more time at that place than they do at lower risk places, irrespective of whether a CAD event is initiated. At lower risk places, AVL-recorded proactive visits are more likely to be swift drive throughs.

On average, a top 5% census block (or "hot spot") experienced about 4 crimes and disorders and 5 officer-initiated CAD events per week. The latter summed to about 174 proactive minutes per week on average (see Table 2). When police proactivity was measured using AVL data, crime and disorder hot spots received an average of 207 proactive visits per week. This number, however, is largely inflated by the common occurrence of officers driving through or passing an area, which was counted as a proactive visit by the rules specified above with AVL data. When looking at the longer proactive visits recorded by AVL, an average higher-risk census block still received about 14 proactive visits that lasted between 5 and 20 mins and 17 that lasted more than 20 mins, which are relatively high dosages even in comparison to some of the hot spot interventions tested in prior studies. In other words, officers, on average, initiated a recordable proactive event in 5 out of 31 (about 17%) of their lengthier proactive visits; the remaining 83% of visits that might indicate some form of proactivity in which officers stayed in the area for more than 5 minutes were not captured by CAD data. Again, we cannot be certain if all of these visits captured by the AVL system were intended as proactive visits. However, even if we assume that half of the AVL captured visits were not for proactive purposes, that still leaves two-thirds of officer visits to a recognized crime hot spots unaccounted for in the CAD system.

Table 3 provides further descriptive information about proactivity to explore potential variation in the quantity and types of proactivity across hot spots. The table shows, for each quartile of CAD proactivity, the average number of CAD proactive calls, crime and disorder events, serious crimes, the trend of CAD proactivity over time, percent of hot spots predominated by each type of proactivity, and the percent of total proactive visits recorded through AVL that are captured in CAD. The univariate trend of CAD proactivity over time is examined to explore changes in the levels of proactivity practiced during the study period and how that might differ across the quartile groups. It is estimated with time trend regression models by regressing proactivity on a linear time trend variable. For the last measure, AVL-recorded proactive visits are treated as the universe of proactive visibility. Only AVL proactive visits that lasted for more than 5 minutes are included in the calculation of total proactive visits because they are more likely to correspond to the more meaningful proactive visits.

*Table 3. Descriptive statistics on proactivity and crime for the top 5% of hot spots, by CAD proactivity quartile*

| CAD proactivity quartile | Weekly CAD proactivity | Weekly Crime | Weekly Serious crime | Time trend on proactivity | Proactivity type | % proactivity captured by CAD[4] |
|---|---|---|---|---|---|---|
| High | 12.8 | 6.8 | 1.5 | Sig. up[1]: 18%<br>Insig.[1]: 74%<br>Sig. down[1]: 8% | Traffic: 49%<br>Patrol[2]: 34% | 50% |
| Med high | 4.2 | 4.3 | .8 | Sig. up: 8%<br>Insig.: 81%<br>Sig. down: 11% | Traffic: 68%<br>Patrol[2]: 15% | 26% |
| Med low | 2.2 | 3.2 | .6 | Sig. up: 8%<br>Insig.: 83%<br>Sig.down:8% | Traffic: 76%<br>Service[3]: 12% | 30% |

| | | | | | | |
|---|---|---|---|---|---|---|
| Low | 1.0 | 2.6 | .5 | Sig. up: 6% Insig.: 88% Sig. down: 6% | Traffic: 63% Service[3]: 26% | 36% |

[1]sig. up means a significant upward trend; insig. means an insignificant trend over time; sig. down means a significant downward trend.
[2]including community foot patrol, school resource officer, community meeting, and others
[3]including follow up investigations and public service
[4]CAD proactivity divided by AVL proactivity that's longer than 5 minutes.

Although the study focuses on the top 5% of census blocks of crime, there is still great variability in the levels of crime, serious crime, and proactivity across these census blocks, as shown in Table 3. Overall, changes in the average number of proactive events recorded in CAD correspond in direction to the increased concentration of crime and serious offenses. The bottom quarter of the hot spots received an average of 1 proactive visit as recorded in CAD per week, but the top quarter received an average of 12.8. The univariate changes of CAD proactivity over time appear to differ across the groups of places. While the vast majority of census blocks did not experience significant changes of CAD proactivity over time, about 12% - 26% of census blocks saw significant trends in CAD proactivity during the study period. The top quarter of census blocks was most likely to have experienced an upward trend of proactivity over time, although CAD proactivity remained stable or even declined in most of the places that make up the quarter. These reductions could have resulted from a combination of factors, including the mobilization of proactive resources to other higher risk locations, increased citizen calls that reduced officers' downtime, or suboptimal allocation of resources that did not adequately take into account crime levels. Given the concentration of crime and serious offenses at these hot spots, reductions in proactivity over time might not be desired.

The types of proactivity across places also exemplify interesting patterns. Traffic enforcement activities continue to be the most frequently practiced type of police proactivity, a pattern repeatedly shown in previous studies (Lum et al., 2018; Wu & Lum, forthcoming).[9] Across these groups of places, traffic enforcement activities were the most frequent type of proactivity in between 49% and 76% of census blocks. However, in about 24% to 51% of census blocks across these quarters, non-traffic proactive activities exceed traffic enforcement activities as the most predominant types of proactivity. These non-traffic proactive activities include preventative patrol, community outreach, service-related activities, and follow up investigations. They are less enforcement-oriented and appear to conform better with community policing and problem-oriented policing ideals. Interestingly, as the level of proactivity and crime goes up at groups of places, the percent of places dominated by traffic enforcement proactive activities generally goes down. Officers are more likely to carry out greater levels and proportions of preventative patrol and community outreach activities at places with more crime and proactivity. Similarly, police proactivity is most likely to involve interactions with citizens or to occur in other recordable forms in the highest quarter of the hot spots. About half of the proactivity was

[9] Note that the pattern has been observed across many jurisdictions and using different data sources. For example, Lum et al. (2018) draws results from a national survey of large police agencies, analyses of administrative data from ten police agencies, and systematic observations at two jurisdictions.

recorded by CAD in the highest quarter, compared to 26% in the second quarter and 30% in the third quarter. Overall, it appears that the police are more likely to resort to a diversified toolkit, one that combines enforcement and non-enforcement approaches, in tackling crime at higher risk places. CAD data also provides a more complete measure of proactivity (relative to AVL measures) in the highest crime locations as compared to the lower crime locations.

Table 4 shows the descriptive statistics of proactivity and crime by police patrol beats. The highest quarter experienced an average of 5,757 proactive call events whereas the lowest quarter received an average of 1,032 proactive calls. The distribution of proactivity corresponds to the distribution of crime and serious offenses in general. Overall, there is great variability in the levels of crime, serious crime, and police proactive activities across police patrol beats. However, the distribution of the types of proactivity appears less drastically different across groups of patrol beats. Traffic enforcement activities continue to be the most dominant type of proactivity officers carry out in the daily context, accounting for between 41% and 49% of all proactivity across the quartiles. Preventative patrol and community engagement activities remain the second most frequent type of proactivity, ranging from 28% to 38%, followed by service-related activities and proactive follow ups. Officers patrolling the beats in the highest quarter do appear more likely to engage in non-enforcement activities, but the differences across groups are rather mild. Police officers seem to approach proactivity in similar fashions across beats. In sum, the profile of proactivity appears to vary more by hot spots than by patrol beats. The differences in the types of proactivity carried out across hot spots do not appear to be due heavily to beat-level differences. As such, beat-level effects are not included in the analyses below.

*Table 4. Descriptive statistics on proactivity and crime by patrol beat*

| CAD Proactivity quartile | Weekly CAD proactivity | Weekly crime | Weekly serious crime | Types of proactivity |
|---|---|---|---|---|
| High | 110.7 | 76.7 | 14.8 | Traffic: 42%<br>Patrol & community[1]: 38%<br>Service & follow-ups[2]: 11%<br>Crime & disorder[3]: 7%<br>Miscellaneous[4]: 1% |
| Med high | 69.8 | 67.9 | 13.3 | Traffic: 47%<br>Patrol & community: 30%<br>Service & follow-ups: 13%<br>Crime & disorder: 9%<br>Miscellaneous: 1% |
| Med low | 50.8 | 51 | 8.9 | Traffic: 49%<br>Patrol & community: 28%<br>Service & follow-ups: 12% |

| | | | | |
|---|---|---|---|---|
| | | | | Crime & disorder: 10% |
| | | | | Miscellaneous: 1% |
| Low | 19.8 | 21.8 | 2.6 | Traffic: 41% |
| | | | | Patrol & community: 36% |
| | | | | Service & follow-ups: 15% |
| | | | | Crime & disorder: 5% |
| | | | | Miscellaneous: 3% |

[1]including community foot patrol, school resource officer, community meeting, and others
[2]including follow up investigations and public service
[3]including events in which officers proactively spotted and dealt with crime and disorder
[4]including proactive events for which the specific nature or goal was not specified

## Causal Modeling Analysis

### *The Granger Causality Test*

Moving beyond the descriptive statistics, Table 5 presents the results of the panel unit root tests. The Granger Causality test examines the relationship between two stationary time series. The panel unit root tests are conducted to assess whether first difference transformation is needed before fitting the Granger test. Two tests are performed specifically on each time series- the Levin-Lin-Chu test which is the most commonly employed, and the Harris-Tzavalis test which is better suited for panels with relatively large cross sections and fewer time points. As shown in Table 5, the null hypothesis of a unit root is rejected across the table, suggesting consistent stationarity that is independent of the specific test conducted or the specific measure of crime and proactivity employed. The results hold consistent under assumptions of cross-sectional dependence or independence. In light of the consistent evidence for stationarity, the Granger test is applied to all outcome series in levels.

