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What Came First: The Police or the Incident? Bidirectional Relationships Between Police Actions and Police Incidents

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Abstract

The present research examines the long-term, bidirectional relationships between calls for service, crime, and two police patrol strategies in Santa Monica, California: foot patrol and police stops. Using nine years of monthly data (2006 to 2014), we estimate two sets of block-level, longitudinal models to tease apart these relationships. In our first set of models, we use police actions and calls for service in the preceding month(s) to predict crime in the subsequent month. In our second set of models, we use calls for service and crime in the preceding month(s) to predict police actions in the subsequent month. We find that while changes in calls for service and crime often precede changes in police action, changes in crime also tend to follow them. For example, police stops appear to be particularly receptive to burglary: blocks with more burglaries receive greater numbers of police stops, and blocks with more police stops have reduced odds of experiencing burglary. We also find that the length of effects of predictors varies as a function of predictor and outcome: whereas some predictors exhibit short temporal effects (e.g., one month), other predictors exhibit much longer temporal effects (e.g., twelve months). Our results thus provide important insight into the spatial and temporal relationships between police actions and police incidents. Police actions must be neatly tailored to police incidents at precise levels if long-term deterrent effects at these levels are to be achieved.

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What Came First: The Police or the Incident? Bidirectional Relationships Between Police Actions and Police Incidents

Scholars have long sought to examine the use, and associated effectiveness, of different police patrol strategies. From the Kansas City Preventative Patrol Experiment (Kelling et al. 1974), to the Newark Foot Patrol Experiment (Police Foundation 1981), to the more recent Philadelphia Policing Tactics Experiment (Groff et al. 2015), patrol strategy research has become a hot topic for social inquiry. Considering the contentious role prescribed to police, the scholarly interest in examining patrol strategies should be no surprise.

Researchers have typically examined the short-term, unidirectional relationships between police strategies and crime, often using experimental, quasi-experimental, and/or cross-sectional designs (e.g., Kelling et al. 1974, Police Foundation 1981, Esbensen 1987, Sampson and Cohen 1988, Sherman and Weisburd 1995, Braga et al. 1999, McGarrell et al. 2001, Braga and Bond 2008, Kubrin et al. 2010, Ratcliffe et al. 2011, Taylor et al. 2011, Piza and O'Hara 2014, Groff et al. 2015). Indeed, scholars recently called for more longitudinal and/or experimental analyses to examine the potentially bidirectional, casual links "between crime and [police] proactivity at places" (Wu and Lum 2016, p. 18). Thus, although police strategies have been hypothesized to have at least some impact on offenders' short-term perceptions of target-rich locations, the long-term, cumulative, and/or bidirectional effects of such strategies may not yet be fully known. Police activity in a given location may take longer than traditionally studied to produce a long-term change in perceived guardianship, and thus a long-term change in crime.[1]

[1] Note that in this context, 'longer' does not necessarily imply consistent police activity throughout the entire period of analysis. It is possible that police activity ebbs and flows in a given location over time, and thus using a longer temporal unit of analysis helps to capture blocks that potentially have systematically sporadic activity over an extended period of time.

The present research, therefore, seeks to complement existing literature on the short-term, unidirectional relationships between police actions and police incidents by exploring the long-term, bidirectional relationships. Using nine years of monthly data (2006 to 2014), we assess whether the level of police activity in a block in the previous month(s) (as measured by the total volume of foot patrol and police stops in the block) has consequences for the level of crime in the subsequent month and vice versa. By providing this temporal assessment of the spatial distribution of police patrol strategies, we test theorized claims about foot patrol and police stops at a precise spatial scale, and offer insight into these practices as they occur over an extended period of time.

In order to outline the foundation from which we constructed our hypotheses, we begin by first reviewing two theoretical frameworks that can be used to understand the relationship between policing and crime: (1) routine activities theory and (2) deterrence theory. In light of these frameworks, we then discuss the role of two specific policing strategies in preventing crime: (1) foot patrol and (2) police stops. Following that, we describe our data and research methods. We then present our results, and conclude with implications.