*Table 5. Results on unit root test for crime and proactivity series*

| | LLC[1] | HT[2] |
|---|---|---|
| Crime | -1.1e+02*** | 0.0586*** |
| Serious crime | -1.3e+02*** | 0.0517*** |
| CAD proactivity | -1.0e+02*** | 0.1977*** |
| CAD proactive time | -1.2e+02*** | 0.2983*** |
| AVL proactive visit | -75.1432*** | 0.1105*** |
| AVL proactive visit (0-5 mins) | -79.4409*** | 0.1020*** |
| AVL proactive visit (5-20 mins) | -1.1e+02*** | 0.0790*** |
| AVL proactive visit (>=20 mins) | -99.6821*** | 0.1138*** |
| AVL proactive time | -1.0e+02*** | 0.1057*** |

[1]The Levin-Lin-Chu test
[2]The Harris-Tzavalis test

Following the panel unit root tests, Table 6 summarizes the results of the Granger Causality tests. Previous applications of the Granger test commonly selected a small number of lag terms (one or two) when using yearly data. Given the weekly data utilized, along with the evidence on the decay of residual deterrence (Koper et al., 2013; Sherman & Rogan, 1995), the current study set out to test for three additional lag terms.

Specifically, it applied the Granger tests at each of the first 4 lags and again at the optimal lag (lag 15) selected by the Akaike information criterion (AIC).[10] As shown in Table 6, the results generally suggest a reciprocal relationship between crime and proactivity. Past proactivity appears to affect current crime when past values of crime are controlled for, although this relationship is noted only for selected measures of proactivity at selected lags. Specifically, proactive visits do not clearly cause crime in a Granger sense when measured with CAD, nor does AVL proactivity that lasted for very brief periods of time. Significant Granger causality, however, is present for proactive time measured with CAD (marginally significant), AVL proactive visits that lasted between 5 and 20 minutes, as well as AVL visits that lasted for more than 20 minutes at certain lags.[11]

*Table 6. Granger causality tests for overall crime and proactivity (adjusted z values reported)*

| | Proactivity → Crime | | | | |
|---|---|---|---|---|---|
| | Lag 1 | Lag 2 | Lag 3 | Lag 4 | Lag |

[10] While the common practice is to select small lag terms in applying the Granger Causality test, the test will be grossly underpowered when the lag order specification is below the true AR structure underlying the data, and therefore less likely to detect a true effect (EViews, 2017). The current study accommodates that by testing out the first 4 lags and again the optimal lag as selected by the AIC. With that said, the AIC selected a very high number of lags in testing for a Granger causal relationship in the current case. With too many lags included, we could potentially allow for a spurious rejection of the null due to some correlations by chance. Also, the introduction of past values of Y and past values of X that are endogenous to the error term could lead to a biased estimation of the results. Readers are therefore advised to focus on the follow up GMM models in understanding the specific interactive relationship between crime and proactivity.

[11] Note that the null hypothesis specifies that past values of X do not contribute to the explanation of Y, after controlling for past values of Y. It is generally used to determine the existence of a sequential relationship. The direction of the z value is not typically used to understand the positive or negative direction of the Granger causal relationship. For this purpose, follow-up models are usually estimated.

| | | | | | |
|---|---|---|---|---|---|
| | | | | | (AIC=15) |
| CAD proactivity | .946 | 1.156 | .606 | .798 | -.743 |
| CAD proactive time | -.829 | .240 | .006 | -.092 | -1.648# |
| AVL proactive visit | -.473 | .791 | -.091 | -.134 | -1.022 |
| AVL proactive visit (0 to 5 min) | -.589 | .181 | -.486 | -.514 | -.988 |
| AVL proactive visit (5 to 20 min) | -.753 | 1.406 | .802 | .072 | -1.993* |
| AVL proactive visit (>= 20 min) | 1.391 | 2.105* | 1.112 | 1.957# | -1.152 |
| AVL proactive time | -1.049 | 1.224 | .575 | 1.203 | -.808 |
| | Crime → Proactivity | | | | |
| | Lag 1 | Lag 2 | Lag 3 | Lag 4 | Lag (AIC=15) |
| CAD proactivity | .875 | 2.497* | 1.295 | 1.226 | -.917 |
| CAD proactive time | .319 | 1.806# | 1.609 | 1.210 | -1.418 |
| AVL proactive visit | 1.949# | .776 | .826 | .091 | -2.414* |
| AVL proactive visit (0 to 5 min) | 2.216* | .892 | 1.097 | .364 | -1.943# |
| AVL proactive visit (5 to 20 min) | -.606 | -.251 | -.484 | -.878 | -1.123 |
| AVL proactive visit (>= | .234 | 1.785# | 1.360 | 2.396* | -3.155* |

| | | | | | |
|---|---|---|---|---|---|
| 20 min) | | | | | |
| AVL proactive time | .359 | 1.047 | 1.235 | 1.303 | -2.987** |

***,**,*,# indicate significance level at .001, .01, .05, and .1 level, respectively.

On the other hand, the temporal relationship from crime to proactivity appears to be more consistent across different measures of proactivity and different lags. Past information on crime significantly affects current levels of proactivity across the table, with the exception of AVL proactive visits that lasted between 5 and 20 minutes. Overall, there is tentative evidence for a reciprocal relationship between crime and proactivity, although proactivity appears to be more responsive to past crime than is crime to past proactivity.

The results are similar when only examining the relationship between serious crime and proactivity (Table 7). Again, the results suggest there is evidence for a reciprocal relationship between serious crime and proactivity. Past information about proactivity at certain lags significantly contributes to the prediction of the current level of serious crime, and vice versa. Similar to the dynamic between general crime and proactivity, the Granger relationship appears to be more consistent from serious crime to proactivity than from proactivity to crime.

*Table 7. Granger causality tests for serious crime and proactivity (adjusted z values reported)*

| | Proactivity → serious crime | | | | |
|---|---|---|---|---|---|
| | Lag 1 | Lag 2 | Lag 3 | Lag 4 | Lag (AIC=15) |
| CAD proactivity | .430 | 1.516 | 1.323 | .925 | -2.055* |
| CAD proactive time | .751 | -.090 | .378 | .417 | -1.163 |
| AVL proactive visit | -.488 | -.193 | .347 | .086 | -2.377* |
| AVL proactive visit (0 to 5 min) | .042 | .829 | .844 | .728 | -2.420* |
| AVL proactive visit (5 to 20 min) | .031 | .386 | .396 | -.468 | -3.634*** |
| AVL proactive visit (>= 20 min) | -.570 | -1.047 | .050 | .311 | -.827 |
| AVL proactive time | -.892 | -.403 | .122 | -.022 | -1.972* |
| | Serious crime → proactivity | | | | |
| | Lag 1 | Lag 2 | Lag 3 | Lag 4 | Lag (AIC=15) |
| CAD proactivity | 2.810** | 3.542*** | 3.076** | 2.262* | -2.377* |
| CAD proactive time | 2.245* | 2.268* | 3.752*** | 3.075** | -1.643 |
| AVL proactive visit | .425 | -.767 | .189 | .349 | -1.717# |
| AVL proactive visit (0 to | .708 | -.586 | .509 | .363 | -1.613 |

| | | | | | |
|---|---|---|---|---|---|
| 5 min) | | | | | |
| AVL proactive visit (5 to 20 min) | .615 | .759 | 1.474 | 1.475 | -.926 |
| AVL proactive visit (>= 20 min) | 2.461* | .687 | .371 | .500 | -1.701# |
| AVL proactive time | 2.057* | .239 | -.042 | -.189 | -2.235* |

***,**,*, # indicate significance level at .001, .01, .05, and .1 level, respectively.

***Generalized Methods of Moment***

In light of the bidirectional relationship observed from the Granger Causality tests, I then proceeded with the system GMM analyses to deal with this potential endogeneity and further explore the nature of the impacts that crime and police proactivity have upon one another. Tables 8 and 9 present the results of the GMM models estimating the reciprocal relationship between proactivity and general crime and disorder. To reiterate the model specification, past values of the dependent variable are included in the model given their correlation with both the current value of the outcome variable and the key independent variable. The number of lags included depends on the autocorrelation structure in the outcome series. Additionally, lags of the independent variable are included to gauge the effect of proactivity on crime (or crime on proactivity) over time.

*Table 8. System GMM models for the effect of proactivity on crime*

| | Proactivity → crime | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. crime[1] | .460 | .518 | .423 | .427 | .451 | .472 | .439 |
| | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L2.crime | .357 | .344 | .338 | .343 | .362 | .322 | .354 |
| | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L3.crime | .007 | .005 | .006 | .006 | .005 | .007 | .010 |
| | (p=.418) | (p=.534) | (p=.398) | (p=.428) | (p=.492) | (p=.382) | (p=.178) |
| Proactivity | .090 | .001 | .007 | .007 | .054 | .027 | .000 |
| | (p=.003) | (p=.000) | (p=.003) | (p=.011) | (p=.000) | (p=.000) | (p=.003) |
| L. proactivity[1,2] | -.064 | -.001 | -.006 | -.006 | -.045 | -.019 | -.000 |
| | (p=.009) | (p=.002) | (p=.008) | (p=.020) | (p=.000) | (p=.002) | (p=.017) |
| N of instruments | 373 | 373 | 373 | 373 | 373 | 373 | 463 |
| Lags used to instrument | 4-6 | 4-6 | 4-6 | 4-6 | 4-6 | 4-6 | 4-7 |
| Hansen's J | .108 | .221 | .547 | .542 | .202 | .134 | .282 |

[1] L. indicates a one week lag

[2] None of the lagged terms of proactivity is significant, or affects the pattern of the results in any meaningful way. They are included in the displayed model for illustrative purposes. In subsequent models,

however, inconsequential lagged terms are not included in displayed models.