THEORETICAL FRAMEWORKS

ROUTINE ACTIVITIES THEORY

Initially proposed by Cohen and Felson (1979), routine activities theory (RAT) argues that crime is an event that results from the convergence of motivated offenders and suitable targets in the absence of capable guardians in both time and space. Although motivated offenders and suitable targets are important elements of the crime equation (from a RAT perspective; e.g., see Cohen and Felson 1979), we focus specifically on the role of capable guardians, defined as any persons or things that can prevent criminal behavior (Cohen and Felson 1979, Felson 1995, Reynald 2010), for the purposes of the present research.

Capable guardians are typically most useful for preventing crime before it happens and/or during the preparatory stages of the crime event (Reynald 2010). They exist along three continuums, (1) their willingness to supervise, (2) their ability to detect potential offenders, and (3) their willingness to intervene in behavior (Reynald 2010), and vary in their levels of responsibility (Felson 1995). For example, capable guardians with personal (e.g., persons who share intimate connections with places) and/or assigned (e.g., security guards) responsibility are believed to be 'better' guardians than guardians with diffuse (e.g., non-specific employees) and/or general (e.g., strangers) responsibility (Felson 1995). These characteristics are particularly important when considering the role of the police as capable guardians. One could argue that the prescribed role of the police scores high on all three guardianship continuums because their role transcends the greatest levels of responsibility. However, the extent to which police officers fulfill their guardianship duties may vary by patrol strategy, and therefore we explore the role of the police in greater detail.

Police as Capable Guardians

Prescribed with the role of preventing crime and maintaining public order (e.g., Menton 2008), the police are often described as the "watchful eye" (Braga et al. 1999, p. 570). In the context of RAT, police can be thought of as guardians who are assigned to supervise, detect, and intervene in behavior in order to prevent crime. The ability of police to act as capable guardians, however, can vary as a function of their patrol strategy (Felson 1995). Police patrol is frequently referred to as the 'backbone' of policing (Kelling et al. 1974); but, not all patrol strategies afford equal probability of being able to detect criminal behavior, a key component of capable guardianship (Reynald 2010), and therefore it is likely that certain patrol strategies (e.g., foot patrol) may be better suited to certain types of places (e.g., promenades) with certain types of

crime (e.g., public disorder) than other patrol strategies. These lines of inquiry foster a discussion of the deterrent effects of different patrol strategies on different types of crime in different places.

DETERRENCE THEORY

Rooted in the classical school of criminology, deterrence theory argues that human beings are rational actors who are motivated to pursue pleasure and avoid pain (e.g., Nagin and Pogarsky 2003, Higgins et al. 2005, Paternoster 2010). In the context of crime, deterrence theory argues that potential offenders refrain from committing crime because they perceive the cost of committing crime (i.e., the punishment) to outweigh the benefit of committing crime (i.e., the financial gain; e.g., Nagin and Pogarsky 2003, Higgins et al. 2005, Paternoster 2010). With that being said, the balance between these costs and benefits can be influenced by the certainty, severity, and/or swiftness of punishment. The role of certainty, defined as the likelihood that an offender will be punished for committing a crime (Paternoster 2010, Nagin 2013), is of particular interest in the present research, and therefore we discuss it in greater detail.

Scholars have empirically tested the role of certainty in a wide variety of contexts, such as cheating (Nagin and Pogarsky 2003), software piracy (Higgins et al. 2005), and police misconduct (Pogarsky and Piquero 2004), and consistently found that it acts as a stronger deterrent than severity. The police's ability to manipulate the certainty of apprehension for committing crime may therefore be fruitful for deterring crime. The primary means by which certainty can be manipulated by the police is via their patrol tactics (Nagin 2013). Depending on the characteristics of a given place, different strategies may be more likely to deter crime because they provide different degrees of certainty of apprehension. For example, it is reasonable to argue that foot patrol provides greater certainty of apprehension when it is conducted in areas where officers could otherwise not easily patrol (Berkley and Thayer 2000).