Results in Tables 8 and 9 confirm a reciprocal relationship between crime and proactivity. Specifically, Table 8[12] reveals a dynamic effect of proactivity on crime that changes in direction from week to week. For all measures of proactivity in Table 8, a significant contemporaneous relationship is noted from proactivity to crime. The direction of relationship is consistently positive across the table, suggesting that increases in proactivity lead to increases in crime, or at least increases in crime reporting in an immediate fashion. Crime goes up by 0.090 for every unit increase in proactive visits recorded in the CAD, and by 0.007 to 0.054 for every unit increase in proactive visits as measured by AVL. Lengthier proactive visits are generally associated with greater increases in crime, although the effect of AVL visits between 5 and 20 minutes is more substantial than that of those lasting for more than 20 minutes. The magnitude of these coefficients translates to about 0.2% to 2.1% of the average amount of crime and disorder

[12] As aforementioned, the specification of the GMM model is determined partially by the AR test on autocorrelation and the Hansen's J test on instruments exogeneity. The most parsimonious model that meets the requirements of both technical tests is typically selected. However, when examining the impact of proactivity on crime at the weekly level, additional sensitivity analyses were conducted and ultimately selected over the parsimonious model. Based on the insignificant AR test at AR(2), the parsimonious model included just one lagged term of crime as regressor. The displayed model, on the other hand, included two extra lags of crime while also satisfying both technical tests. The displayed model is desired over the parsimonious model on two accounts. One, the displayed model is consistent with subsequent sensitivity analyses using biweekly time units, both noting a residual deterrent effect during subsequent weeks following the initial reporting effect, whereas the parsimonious model failed to capture such an effect. Two, the coefficients of the lagged terms of crime are substantially larger in the displayed model than in the parsimonious model. These large coefficients of the autoregressive terms are consistent with most other models on crime and serious crime in the study. They are also consistent with the empirical understanding that crime is highly affected by past crime. Again, the parsimonious model failed to capture the large and persistent autocorrelation in crime series although it passes both technical tests. The reason for the discrepancy could be that, in the parsimonious model, past proactivity picked up part of the positive correlation between past crime and current crime, which then disguised the residual deterrent effect past proactivity has on current crime.

recorded weekly at an average top 5% census block, with CAD proactive visits associated with the largest effect. Summing across visits using the standard deviation of proactive visits and proactive time reported in Table 2, which provides a sense of how much proactivity measures change from week to week and across hot spots, this could lead to changes in crime and disorder of between 0.172 and 0.322 incidents per week. The presumptive reporting effect occurs predominantly within the same week.

On the other hand, evidence of a deterrent effect is noted at week 2. Proactivity in the previous week is associated with significant reductions in crime, consistently across all measures of proactive work. Crime goes down by 0.064 for every unit increase in CAD proactive events in the prior week, and by 0.006 to 0.045 for every unit increase in proactive visits from the previous week as measured through AVL. Again, the largest deterrent effect is associated with CAD proactive events or AVL visits between 5 and 20 minutes. Deeper lags of proactivity do not affect the results in any fundamental way and therefore are not included in the displayed model. The residual deterrent effect translates to between 0.1% and 1.5% of the baseline crime level (per census block per week) for single proactive visits, or between 7.6% and 29.2% of the baseline crime level when summing up the effect across the average weekly amount of proactive events per census block. Overall, increases in proactivity lead to immediate increases in crime and disorder, which is then followed by significant reductions in crime in the subsequent week.

Table 9 shows the impact of crime on proactivity. Deeper lags of proactivity are included as regressors due to the highly persistent autocorrelation in the weekly series of proactivity. Lags of crime are also included if they are significant or marginally significant to assess the effect of crime on proactivity over time. The coefficients for the lagged terms of proactivity almost sum up to 1, suggesting considerable stability in the spatial and temporal distribution of proactivity over time. The contemporaneous measure of crime significantly and positively affects proactivity for all measures except for proactive CAD events. While officers did not seem to generate more CAD proactive events at places with greater levels of crime, they did spend longer periods of time on self-initiated calls at those places. Each crime leads to about 17 extra minutes spent on CAD proactive calls, which is about 10% of the average time spent on proactivity recorded by CAD in a hot spot per week. An increase of a few crimes in a week, therefore, might have a notable impact on the amount of time officers spent carrying out proactive work. Officers also made increased levels of AVL proactive visits to higher crime places. Every unit increase in crime is associated with 0.040 unit increases in proactive CAD events, about 3 to 4 unit increases in AVL visits under 5 minutes, and between 0.190 and 0.853 unit increases in AVL visits longer than 5 minutes. These equal to about 0.8% to 5.1% of proactivity recorded in an average hot census block per week.

*Table 9. System GMM models for the effect of crime and disorder on proactivity*

| | Crime → proactivity | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. proactivity[1] | .435 | .759 | .291 | .278 | .188 | .261 | .283 |
| | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| L2.proactivity | .262 | .113 | .315 | .335 | .182 | .380 | .346 |
| | (p=.000) | (p=.002) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L3.proactivity | .140 | | .158 | .159 | .298 | .176 | .162 |
| | (p=.008) | | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L4.proactivity | .131 | | .233 | .237 | .376 | .174 | .202 |
| | (p=.000) | | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L5.proactivity | | | | | -.052 | | |
| | | | | | (p=.001) | | |
| crime | .040 | 17.405 | 4.243 | 3.271 | .190 | .853 | 50.939 |
| | (p=.247) | (p=.000) | (p=.000) | (p=.000) | (p=.011) | (p=.000) | (p=.000) |
| L.crime | | | 4.392 | 4.408 | | .452 | 33.243 |
| | | | (p=.000) | (p=.000) | | (p=.055) | (p=.106) |
| L2.crime | | | -3.135 | -2.980 | | -.343 | -37.793 |
| | | | (p=.000) | (p=.000) | | (p=.088) | (p=.010) |
| L3.crime | | | -4.602 | -3.884 | | -.809 | -33.333 |
| | | | (p=.000) | (p=.000) | | (p=.000) | (p=.074) |
| L4.crime | | | -.179 | -.169 | | | |
| | | | (p=.040) | (p=.040) | | | |
| N of instruments | 453 | 475 | 449 | 449 | 268 | 272 | 450 |
| Lags used to instrument | 5-8 | 3-6 | 5-8 | 5-8 | 6-7 | 5-6 | 5-8 |
| Hansen's J | .351 | .262 | .209 | .134 | .114 | .181 | .234 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2

suggests a two-week lag.

The coefficients for the lagged terms of crime in Table 9 reveal some interesting findings. Crime in previous weeks does not significantly affect current levels of CAD proactivity, CAD proactive time, or AVL proactive visits between 5 and 20 minutes; therefore, it is not included in the displayed models. When looking at these proactivity measures, the police seem to be taking an immediate and short-term approach in their responses to crime. By all measures but CAD proactive visits, police significantly increase their proactive presence within the week that new crimes occur. However, for AVL visits below 5 minutes, AVL visits more than 20 minutes, or overall AVL proactive time, changes in crime have immediate effects as well as lagged effects that last for up to a month. According to these measures, increases in crime during the current and last week lead to increases in the current level of proactivity. However, increases in crime that occurred more than one week before are consistently and negatively associated with current levels of proactivity. In other words, in the event of crime increases, police proactive responses will spike within a short period of time (1-2 weeks) before quickly going down, unless the increases in crime remain persistent. Also, while officers might take into account recent increases in crime at places and respond with increased proactive visits, those visits are not translated into recordable events by CAD. The types of presence that do persist longer (i.e., short AVL visits) also might not be the most effective based on the "Koper curve". Overall, police responses to crime, as currently practiced, have had very limited effect in reducing calls related to crime and disorder.

Tables 10 and 11 present the results of the system GMM models on serious crime and proactivity. Across different measures, proactivity significantly and consistently affects serious offenses. Again, the relationship is initially positive such that increases in proactivity lead to increases in serious crime or reporting of serious crime. Each unit increase in proactivity is associated with .002 -.046 unit increases in serious crime within the same week, with CAD proactivity events and AVL visits between 5 and 20 minutes associated with the greatest impact. These numbers translate to between 0.2% - 5.5% of the baseline level of serious crime in an average top 5% crime census block. Mirroring results from Table 8 on general crime, a deterrent effect is noted on serious crime at week 2. Proactivity during the prior week is associated with significant reductions in serious offenses. The residual deterrence, however, is manifested through AVL proactive visits only. For each unit increase in AVL proactivity, serious crime goes down by .001 - .021 units depending on the length of officer stay. Within the parameters of 0 to 20 minutes, the longer the AVL visits, the stronger the reduction of serious crime in the following week. These numbers translate to a 0.1% to 2.5% reduction from the baseline level of serious crime in a top 5% census block, with the greatest effect associated with AVL proactive visits between 5 and 20 minutes. Based on the standard deviation from week to week and across census blocks, these AVL proactive visits could lead to between 0.166 and 0.435 fewer serious crimes in the following week, which seems considerable relative to the 0.84 count of serious offenses at the baseline level. Interestingly, AVL visits over 20 minutes do not seem to affect crime in the following week, nor does the overall amount of proactive time officers allocated at places. It appears that longer proactive visits from the police do not necessarily lead to better results. Officers might increase their impact by proactively staying in a hot spot for under 20 minutes.

*Table 10. System GMM models for the effect of proactivity on serious crime.*

| | Proactivity → serious crime | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. crime[1] | .535 | .570 | .691 | .713 | .540 | .494 | .530 |
| | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L2.crime | .029 | .041 | .030 | .031 | .029 | .035 | .034 |
| | (p=.063) | (p=.016) | (p=.076) | (p=.062) | (p=.077) | (p=.042) | (p=.051) |
| Proactivity | .046 | .000 | .002 | .002 | .038 | .009 | .000 |
| | (p=.013) | (p=.010) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L.Proactivity | | | -.001 | -.001 | -.021 | | |
| | | | (p=.001) | (p=.001) | (p=.001) | | |
| N of instruments | 193 | 193 | 192 | 192 | 192 | 193 | 193 |
| Lags used to instrument | 2-2 | 2-2 | 3-3 | 3-3 | 3-3 | 2-2 | 2-2 |
| Hansen's J | .137 | .155 | .171 | .168 | .169 | .134 | .117 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests

a two-week lag.

The GMM relationship from serious crime to proactivity resembles the pattern of the relationship from crime and disorder to proactivity, but with greater magnitudes. Again, deeper lags of proactivity and serious crime are included in the models to control for autocorrelation or to detect residual effects. As shown in Table 11, each unit increase in serious crime at a census block is associated with 0.075- 10.033 unit increases in proactivity, which is equivalent to between 1.5% and 10.2% of proactivity recorded per week for an average hot census block, depending on the measure used. This contemporaneous impact does not reach statistical significance for CAD proactive calls and is marginally significant for AVL proactive visits that lasted between 5 and 20 minutes. The effect is highly significant, in contrast, for proactive time officers spent at those census blocks and for AVL proactive visits that lasted below 5 minutes or more than 20 minutes.

*Table 11. System GMM models for the effect of serious crime on proactivity*

| | Serious crime → proactivity | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. proactivity[1] | .423 | .745 | .298 | .282 | .243 | .274 | .312 |
| | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| L2.proactivity | .276 | .112 | .274 | .292 | .212 | .367 | .306 |
| | (p=.001) | (p=.004) | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L3.proactivity | .135 | | .175 | .173 | .267 | .149 | .151 |
| | (p=.017) | | (p=.000) | (p=.000) | (p=.000) | (p=.001) | (p=.000) |
| L4.proactivity | .130 | | .252 | .256 | .326 | .192 | .213 |
| | (p=.000) | | (p=.000) | (p=.000) | (p=.000) | (p=.000) | (p=.000) |
| L5.proactivity | | | | | -.056 | | |
| | | | | | (.001) | | |
| Serious crime | .075 | 39.855 | 10.033 | 8.401 | .725 | 1.710 | 109.293 |
| | (p=.573) | (p=.001) | (p=.000) | (p=.000) | (p=.055) | (p=.000) | (p=.000) |
| L. Serious | .603 | | -4.459 | -5.413 | .774 | 1.038 | 64.607 |
| crime | (p=.001) | | (p=.006) | (p=.000) | (p=.007) | (p=.007) | (p=.149) |
| L2.Serious | -.204 | | -5.008 | -3.808 | -.310 | -1.286 | -93.859 |
| crime | (p=.186) | | (p=.001) | (p=.005) | (p=.410) | (p=.003) | (p=.031) |
| L3.Serious | -.309 | | | | -.784 | -.552 | |
| crime | (p=.044) | | | | (p=.065) | (p=.044) | |
| N of instruments | 450 | 383 | 451 | 451 | 265 | 362 | 363 |
| Lags used to instrument | 5-8 | 3-5 | 5-8 | 5-8 | 6-7 | 5-7 | 5-7 |
| Hansen's J | .192 | .258 | .276 | .353 | .155 | .217 | .142 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.

Lagged terms of serious crime emerge as significant predictors of proactivity for all but the amount of time officers spent on proactive CAD events. The residual effect of serious crime on proactivity remains positive for one more week for CAD proactive visits, AVL proactive visits between 5 and 20 minutes, AVL visits above 20 minutes, and AVL proactive time. When looking at AVL total visits and AVL visits under 5 minutes, however, proactivity started to decline significantly after the initial week. Two weeks after increases in serious crime, proactivity starts to pull back significantly and consistently across measures. Taken together, the occurrence and concentration of serious crime, including violence and property offenses, leads to major and immediate increases in police proactivity at those places. These increases in proactivity quickly become less prominent following the next few weeks, unless increases in serious crime remain persistent. This echoes the results from Table 9 and reveals an immediate but short-term approach the police employ to deal with crime. Near-term increases in crime trigger short-term spikes of proactivity, which reverse back to the mean quickly after. There might even be a short-term back-off effect in the following weeks during which the levels of proactive visits fall significantly under the mean. In terms of different types of crime, the police do not appear to adopt a differentiating strategy other than responding to serious crime with more short-term proactivity. Such strategy has had little deterrent effect on crime and disorder. Serious offenses might be more susceptible to the impact of frequent proactive police visits, but reductions of these offenses over the following weeks are small relatively to the initial increases and only last for short time periods.

## Robustness Checks

### *Biweekly measures*

Results of the GMM models on crime and proactivity using biweekly time units are displayed in Appendices B and C. Overall, the results remain consistent with the main models using weekly time units. A significant and contemporaneous positive effect on crime is noted for most measures of proactivity using AVL. The effect turns negative and becomes consistent with a deterrent effect during the following biweekly time unit. This residual deterrent effect is observed with AVL measures of proactivity only. Again, AVL proactive visits between 5 and 20 minutes generated the largest deterrent effect. When CAD data is used, proactive visits are associated with significant increases in crime in the following week. No evidence is noted for a deterrent effect associated with CAD proactive events.

Consistent with the main results, proactivity is highly affected by past behaviors and patterns of proactivity, as shown in Appendix C. Increases in crime lead to significant and immediate increases in proactivity for most AVL measures and CAD proactive time, which is then followed by a significant back-off effect during the subsequent two to four weeks. CAD proactive events and time see significant increases following increases in crime, but do not experience the same downward residual effect as do AVL measures.

In general, the results mirror the main findings. Officers in the jurisdiction reacted to recent increases in crime by immediately increasing the levels of proactivity at those places. These increases were often pulled back shortly after the initial reactions. In terms of the impact of the current practice of proactivity, increased proactive work generally led to an immediate reporting effect, which was then followed by a significant residual deterrent effect for most AVL measures of proactive work. That being said, when longer time periods are used, the week-to-week dynamic between crime and proactivity became no longer evident for certain measures. For example, the residual deterrent effect occurred at about week 2 and consistently for all measures of proactivity in the weekly model; such effect was pushed to weeks 3 and 4 and faded away for CAD proactive events and proactive time, AVL proactive visits, and AVL visits under 5 minutes. It appears that, at least for these measures of proactivity, the deterrent effect did not last beyond week 2. Using biweekly measures, therefore, confounds the initial reporting effect and the subsequent deterrence (which cancelled out one another at the biweekly level) by ignoring the week-to-week variability. Similarly, both weekly and biweekly terms revealed the short-term orientation police adopt in their responses to changes in crime. But again, changes in proactive deployment occurring at the weekly level would be disguised with longer time units.

***The grid cell approach***

Appendices D and E present the results of the GMM models on crime and proactivity using a grid approach to identify the micro hot spots. Only CAD measures of proactivity are examined in this step for illustrative purposes. Due to the reduced size of the hot spots and, accordingly, smaller numbers of events occurring at those places, the top 1% of hot spots with the most crime are examined. According to Appendix E, police responded to changes in crime with increased proactive CAD events in an immediate manner. These responses lasted for a week and appeared even more fleeting than those observed at the census block level. On the other hand, increased proactivity led to significant increases in crime in an instantaneous fashion, suggestive of a reporting effect similar to those observed earlier (see Appendix D). Finally, evidence is inconclusive regarding the residual deterrent effect associated with the current practice of proactivity. While CAD proactive events failed to generate a discernable deterrence over time, AVL proactive visits are not directly tested which may have generated different patterns.

***Subgroup analysis***

Finally, Appendices F to I present the subgroup analyses by the types of proactive activities most frequently carried out in the top 5% census blocks. In traffic-dominated census blocks, police proactivity generated an immediate positive effect on crime, consistently across measures of proactive work (see Appendix F). Significant deterrent effects are noted in the subsequent week for all but CAD proactive events and AVL proactive visits longer than 20 minutes.[13] The largest deterrent effect is associated again with AVL proactive visits between 5 and 20 minutes. Similar patterns emerged in census blocks predominated by non-traffic related proactive activities, as shown in Appendix H. Crime went up immediately following increases in police proactive work, and subsequently went down during the following week(s) for all measures except for AVL

[13] Similar to the situation in Table 8, the consistent coefficient model (which included two extra lags of crime) is selected over the parsimonious model for reasons of model and empirical consistency, both satisfying the technical requirements of the GMM method. Readers are reminded about the potential discrepancies between models depending on the lag term specification. As opposed to the displayed model, the parsimonious model did not capture a residual deterrent effect of crime associated with increases in proactivity during the prior week(s) in census blocks that received primarily traffic stops. That being said, the displayed model is deemed desirable given the overall model performance and its consistent coefficients.

visits between 5 and 20 minutes. Interestingly, CAD events appeared to matter more than the length of AVL visits in terms of deterring crime in census blocks that received primarily non-traffic proactive work. When the primary proactive work involved activities that are non-traffic-oriented, it appears that the actual interaction with citizens or engagement in other recordable events (in CAD) fared better than proactive visits of any length captured through AVL. Finally, for CAD visits as well as AVL proactive visits lasting between 5 and 20 minutes, there also appears to be an adjusting effect a few weeks later when the residual deterrence fades away and crime goes back up.

In terms of police responses to changes in crime, the patterns are similar across different types of proactivity. Police adjusted the levels of proactivity at micro places based on short-term changes in crime. Specifically, increases in crime were followed by immediate increases in proactivity within the first one or two weeks, which were then followed by reductions in proactivity during subsequent weeks (see Appendices G and I).

Overall, the sensitivity analyses provide fair support to the original findings. A reciprocal relationship is consistently observed between crime and proactivity. Officers respond to changes in crime by altering the levels of proactivity at micro geographic places. These strategies, however, are carried out mostly with a short-term orientation and do not consistently last into subsequent weeks. Both CAD and AVL measures suggest that the police tend to adjust their proactive presence on a weekly basis according to near-term changes in crime, but these changes are more pronounced in measures based on AVL data. Specifically, CAD proactive visits do not consistently go up instantaneously following increases in crime, but when they do, they are also generally less likely to experience a significant backfire effect during following weeks. On the other hand, AVL proactive visits experience more consistent spikes immediately after increases in crime (although this week-by-week adjustment is disguised when using biweekly measures), but these spikes are often followed by significant reductions in proactive presence, or a back-off effect, during subsequent weeks.

In terms of the impact of the current practice of proactivity on crime, evidence points to a consistent contemporaneous reporting effect and a plausible residual deterrence that emerged at about week 2. The deterrent effect was often temporary and typically lasted for a week or two before quickly fading away. These overall patterns remain consistent for crime and serious crime, using weekly or biweekly measures, and in census blocks that received primarily traffic or non-traffic proactivity. Compared with CAD proactive events, AVL measures of proactive visits were associated with a deterrent effect that was more robust than to different specifications of the model. Specifically, a residual deterrence was observed primarily with AVL measures when examining serious crime, using biweekly time unit, and in census blocks that received mostly traffic stops. The largest deterrent effect was typically associated with AVL proactive visits between 5 and 20 minutes. Weekly measures appeared adequate in capturing the nuanced impact of police proactive work as currently practiced in the jurisdiction. When using biweekly time measures, however, the week-to-week variability in the impact of particularly CAD proactive events on crime might be disguised. The grid-cell approach to identify hot spots generated little evidence of a deterrent effect, but the results are inconclusive given that the approach was tested with CAD proactivity alone and not with AVL measures.