It is possible that these deterrent effects may be achieved by the mere presence of police in these areas, which signifies the potential for arrest: an indirect effect (e.g., Wilson and Boland 1978, Sampson and Cohen 1988, Nagin 2013). It is also possible that actions of the police that directly impact the likelihood of being arrested for committing crime (e.g., stop, question, and frisks) may be required in order to actually deter crime: a more direct effect (e.g., Wilson and Boland 1978, Sampson and Cohen 1988, Nagin 2013**)**. Regardless of the mechanism, however, foot patrol and police stops are believed to offer advantages for increasing both the perceived and actual certainty of apprehension.

PATROL STRATEGIES

FOOT PATROL

Numerous studies have examined the use of foot patrol in policing. Proponents for foot patrol argue that it can reduce crime as well as foster relationships between the community and the police. Research has largely found evidence for the latter. For example, scholars have found that foot patrol fosters the development of local knowledge about patrol beats to a greater degree than vehicle patrol, and that this extended knowledge allows foot patrol officers to tailor their responses to community problems to suit the needs of the community (Berkley and Thayer 2000, Wood et al. 2014). Scholars have also found that foot patrol can increase contacts with the public and improve access to areas not easily accessible by vehicle (Berkley and Thayer 2000). The empirical evidence for foot patrol's ability to reduce crime, however, is less clear. Despite advocates' optimistic predictions, the results of previous research examining the relationship between foot patrol and crime have been mixed.

In the landmark Newark Foot Patrol Experiment, Police Foundation (1981) examined the effect (or lack thereof) of a one-year foot patrol experiment on crime in New Jersey. The results

revealed that foot patrol had no significant effect on overall crime rates, but that foot patrol increased citizens' perceptions of safety in their neighborhood (Police Foundation 1981). The results also revealed that residents were more aware of the levels of foot patrol in their neighborhood than the levels of vehicle patrol (Police Foundation 1981).

Many follow-up studies to the Newark Foot Patrol Experiment observed similar results. One evaluation study found that foot patrol was effective in reducing public disorder crime in target areas (which were composed of approximately five city blocks), but not effective in reducing overall crime rates, when analyzed at four different time points over a three-year-period (Esbensen 1987). A similar evaluation study (which examined the effects of the Boston Reallocation Plan over an approximate four-year period) found that beats that had greater foot patrol had fewer priority calls for service, but that foot patrol had no overall order maintenance or crime control effects (Bowers and Hirsch 1987).

Some more recent research has shown a negative relationship between foot patrol and specific types of crime in specific types of places. For example, Ratcliffe and colleagues (2011) examined the effects of a three-month foot patrol program in violent crime hotspots (which included "an average of 14.7 street intersections and 1.3 miles of streets" (p. 806)) in Philadelphia, Pennsylvania, and found that it reduced violent crime by 23%. However, a later study by Groff and colleagues (2015) found that lower doses of foot patrol during a similar-length intervention period did not significantly reduce violent crime in hot spots in Philadelphia, which averaged "the size of 22 American football fields" (p. 28). Jones and Tilley (2004) also found that the introduction of high-visibility foot patrols in a high-crime, urban city-center was associated with significant decreases in personal robberies over the course of a year, Piza and O'Hara (2014) found that a one-year saturation foot patrol program reduced a number of violent

offences in a high-violence precinct in Newark, New Jersey, and Andresen and Lau (2014) reported that increased foot patrol was associated with declines in crime (and particularly, property crime) in a relatively low crime 30-block area in North Vancouver, British Columbia.