Finally, census blocks that experienced primarily traffic stops or non-traffic proactive work both experienced a residual deterrence. That being said, it appeared that the specific types of activities carried out by the police matter. While AVL visits between 5 and 20 minutes were associated with the largest deterrence in traffic-dominated census blocks, the actual engagement in a CAD proactive events appeared more important in census blocks with primarily non-traffic work.

# Chapter 5. Discussion and Conclusion

The current study was motivated by the growing evidence that certain proactive policing strategies promote crime control and community well-being, coupled with a scarcity of research examining the realities of police proactive work as practiced in the daily operational context and how those daily practices affect crime. This gap resulted mainly from a combination of scholarly emphasis on programmatic testing of regimented interventions, inadequate measurement of police proactive work in the daily context, and the methodological challenges of drawing temporal-order inferences using correlational data and nonexperimental methods. In light of these, the study explored everyday proactivity and its dynamic relationship with crime at the micro geographic and time levels, using data from CAD and AVL that offer the best existing recording of officer self-initiated events and proactive patrol and statistical frameworks that directly tease out the reciprocal impacts that crime and proactivity have on one another.

## The Realities of Everyday Proactivity

The descriptive analyses provided a sense of how officers generally patrol hot spots with respect to dosage and the types of activities. Overall, the baseline dosage of proactivity appears fairly high. Results from AVL suggest that officers in the jurisdiction paid an average of 31 proactive visits of 5 minutes and longer to a typical hot spot per week, translating to 4 to 5 potentially proactive visits of such length per day. These numbers seem comparable to or higher than some of those prescribed by or achieved in hot spots interventions tested in prior studies (e.g., Ariel et al., 2016; Hegarty et al., 2014; Rosenfeld et al., 2014). Besides, total AVL proactive visits averaged to about 30 proactive appearances per day, which seems quite high even if officers do not always stay for meaningful amounts of time. This high baseline value might limit the extent to which a strong deterrent effect could be observed from marginal changes in police presence. Crime and disorder events might already be suppressed, leading to persistent low baseline values, when officers are delivering such high dosages of proactive visits to the hot spots on a regular basis.

Among self-initiated events recorded through the CAD system, officers most frequently engaged in traffic enforcement activities, followed by preventative patrol and community engagement, public service and follow up investigations, miscellaneous events, and proactive work related to crime and disorder. Generally, the police carried out increased amounts of CAD proactive events at places at greater risk for crime, disorder, and serious crime. They were also more likely to conduct non-enforcement motivated proactive work and interact with citizens in recordable ways at higher crime places. The variations in the types of proactive activities carried out across hot spots, however, do not appear to be explained by beat-level differences. Across patrol areas, police seem to have adopted similar approaches in the everyday practice of proactivity. While the quantity of proactive events varied greatly, this might have to do with the variation in the citizen call volumes across beats and differences in the manpower assigned accordingly.

## The Reciprocal Relationship between Crime and Proactivity

The statistical models then explored how police typically adjust to changes in crime and whether those adjustments affect crime. Overall, evidence suggests that the police make week-to-week adjustments of their proactive deployment based on short-term changes in crime. Each crime is associated with between 3 and 4 additional AVL proactive visits under 5 minutes, between 0.190 and 0.853 additional AVL proactive visits longer than 5 minutes, and between 17 and 51 extra minutes proactive time within the same week of the crime occurrence. These increases can be quite sizable when summing up across the baseline crime and disorder events occurring at a hot spot per week. Proactive visits continued to go up in the subsequent week based on most AVL measures, but were typically followed with significant reductions during the next 2 to 3 weeks. Compared with proactive visits recorded through AVL, changes in proactive events and proactive time captured through the CAD system were smaller in magnitude, less likely to be significant, and shorter in duration. Overall, it appears that increases in crime and disorderly events prompted police to spend more time in the area, mostly for short drive-throughs, but officers were not necessarily engaging in events that were recorded through CAD.

The patterns are largely similar for police reactions to serious crime. Police responded to incidents of serious offenses with immediate increases in proactive visits at greater magnitude (in comparison to changes in proactivity following incidents of crime and disorder), which might last into the subsequent week but were often followed by substantial reductions 1 to 3 weeks after the initial increases. These back-off activities could be counterproductive if they lowered police presence too much. Again, changes in CAD measures tend to be smaller in size but the general pattern remains similar. Overall, everyday police proactivity demonstrates an important characteristic that is distinct from proactive policing as examined under a programmatic setting. That is, routine proactivity is highly impacted by past patterns of proactivity and is endogenous to crime. Future studies of police proactivity in a non-programmatic setting should account for this dynamic and endogenous characteristic.

Current strategies by which police respond to near-term changes in crime in the jurisdiction generated a temporary yet dynamic effect on crime. Overall, the study observed a consistent and instantaneous reporting effect of everyday proactivity on crime (assuming that increases in proactivity do not lead to an increased occurrence of crime). Each unit of proactivity is associated with 0.090 increases in crime for CAD proactive events, between 0.007 and 0.054 increases for AVL proactive visits, and between 0.000 and 0.001 increases in crime for each extra minute officers stayed proactively at those places. Again, these could translate to a considerable effect given the relatively high dosages of proactivity and low counts of crime at the baseline level. Among these measures, CAD proactive calls and AVL proactive visits between 5 and 20 minutes appear to have had the largest reporting impact.

Evidence is plausible on a potential residual deterrent effect after the initial reporting effect faded away. The deterrent effect typically emerged the week after increases in proactivity and rarely lasted beyond that week. A longer-lasting deterrent effect was observed in census blocks predominated by non-traffic proactive activities, where lengthier AVL proactive visits (those longer than 20 minutes) appear to have generated a deterrence of two weeks. Each unit increase in proactivity is associated with 1.5% reductions in crime relative to the baseline crime level for CAD proactive events and between 0.1% and 1.1% reductions for AVL proactive visits. Compared with CAD proactive events, AVL proactive visits were associated with more consistent evidence of residual deterrence. Specifically among AVL measures of proactive visibility, the largest deterrent effect was typically associated with those between 5 and 20 minutes, which consistently outperforms other shorter or longer AVL proactive visits in deterring crime. On the other hand, when examining places that received primarily non-enforcement oriented proactive activities, CAD proactive events generated a significant reduction in crime in the following week that marginally exceeded the initial reporting effect and outperformed other AVL visits. While the types of activities mostly carried out in a hot spot did not categorically affect the outcome with regards to deterrence, officers could potentially be more efficacious by engaging in actual CAD events if the primary goal is to carry out proactive work that is not traffic enforcement in nature. In summary, the study observed a residual deterrent effect associated with the everyday practice of proactive work that is reasonably consistent, temporary, and modest in size. Such deterrence is also likely at least partially disguised by the reporting effect that occurs instantaneously following increases in police proactive presence. That being said, certain types of proactivity, specifically, AVL visits that lasted between 5 and 20 minutes and CAD events in census blocks predominated by non-enforcement related activities, demonstrated greater odds of preventing crime.

Several factors might account for the temporary and relatively modest deterrent effect. The first possibility is a floor effect. The jurisdiction under examination is not one with particularly heavy crime problems, as suggested by the relatively modest number of crime and disorder events even in the top 5% of census blocks on the scale of crime. When the baseline proactive visits are as high as those demonstrated here, marginal changes from those baseline levels of proactive presence might not have much impact unless they are greater, more sustained, and optimally configured in terms of their dosage and types. Second, the significant and substantial reporting effect could be masking any deterrent effect those proactive responses from the police have generated. The deterrent effect might have been more discernable had we controlled for the reporting effect that occurred immediately following police responses.

Current practice of police proactivity might also not be conducted in the most effective way in terms of its deployment, the level of concentration, how long it is sustained, and the types of activities implemented. Everyday proactive work is highly affected by past practices and patterns. In terms of dealing with crime and serious crime problems, the police in the jurisdiction generally took a short-term approach by adjusting their proactive presence based on changes in crime within the last one to two weeks. Some might argue that proactive responses to short-term spikes in crime are reactive in spirit and the police should take a long-term perspective to be more efficacious, although others suggest that the police could still reduce crime by responding to the temporary flare ups in crime at micro places (Santos & Santos, 2015). Increased proactive visibility also tended to be followed by significant reverse effects one or two weeks after, and therefore was not typically sustained over longer periods of time. Further, increased levels of proactivity might not be enough dosage relative to the baseline values to generate a discernable deterrence similar to those noted from previous hot spots studies that employed a crackdown type of intervention.

The types of proactivity also matter in terms of its crime deterring effect. Officers might not be carrying out the right type of proactivity. Subgroup analyses provide preliminary evidence that proactive work comprised mainly of non-enforcement motivated activities fared better than those made up of mostly traffic enforcement activities. The mechanism underlying this differential effect is less clear, but officers will likely be more effective by taking into account the types of crime problems and opportunities abundant in the local context and adopt proactive activities accordingly. Also, proactive CAD events that capture most of the interactions that officers have with citizens do not consistently increase following increases in crime. This reduces the chance for problem-solving activities, intelligence-gathering, and specific deterrence to occur. While enhanced police presence in itself was found to be effective, it needs to be conducted in a way that maximizes the perceived presence, which might be lacking if officers simply drive around or sit at obscure locations.

Previous experimental and quasi-experimental studies of hot spots policing interventions suggested an overall significant and small crime reduction effect (Braga, Turchan, papachristos, & Hureau, 2019). In this regard, the current study of everyday proactivity as currently practiced generated similar evidence with regards to the overall benefits of patrol activities targeting micro geographic locations, which are consistently significant but of a small magnitude. That being said, several factors preclude a rigorous and direct comparison between everyday patrol and hot spots interventions. In the field experiments, any impact of hot spot treatments was often an enhancement from those already generated by existing practices. The current study, on the other hand, is an observation of the impact of proactive patrol activities in absence of a treatment protocol. The week-to-week changes in the dosages of proactive patrol in the everyday setting are also small relative to the exogenous treatment conditions typically imposed by experimental studies. Besides, jurisdictions could vary in important aspects such as baseline crime level and patrol dosage, which serves as a benchmark against which an effect could be observed. Overall a systematic patrol approach that rotates across micro crime hot spots during high risk time could potentially further improve the crime prevention efficacy of police proactive work.