Before transitioning to a discussion of police stops, it is important to first highlight a number of caveats of foot patrol research. First, it is reasonable to argue that much of foot patrol's inability to impact overall crime rates is likely associated with foot patrol's inability to deter more serious crimes, such as sexual assault, murder, and burglary, which tend to be committed in private spaces (Esbensen 1987). If crimes are not visible to foot patrol officers, and/or if foot patrol officers are not visible to motivated offenders, then it is less likely that their occurrence will be impacted by the presence of foot patrol officers (e.g., Police Foundation 1981, Esbensen 1987). Second, the mobility of foot patrol is inherently limited in space due to its slow travelling speed (Berkley and Thayer 2000). Foot patrol officers are unable to cover nearly as much territory as vehicle and/or bicycle patrol officers, and therefore depending on a study's unit of analysis, different results will likely be observed.

POLICE STOPS

Unlike foot patrol, research on police stops has been much less specific, in part due to their relatively ambiguous nature. Most studies that have examined the effects of police stops have done so as part of their assessments of broader policing strategies, such as hot spot policing and/or proactive policing. As part of these strategies, the need to stop potential offenders is generally heightened. For example, Taylor and colleagues (2011) found that police officers assigned to directed saturation patrol for a three-month period conducted significantly more field stops during their study's intervention period than control officers, but that these stops did not result in any significant declines in crime. A similar quasi-experiment found that traffic enforcement

crackdowns (as measured by the number of moving citations issued over a two-month period) had no effect on the frequency or severity of traffic accidents at the city-level (Carr et al. 1980). In contrast, a quasi-experiment by McGarrell and colleagues (2001) found that a three-month period of directed police patrol had significant impacts on violent crime in patrol beats that averaged two square miles (or 15,000 residents).

In addition to these experimental designs, a growing body of literature has also used non-experimental designs to evaluate the use and associated effectiveness of police stops. For example, Wilson and Boland (1978) found that aggressive patrol tactics (as defined by the number of moving traffic citations issued per patrol unit) and greater police resources (as defined by the number of patrol units on the street per capita) "separately and in combination, will lead to a higher arrest ratio for robbery" (p. 380), and that higher arrest ratios are associated with lower robbery rates at the city-level. Sampson and Cohen (1988) and Kubrin and colleagues (2010) also found negative relationships between proactive policing (as defined by the number of arrests per officer for disorderly conduct and driving under the influence) and robbery rates at the city-level. Lastly, Weisburd and colleagues (2016) reported that stop, question, and frisks produced modest (but still significant) deterrent effects on crime "within small areas and across short time periods" (p. 16). In these cases, police stops appear to be having at least some deterrent effect on crime.

TEMPORAL SCALE OF PATROL STRATEGIES?

Thus far we have highlighted that much of the existing research on the relationship between patrol strategies and crime focuses on short-term temporal scales. Studies typically examine whether short-term interventions (e.g., three months) reduce levels of crime at given locations, often relative to the same length pre- and/or post-periods. Although such strategies are assumed to directly impact offenders' activity by altering their views of suitable target locations,

such that locations are no longer considered attractive as a result of police activity, the temporal scale is still important. One alternative explanation is temporal displacement, whereby an offender shifts their activity temporally, and simply does not offend for the period of time in which the intervention is in place, but then returns to their normal activity after the intervention ends. This raises the question of how to shape offenders' long-term perceptions such that they no longer view a location as an attractive target, even after the intervention ends. Sherman (1990) suggested that rotating interventions across targets might be most effective for changing perceptions because rotations help to create residual deterrence (rather than just initial deterrence). This hints that the long-term impact of such strategies may come from the number of events at a location. Therefore, a single foot patrol would arguably not impact offenders' perceptions. Instead, bouts of more sustained presence over longer periods of time would likely be necessary to change long-term perceptions. Indeed, offenders must likely be aware (to some extent) of police activity for it to change their perceptions and associated behaviors.

Given the low counts of proactive police activities in any given block at small temporal scales (e.g., in a day or week), we expect that it may take longer than traditionally studied in order for offenders to accurately classify the *long-term, cumulative* risk of detection and/or apprehension of committing crime in that block. It is possible that short study periods may not allow enough time for the effects of a given intervention to materialize into long-term benefits and/or enough time for potential long-term benefits to even be realized. For example, it is unlikely that offenders would be present in a given block at all times to actually notice the infrequent police activity if a small temporal unit was used. Similarly, and even *if* offenders did observe the infrequent police activity, if there was not enough activity in the block over time, then we would not likely predict it to impact their long-term risk of offending in that block (e.g.,

offenders could simply perceive the infrequent police activity as a ‘one-off’). In order to effectively handle these concerns, we employ a multi-length-lag analytic strategy over a nine-year period to assess the monthly temporal variation in the effects of given predictors on police actions and/or police incidents. We begin by first assessing the effects of predictors in the preceding month on our outcome variables in the current month. If significant, we then sequentially assess the cumulative effect of such predictors in earlier months on our outcome variables in the current month.

Our rationale for this approach is three-fold. First, monthly lags provide sufficient time for offenders to perceive a long-term change in guardianship at a given location, and hence sufficient time to impact their perceived certainty of apprehension for committing crime in that location. This is particularly important given our focus on the more long-term, agglomeration effects of police activity. In contrast to some related research which has examined the *specific* effects of *specific* stops (e.g., Wooditch and Weisburd 2016), we are primarily interested in the *cumulative* effects of these activities over time (e.g., the effects of *repeated* stops and/or foot patrols). Second, and in terms of methodology, monthly lags allow us to identify blocks that have systematically sporadic activity, such as crackdowns, throughout the course of a month. Third, and finally, monthly lags provide sufficient time for police to accurately classify high/low crime blocks, and adapt their policing strategies in hopes of changing offenders’ long-term perceptions of such blocks. By explicitly assessing the appropriate length lag as part of our analyses, we provide precise insight into the spatial and temporal relationships between police actions and police incidents.

DETERMINANTS OF PATROL STRATEGIES?

Although scholars have been primarily interested in examining how patrol strategies can impact crime, a secondary question we explore here is whether environmental features can also impact patrol strategies. For example, given that foot patrol and/or police stops might be able to address social disorder in a location, it is likely that the police will target areas with higher levels of social disorder for these policing strategies. As a consequence, a block that experiences an increase in social disorder, or one that is near locations that experience an increase in disorder, may be targeted for additional foot patrol and/or police stops: potentially in hopes of preventing a spiral of decay, as typically referenced by broken window theorists. Likewise, a sustained spike in certain types of crime in a location may attract specific policing strategies to that location. With that being said, existing research has typically not asked whether patrol strategies are specifically deployed in response to disorder and crime events at precise spatial and temporal scales (although for related discussions on bidirectionality, see e.g. Decker and Kohfeld, 1985; Garrett and Ott 2011; Jacob and Rich 1980; Wu and Lum 2016). Thus, we further unpack this relationship by empirically testing the effects of characteristics of space *on* police practices. Although these particular analyses are largely explorative, understanding whether certain types of incidents impact the police's decision to employ different patrol strategies is critical to understanding the potential long-term, bidirectional relationships between police actions and police incidents.

DATA AND METHODS

SETTING

The present study examines data for Santa Monica, California. Situated on the west coast of Los Angeles County, Santa Monica spans 8.42 square miles, and in 2010, had a full-time resident population of 89,736 (N = 1,467 blocks; U.S. Census Bureau 2015). Of its resident

population, 77.6% self-identify as White and 51.8% self-identify as female (U.S. Census Bureau, 2015). Its median household income in 2009-2013 was $73,649, and its homeownership rate for this same time period was 27.4% (U.S. Census Bureau 2015). We chose Santa Monica to study given that (1) it has a violent and property crime rate very near the average for all cities in the United States in recent years (and therefore is a 'typical' city based on level of crime) and (2) its police department uses a comprehensive classification scheme for their calls for service.