On the other hand, the study concurs with previous empirical studies with regard to the optimal dosage of police proactive visits. Koper (1995) suggested that police can maximize their residual deterrent effect by staying at a hot spot for between 11 and 15 minutes (see also Sherman, 1990). Later, Hutt et al., (2018) found that police foot patrols are effective only when they last between 10 and 20 minutes. In the current study, proactive visits recorded through AVL that lasted between 5 and 20 minutes consistently fared better than shorter or longer visits in terms of their crime deterrence value on a week-to-week basis. The size and the sustainability of the deterrent effect appears malleable to the implementation of place-based patrol and the specific activities carried out. The police could optimize their patrol through intensified visibility for under 20 minutes and engaging in activities beyond traffic stops, patterns supported by both the current study and previous field experiments. Additionally, in the current study, proactivity generated a fleeting deterrent effect that rarely goes beyond a week, in part due to the short-term approach police generally take in tackling crime. The quick decay of deterrence can be traced in some previous experiments (Sherman & Rogan, 1995; Koper et al., 2013), but deterrence was also observed within longer time frames for interventions that lasted for lengthier periods of time (e.g., Braga & Bond, 2008; Hope, 1994; Mazerolle et al., 2000; Sherman & Weisburd, 1995; Weisburd & Green, 1995b).

### Measuring Proactivity with AVL Data

AVL emerges as a useful source for measuring police proactivity more comprehensively. It captures police visits in which no citizen contact or interaction was initiated, many of which are likely proactively motivated. In the jurisdiction examined, AVL recorded large amounts of police visits that occurred during the time when officers were not committed to calls for service or other administrative duties. Most of these visits by nature are fairly brief and associated with officers driving through an area. But about 7% of AVL proactive visits lasted between 5 and 20 minutes and about 11% lasted for more than 20 minutes in the top 5% of census blocks of crime. An average hot spot of crime and disorder received about 30 proactive visits per week that lasted for more than 5 minutes according to AVL measures, but officers only generated a recorded CAD event in 5 of these visits (17%) on average.

The geographic information recorded by AVL, therefore, revealed a gap in the current CAD recording practice in measuring police proactivity. The CAD system was designed primarily for dispatching and management purposes. It adequately captures citizen-initiated calls for service to the extent that an officer is dispatched to that call. Similarly, administrative duties are recorded so long as officers are taken away from their responsibilities to respond to citizen calls. During their noncommitted time, however, officers are usually not expected to generate a record unless they engage in certain types of interactions with citizens with implied potential for escalation, or other activities that will make them unavailable from taking calls. This recording practice, again, is prompted by purposes of management and concerns for officer safety. The objective of measuring or promoting officer proactivity is not directly built into the CAD system.  A direct result is that a large chunk of police proactive work goes unrecorded, if no discernable threat is immediately posted to officer safety or if officers are not tied up in an event that prevents them from answering other calls. These unrecorded proactive efforts may include common activities such as directed patrol activities, hot spot visits, casual conversations with citizens, and so forth.

The lack of motivation to capture these proactive activities in a nonprogrammatic everyday setting is in direct dissonance with the growing demand for better tracking and refinement of police proactive work. Proactivity is not adequately measured by many police agencies essentially because evidence-based crime prevention is not yet a goal in everyday practice. For evidence-based practices to occur in a sustained fashion, they have to be institutionalized in everyday practice and supported by organizational infrastructure

(Lum & Koper, 2017). They also need to be consistent with the overarching goals of police agencies that drive their daily operations and data recording practices. Currently, our understanding of police proactive work in the operational context and its dynamic with important outcomes is limited by a lack of adequate measures of proactivity. A practical first step is perhaps for agencies to incorporate CAD call codes designed to capture important proactivity such as hot spot visits and problem-solving activities. This might help capture the longer proactive visits more so than the quick drive-throughs, which may not pose a problem given that those meaningfully long proactive visits matter more in deterring crime. Simple as this may appear, it requires agencies to actively engage in various evidence-based practices such as identifying hot spots using crime data on an ongoing basis, identifying the underlying problems in communities, and developing problem solving strategies that can be carried out in the everyday context. Until the CAD system is constructed to adequately capture proactivity, AVL provides a useful source to measure officer allocation of time across space and to corroborate the proactivity captured by CAD.

AVL-measured proactive work also helps us better understand the relationship between police visibility and crime. The instantaneous reporting effect of proactive presence on crime and serious crime is observed irrespective of the specific data source used to measure proactivity. The residual deterrent effect in the following week, however, is observed with AVL data in a more consistent manner. CAD proactivity appeared more sensitive to model specification and was associated with a deterrent effect when examining general crime and disorder using weekly units and particularly in census blocks predominated by non-traffic proactive activities. Similarly, increases in crime and serious crime lead to immediate increased levels of police proactive visits and proactive time officers spend at those places, but not necessarily increases in proactive CAD events. The longer-term dynamic effect of crime on proactivity is mainly manifested in AVL proactive visits as well. Officers responded to changes in crime and serious crime with increased proactive presence that spikes in the short term and quickly dissipates, but this dynamic would have been disguised if examining only the recordable CAD proactive calls. Overall, CAD data does not capture police proactive visits during which no recordable event occurred and the effect of those proactive activities that were not reported into the CAD system.

**Examining Crime and Proactivity with Weekly and Biweekly Data**

The dynamic relationship between crime and proactivity at the micro time level remains an underexplored realm. Previous studies have observed short-term residual effects of police proactive interventions that last from a few days to a couple of weeks (Koper et al., 2013; Sherman & Rogan, 1995). Some scholars have also suggested the practical value of focusing on micro temporal units such as days or weeks when examining police proactive work (Santos & Santos, 2015; Weisburd et al., 2016). The current study further supports the utility of using micro time data to understand the operational relationship between crime and proactivity in practice. Police often operate under immediate pressure to react, as commanders may find themselves navigating through situations in which timely and visible responses are called for. While research evidence often suggests effective long-term approaches to crime and disorder problems, the everyday allocation of police proactivity reflects a combination of long-term inertia (high persistence to past patterns) and short-term mobilizations in response to recent changes in crime. Weekly data like those used in this study offer a practical lens through which we can view the empirical realities of police operations in a way that resonates with police commanders and supervisors.

Weekly measures employed in the study highlighted the short-term orientation of police reactions to changes in crime. Under current practices, police respond to near-term changes in crime by altering their proactive presence across locations and time on a week-to-week basis. These changes typically occur within one week or two following increases in crime before pulling back significantly over the next few weeks. This is consistent with the tempo of police management, which involves daily, weekly, and multi-week adjustment to community conditions. Weekly measures also illuminated the effect of police activity on crime which evolved over time. Changes in police patrol activities created immediate and consistent increases in crime reporting that could mask any deterrent effect these activities might have. Over the next week or two, the reporting effect decays and we started observing evidence of a residual deterrent effect. In particular, the weekly measures demonstrated a deterrent effect associated with CAD proactive events at week 2, which was masked by the initial reporting effect when biweekly units are employed. This week-to-week variability in the dynamic relationship between crime and proactive police patrol suggests the importance of taking a micro temporal lens to understand everyday police patrol, as currently practiced. On balance, the results seem to suggest that weekly measures are adequate in capturing police responses to crime, as well as the impact of proactivity as currently practiced. However, more sustained increases in proactive over multiple weeks may be needed to produce stronger and longer-lasting deterrent effects. Indeed, Santos and Santos (2015) examined the short-term responses police made to changes in crime and observed significant crime reductions following intense police responses that lasted between 2 and 3 weeks.

**Limitations**

A few limitations of the study are worth mentioning. The study examined the everyday police practice of proactivity and its reciprocal relationship with crime over time at micro spatial and time units. It sought to understand how police respond to changes in crime in the operational, nonprogrammatic context and whether current practice is effective at reducing crime. These research questions are exploratory in nature and were probed with correlational data. With the understanding of the challenges often presented by nonexperimental methods, the study directly addressed issues pertaining to endogeneity and dynamic bias. It estimated a complex, autoregressive feedback relationship between crime and proactivity, one that mimics the complex decision-making process in real life practice, using the panel Granger Causality test and the Generalized Methods of Moments framework. These methods, while warding off biases caused by certain third variables (i.e., past values of crime or proactivity), individual heterogeneity, and the endogenous relationship between key variables, are still based on correlational data and could potentially suffer from threats associated with omitted variables or otherwise inadequate model specifications. With that said, these methods are among the best nonexperimental methods and are designed to tackle issues related to cause and effect. They are also best suited for panels with relatively large cross sections and fewer time points and in the absence of external instruments. It is important to continue to improve the nonexperimental methods used to understand everyday police patrol and deployment, the results of which can then be used to propel experimental testing of the preliminary findings.

Another limitation pertains to the measurement of proactivity. Previous research has shown that more than half of officers' daily proactive work goes unrecorded in CAD systems, either because officers fail to report it or because those proactive activities do not involve events typically recorded in CAD systems. The present study supplemented CAD events using data on the locations of police patrol vehicles as recorded by AVL. By calculating the amount of proactive visits and proactive time officers spent across places, the study focused on the dosage of police presence without delving into the types of proactive activities officers engaged in. What officers do at crime hot spots, however, matters to the impact of their efforts (in terms of crime control), the sustainability of their efforts, and also the collateral consequences of their efforts. Officer activities at hot spots certainly matter to the tactical planning by police managers and supervisors who are concerned about the long-term impact of policing, resource efficiency, and community impact. The potential utility of AVL as a source of measurement of proactivity is largely limited to measuring the impacts of police visibility.

Even then, the AVL-generated location data may not be an optimal measurement of police proactive patrol. In theory, the effectiveness of preventative patrol to hot spots depends on officers maximizing their visibility to the general public or a small group of high-risk individuals. The AVL geographic pings do suggest that a given officer showed up at a certain location for certain periods of time when they were not committed to other CAD activities, but the officers may or may not have been proactive or visible. Officers might be engaging in personal errands or sitting at obscure locations to fill out paperwork. As aforementioned, a practical solution is for police agencies to reconstruct their CAD system to incorporate call-in codes related to common proactive activities that involve no participation from citizens (e.g., hot spots patrol). But before changes occur on the existing tracking practices of police patrol activities, AVL data along with CAD call activities still offer the most comprehensive measurement of officer movement and activities.

Finally, the study is limited to a single agency serving a suburban jurisdiction with generally low rates of crime. The results may not be generalizable to other agencies especially those serving urban and/or high-crime jurisdictions. With that said, the short-term approach through which police respond to crime in the everyday context seems typical of many agencies.

## Future Study

The study observed an instantaneous reporting effect on crime immediately following increases in proactive presence that is consistent across all measures of proactivity. Any deterrent effect generated from these police responses might have been masked by the initial increases in crime reporting. Increased reporting of crime has been considered as a positive reaction from communities, suggestive of increased levels of community cooperation and trust towards the police. A typical example is community policing, the evidence on the effect of which has generally pointed to an increased reporting of crime but inconsistent crime reductions (Gill et al., 2014). Increased reporting of crime could also have independent implications for the future occurrence of crime through mechanisms of informal social control and collective efficacy (Sampson et al., 1997). Future studies may examine ways to tease out the reporting effect and the collateral effect increased reporting may have on crime. This could benefit the understanding of everyday adjustment of patrol presence, which tends to have a lesser deterrent effect than those observed from experimental testing of interventions.

The study offered some preliminary evidence that certain practices of proactive patrol seem to be more efficacious in deterring crime. Specifically, proactive visits that last between 5 and 20 minutes and proactive CAD events that focus more on the non-enforcement aspect of police work appear to have increased the chance of observing a deterrent effect. However, evidence is inconclusive on the optimal specification of police patrol. Future endeavors are needed to further refine our understanding of how police patrol should be conducted to increase its residual deterrence. This will require a better understanding of the length and dosage of patrol, frequency of visits, and types of activities that can be sustained in an operational setting.

Proactive patrol activities recorded through CAD and AVL demonstrate both similarities and differences with regards to their interaction with crime. CAD-recorded proactivity appears to be more resistant to short-term fluctuations as compared with AVL-recorded proactive visits. They are less likely to change significantly following near-term changes in crime; but when they do, they are also less likely to last into subsequent weeks. More studies are needed to understand the systematic differences between the proactive events reported to CAD systems and those only recorded through AVL. Prior studies suggest that proactive events are more likely to be reported into the CAD system if they involve significant interactions with citizens, have implication for potential escalation, or prevent officers from taking calls for discernable amounts of time. Studies could explore ways to increase the reporting of other proactive visits and how those in turn propel changes in the practice of proactive patrol.

Future studies could further examine the geographic effects on the dynamic relationship between crime and proactivity. For example, to what extent are the hot blocks for crime also the hot blocks for police proactivity? Analyses could be conducted to compare two point-based datasets to study the overlap of crime and police events at the micro geographic level. Studies might also examine the spatial autocorrelation between crime and proactivity. Spatial techniques such as the Moran scatter plot could be utilized to study the univariate autocorrelation, or the association between a variable and its spatial lag. Considering the spatial effects is crucial particularly in light of the micro spatial units employed. Given that most proactive activities examined in the study were carried out through vehicle patrol, the patrol dosage in one census block should be closely related to the patrol dosage on adjacent blocks. Although the study focused on the top 5% of hot spots, many of these micro locations are adjacent to each other and therefore subject to a spatial correlation. That being said, cross-sectional dependence and heteroskedasticity in the residuals are controlled for in the GMM models, which might partially alleviate the bias resulted from spatial autocorrelation. In addition, a bivariate

LISA method can be applied to the bivariate context to examine the degree to which police proactivity at a location is related to crime in the surrounding locations, or vice versa. Temporal aspects could be similarly included in the spatial model to study the lagged effect proactivity and crime has on one another.

The geographic aspect can be further expanded to understand the practice of proactivity and its impact on crime. For example, the inclusion of land use variables, residential population, and other place characteristics may help explain the types of proactive activities undertaken across micro places and how that differentially affect crime. By employing census blocks as the spatial unit, the study could be aggregated up to the block group level to allow for the inclusion of demographic and other information. This could open up additional avenues to examine the interaction between characteristics of places and the opportunities for specific types of proactive work to occur.

In a similar vein, the temporal aspect of the study could be further expanded to refine our understanding about crime and proactivity at the micro time level. The study investigated the week-to-week variability in the relationship between crime and proactivity measured through CAD and AVL. Future studies might investigate the relationship at a more nuanced level. For example, how do opportunities vary for crime and proactive work to occur across time of the day. Hot spots patrol entails proactive work targeting high risk locations during high risk hours to optimize its efficacy. At the same time, during high risk hours when the volume of citizen calls is high, police might have limited capacity to carry out proactive work. A hour of the day analysis could shed lights on the dynamic relationship between crime and proactive work that might vary depending on the real-time baseline level of crime or proactivity.

Finally, the study observed some systematic differences across hot spots in the types of proactivity officers carry out but does not explain what drives those differences. Future studies might investigate why officers focus on traffic enforcement activities at some hot spots but non-enforcement activities in others. The study also focuses solely on the crime prevention outcome. Other important outcomes such as community and officer satisfaction and resource efficiency could be explored in the future. To sum up, police reacted to recent changes in crime by adjusting the levels of their proactive presence in the everyday context. These responses were typically made on a week-to-week or day-to-day basis, have taken a primarily short-term approach, and were generally pulled back one or a few weeks after. The deterrent effect generated from these strategies have been inconsistent. Towards more effective patrol practices, the police might consider better targeting their proactive patrol work to the concentration of crime, adopting a longer term and more sustained approach in response to crime problems, and carrying out proactive activities tailored specifically to local problems.

## Appendix A

Summaries on the Types of Calls Included in the Measure of Crime and Disorder,

Serious Crime, and Proactivity

| Variables | Types of calls included |
| --- | --- |
| Crime and disorder | Citizen calls for domestic dispute/violence, assault, fight, robbery, abduction, weapon-related incidents, larceny, burglary, other violence and property-related offenses, drug and alcohol related, suspicious event/person, disorderly conduct, vice, mentally disturbed person/incident, loitering, traffic and parking violations, animal-related trespassing, property destruction, and others. |
| Serious crime | Citizen calls for domestic dispute/violence, assault, fight, robbery, abduction, weapon-related incidents, larceny, burglary, and other violence and property-related offenses. |
| CAD proactivity | Officer calls for traffic/subject stops, miscellaneous complaint, community foot patrol, investigation, school-related activities, public service, assisting citizens, narcotics stakeouts, suspicious activities/person, accidents, parking violations, crime-related events, and others. Administrative activities such as paper work or attending court are removed. . |

## Appendix B

GMM Models for the Effect of Proactivity on Crime, using Biweekly Measures

| | Proactivity → crime | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. crime[1] | .801 (p=.000) | .822 (p=.000) | .802 (p=.000) | .811 (p=.000) | .814 (p=.000) | .793 (p=.000) | .810 (p=.000) |
| L2.crime | .014 (p=.160) | .018 (p=.126) | .022 (p=.084) | .027 (p=.051) | .017 (p=.139) | .010 (p=.316) | .014 (p=.170) |
| Proactivity | -.031 (p=.354) | .000 (p=.222) | .007 (p=.039) | .005 (p=.169) | .069 (p=.000) | .050 (p=.001) | .001 (.002) |
| L.Proactivity | .070 (p=.026) | .000 (p=.481) | -.007 (p=.087) | -.007 (p=.174) | -.062 (p=.003) | -.039 (p=.004) | -.000 (p=.003) |
| L2.Proactivity | -.003 (p=.868) | -.000 (p=.398) | .002 (p=.349) | .003 (p=.212) | .008 (p=.462) | -.004 (p=.639) | -.000 (p=.889) |
| Lags used to instrument | 3-9 | 3-10 | 3-12 | 3-13 | 3-12 | 3-7 | 3-8 |
| N of instruments | 321 | 353 | 411 | 437 | 411 | 251 | 287 |
| Hansen's J | .108 | .154 | .109 | .121 | .119 | .143 | .235 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.

## Appendix C

GMM Models for the Effect of Crime on Proactivity, using Biweekly Measures

| | Crime → proactivity | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L.proactivity[1] | .803 (p=.000) | .596 (p=.000) | .423 (p=.000) | .433 (p=.000) | .902 (p=.000) | .732 (p=.000) | .681 (p=.000) |
| L2.proactivity | .143 (p=.004) | .312 (p=.000) | .191 (p=.000) | .184 (p=.000) | .077 (p=.006) | .265 (p=.000) | .315 (p=.000) |
| L3.proactivity | | .015 (p=.663) | .270 (p=.000) | .256 (p=.000) | | | |
| L4.proactivity | | | .120 (p=.000) | .131 (p=.000) | | | |
| crime | -.059 (p=.533) | 6.265 (p=.032) | 1.191 (p=.027) | .261 (p=.538) | .418 (p=.000) | .776 (p=.000) | 61.660 (p=.000) |
| L.crime | .136 (p=.078) | | -.303 (p=.573) | .556 (p=.350) | -.325 (p=.000) | -.688 (p=.001) | -55.125 (p=.000) |
| L2.crime | | | -.870 (p=.087) | -.877 (p=.041) | | | |
| N of instruments | 322 | 336 | 407 | 425 | 412 | 412 | 462 |
| Lags used to instrument | 3-9 | 4-11 | 5-16 | 5-17 | 3-12 | 3-12 | 3-14 |
| Hansen's J | .135 | .132 | .196 | .149 | .172 | .260 | .248 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.

## Appendix D

GMM Models for the Effect of Proactivity on Crime, using Weekly Measures and A Grid-Cell Approach

| | Proactivity → Crime | |
|---|---|---|
| | CAD proactivity | CAD proactive time |
| L.Crime[1] | .323 (p=.000) | .294 (p=.000) |
| L2.Crime | .117 (p=.093) | .203 (p=.001) |
| L3.Crime | .230 (p=.000) | .238 (p=.000) |
| L4.Crime | -.007 (p=.709) | -.038 (p=.505) |
| L5.Crime | | -.014 (p=.127) |
| Proactivity | .043 (p=.006) | .000 (p=.045) |
| L.Proactivity | | -.000 (p=.988) |
| L2.Proactivity | | -.000 (p=.727) |
| L3.Proactivity | | .000 (p=.597) |
| L4.Proactivity | | -.000 (p=.013)[2] |
| lags used to instrument | 5-5 | 6-6 |
| N of instruments | 183 | 174 |
| Hansen's J | .363 | .182 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.
[2] Up to five lags of proactivity are tested, based on the number of lags included for the autoregressive term. Only four lags are included in the displayed model because of the significant pattern shown at the 4th lag (although very negligible). Adding a 5th lag did not change the results.

## Appendix E

GMM Models for the Effect of Crime on Proactivity, using Weekly Measures and A Grid-Cell Approach

| | Crime→ Proactivity | |
|---|---|---|
| | CAD proactivity | CAD proactive time |
| L.Proactivity | .601 (p=.000) | .651 (p=.000) |
| L2.Proactivity | .275 (p=.000) | .319 (p=.000) |
| Crime[2] | .268 (p=.009) | 75.254 (p=.019) |
| Lags used to instrument | 3-3 | 3-4 |
| N of instruments | 193 | 289 |
| Hansen's J | .271 | .854 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.
[2] lagged terms are tested and insignificant, therefore not included in the displayed model.

## Appendix F

GMM Models for the Effect of Proactivity on Crime in the Top 5% Census Blocks that Received Primarily Traffic Proactive Activities

| | Proactivity → crime | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. crime[1] | .349 (p=.000) | .414 (p=.000) | .323 (p=.000) | .336 (p=.000) | .414 (p=.000) | .289 (p=.000) | .240 (p=.000) |
| L2.crime | .340 (p=.000) | .308 (p=.000) | .302 (p=.000) | .295 (p=.000) | .300 (p=.000) | .324 (p=.000) | .312 (p=.000) |
| L3.crime | .002 (p=.710) | .003 (p=.705) | .003 (p=.606) | .004 (p=.557) | .001 (p=.812) | .004 (p=.549) | .005 (p=.387) |
| Proactivity | .162 (p=.031) | .003 (p=.096) | .007 (p=.020) | .007 (p=.024) | .107 (p=.000) | .066 (p=.000) | .001 (p=.000) |
| L.Proactivity | -.052 (p=.416) | -.004 (p=.009) | -.005 (p=.047) | -.006 (p=.049) | -.088 (p=.000) | -.025 (p=.161) | -.001 (p=.050) |
| L2.Proactivity | | .006 (p=.002) | | | | | |
| Lags used to instrument | 281 | 280 | 281 | 281 | 281 | 281 | 281 |
| N of instruments | 4-5 | 4-5 | 4-5 | 4-5 | 4-5 | 4-5 | 4-5 |
| Hansen's J[2] | .303 | .358 | .418 | .305 | .277 | .194 | .290 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.
[2] These large values for the Hansen's J might raise concern about overidentification and reduced efficiency of the models. With that said, reducing the number of instruments did not affect the patterns of the coefficients and their significance levels in the results (see Roodman, 2007).

## Appendix G

GMM Models for the Effect of Crime on Proactivity in the Top 5% Census Blocks that Received Primarily Traffic Proactive Activities

| | Crime → proactivity | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L.proactivity[1] | .087 (p=.144) | .073 (p=.345) | .112 (p=.000) | .116 (p=.000) | .391 (p=.000) | .170 (p=.037) | .053 (p=.437) |
| L2.proactivity | .217 (p=.000) | .020 (p=.756) | .353 (p=.000) | .355 (p=.000) | .163 (p=.015) | .251 (p=.004) | .350 (p=.000) |
| L3.proactivity | .028 (p=.579) | .163 (p=.012) | .045 (p=.025) | .053 (p=.007) | -.071 (p=.246) | .153 (p=.013) | .167 (p=.002) |
| L4.proactivity | .218 (p=.000) | -.002 (p=.876) | .269 (p=.000) | .255 (p=.000) | .436 (p=.000) | .227 (p=.009) | .329 (p=.000) |
| L5.proactivity | .091 (p=.047) | | .146 (p=.000) | .144 (p=.000) | .028 (p=.628) | -.015 (p=.839) | -.031 (p=.536) |
| L6.proactivity | .219 (p=.000) | | .068 (p=.000) | .071 (p=.000) | | .135 (p=.000) | .066 (p=.008) |
| L7.proactivity | -.002 (p=.872) | | | | | | |
| crime | .116 (p=.002) | 2.473 (p=.315) | 8.016 (p=.000) | 7.434 (p=.000) | .827 (p=.000) | .237 (p=.126) | 17.664 (p=.059) |
| L.crime | | 4.922 (p=.044) | 3.347 (p=.002) | 3.042 (p=.002) | -.090 (p=.568) | .190 (p=.189) | 17.852 (p=.063) |
| L2.crime | | | -3.286 (p=.000) | -2.859 (p=.001) | -.220 (p=.239) | .183 (p=.381) | 12.704 (p=.311) |
| L3.crime | | | -4.457 (p=.000) | -4.083 (p=.000) | .017 (p=.907) | -.155 (p=.213) | -7.132 (p=.394) |
| L4.crime | | | -2.956 (p=.019) | -2.947 (p=.019) | -.214 (p=.074) | -.294 (p=.048) | -26.006 (p=.042) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| L5.crime | | | 1.869 (p=.053) | 1.896 (p=.047) | | | |
| N of instruments | 254 | 182 | 342 | 342 | 170 | 169 | 257 |
| Lags of instrumental variables | 8-9 | 5-5 | 7-9 | 7-9 | 7-7 | 7-7 | 7-8 |
| Hansen's J[2] | .300 | .418 | .715 | .704 | .361 | .312 | .448 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.

[2] These large values for the Hansen's J might raise concern about overidentification and reduced efficiency of the models. With that said, reducing the number of instruments did not affect the patterns of the coefficients and their significance levels in the results (see Roodman, 2007).

## Appendix H

GMM Models for the Effect of Proactivity on Crime in the Top 5% Census Blocks that Received Primarily Non-Traffic Proactive Activities

| | Proactivity → crime | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L. crime[1] | .432 (p=.000) | .490 (p=.000) | .394 (p=.000) | .418 (p=.000) | .409 (p=.000) | .387 (p=.000) | .396 (p=.000) |
| L2.crime | .244 (p=.000) | .211 (p=.000) | .256 (p=.000) | .257 (p=.000) | .263 (p=.000) | .272 (p=.000) | .278 (p=.000) |
| L3.crime | .073 (p=.020) | .075 (p=.008) | .075 (p=.009) | .074 (p=.012) | .075 (p=.016) | .081 (p=.007) | .078 (p=.007) |
| Proactivity | .070 (p=.037) | .001 (p=.000) | .009 (p=.000) | .008 (p=.006) | .034 (p=.012) | .035 (p=.000) | .000 (p=.000) |
| L.Proactivity | -.074 (p=.036) | -.001 (p=.009) | -.007 (p=.003) | -.006 (p=.047) | -.015 (p=.450) | -.003 (p=.649) | -.000 (p=.660) |
| L2.proactivity | .008 (p=.822) | .000 (p=.625) | | | -.026 (p=.283) | -.023 (p=.004) | -.000 (p=.005) |
| L3.proactivity | .033 (p=.075) | | | | .019 (p=.020) | | |
| Lags used to instrument | 4-4 | 4-4 | 4-4 | 4-4 | 4-4 | 4-4 | 4-4 |
| N of instruments | 185 | 186 | 187 | 187 | 185 | 186 | 186 |
| Hansen's J[2] | .534 | .675 | .666 | .602 | .510 | .613 | .566 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.

[2] These large values for the Hansen's J might raise concern about overidentification and reduced efficiency of the models. With that said, reducing the number of instruments did not affect the patterns of the coefficients and their significance levels in the results (see Roodman, 2007).

Appendix I

GMM Models for the Effect of Crime on Proactivity in the Top 5% Census Blocks that Received Primarily Non-Traffic Proactive Activities

| …….. | Crime → proactivity | | | | | | |
|---|---|---|---|---|---|---|---|
| | CAD | CAD time | AVL | AVL 0_5 | AVL 5_20 | AVL >20 | AVL time |
| L.proactivity[1] | .408 (p=.000) | .733 (p=.000) | .368 (p=.000) | .361 (p=.000) | .728 (p=.000) | .278 (p=.000) | .274 (p=.000) |
| L2.proactivity | .152 (p=.055) | .097 (p=.069) | .135 (p=.000) | .100 (p=.001) | .239 (p=.000) | .239 (p=.000) | .257 (p=.000) |
| L3.proactivity | .106 (p=.005) | | .066 (p=.092) | .205 (p=.000) | | .208 (p=.000) | .192 (p=.000) |
| L4.proactivity | .311 (p=.000) | | .480 (p=.000) | .305 (p=.000) | | .266 (p=.000) | .269 (p=.000) |
| L5.proactivity | | | -.044 (p=.091) | | | | |
| crime | .092 (p=.068) | 42.552 (p=.000) | 1.075 (p=.142) | .735 (p=.131) | .260 (p=.000) | 1.126 (p=.002) | 87.936 (p=.000) |
| L.crime | | -26.720 (p=.002) | 2.729 (p=.008) | .436 (p=.368) | | .104 (p=.687) | 20.021 (p=.456) |
| L2.crime | | | -3.094 (p=.000) | -1.020 (p=.012) | | -.196 (p=.423) | -36.220 (p=.160) |
| L3.crime | | | | | | -.720 (p=.000) | -44.793 (p=.002) |
| L4.crime | | | | | | -.023 (p=.778) | |
| N of instruments | 185 | 192 | 176 | 181 | 193 | 179 | 180 |
| Lags used to instrument | 4-4 | 3-3 | 6-6 | 5-5 | 3-3 | 5-5 | 5-5 |
| Hansen's J[2] | .560 | .715 | .365 | .429 | .674 | .515 | .473 |

[1] The number after L indicates how many weeks are lagged for the lagged term. For example, L2 suggests a two-week lag.
[2] These large values for the Hansen's J might raise concern about overidentification and reduced efficiency of the models. With that said, reducing the number of instruments did not affect the patterns of the coefficients and their significance levels in the results (see Roodman, 2007).

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