Santa Monica Police Department

The Santa Monica Police Department (SMPD) is composed of approximately 215 sworn officers and 200 civilian support personnel (Santa Monica Police Department 2015). In addition to its patrol section, the SMPD also has a number of smaller, and more specialized, sections including the youth services unit, traffic services unit, and property crime unit.

DATA

The present study utilizes two forms of data: (1) police calls for service and (2) official crime reports.

Police Calls for Service

In order to investigate police response to calls for service, we examined nine years of calls for service data (2006 to 2014[2]) provided by the SMPD (N = 1,001,191). All calls provided by the police department were pre-classified by police officials as belonging to one of 254 different call-types (e.g., "Loitering", "Suspicious Vehicle", etc.). Of the total incidents, 1,832 (i.e., 0.18%) were missing *both* addresses and geographic coordinates, and therefore were excluded from our analyses because their locations could not be identified. Using ArcGIS, the remaining incidents (n = 999,359) were geocoded (with an overall match rate of 99%) and then aggregated to the block-level by month. This resulted in a final sample of 989,615 calls in 1,467 blocks across 108 months

[2] These years of data have been publically released by the SMPD.

(our maximum N is 158,436 block/months: we lose up to twelve months in our models due to our monthly lag strategy). Blocks were chosen as our unit of analysis for theoretical reasons (Hipp 2007). We hypothesized that the relationship between police actions and police incidents would be limited in space, and therefore blocks (rather than larger units, such as block groups or tracts) were believed to provide the best fit to explore this relationship.

Official Crime Reports

In addition to calls for service data, we also examined nine years of official crime data (2006 to 2014) provided by the SMPD (N = 80,729). In particular, we examined the following five different crime types: (1) aggravated assault, (2) burglary, (3) larceny, (4) motor vehicle theft, and (5) robbery. Murder and rape were not examined due to their infrequent nature. All crime incidents with location information (n = 78,704) were geocoded to the block-level using ArcGIS (with an overall match rate of 99%).

VARIABLES

In order to manage the vast number of classifications of calls for service provided by the SMPD, we generated a number of new variables to represent (1) different *types* of police incidents and (2) different *types* of police response. All variables are count variables that represent the *number* of specified events during *each* month in *each* block. To test for possible proximate effects, we constructed spatial buffers of three sizes for each of our variables: 400 feet, 800 feet and ¼ mile.[3] Given that the ¼ mile spatial buffers were found to have the best fit compared to the other distances, we used these buffers. This size buffer also aligned best with the

[3] All spatial buffer computations were performed in Stata. We used the latitude/longitude of the centroid for each block (rather than block polygons), given that their small size relative to the buffer sizes results in a very small proportion that would be bisected by the buffer boundary. Our looping code: 1) takes the latitude/longitude for a block centroid, 2) computes the distance to all other block centroids in the study area, 3) keeps those within the specified distance, 4) computes the average value of the variable of interest for these blocks in the buffer weighted by inverse distance to the focal block. The looping code operates similarly for the remaining blocks in the study area.

theoretical rationale of our study and the types of questions that we wished to answer using these data. For example, we did not have reason to predict that conducting foot patrol in areas more than a ¼ mile from a focal block of interest would have much of an effect on outcome variables in that focal block. In the next section, we outline each of our variables of interest. See Table 1 for the descriptive statistics for all of these variables and Table 1A in Appendix A for the correlations among them.

<<<Table 1 about here>>>

Disorder

First, we generated an index to represent *social* disorder. This is a count variable that encompasses 31 different call-types that relate to intoxication, disturbances, loitering, and suspicious activity. Second, we generated an index to represent *physical* disorder. This is a count variable that encompasses 18 different call-types that relate to parking infractions, mischief, and abandoned property. These call-types are believed to represent the most common, and most visible, forms of disorder (see Appendix B for the full lists of call-types). The creation of these indices was theory-driven, and therefore their composition is largely consistent with much of the past research examining disorder (e.g., Kurtz et al. 1998, Wallace et al. 2012, Boggess and Maskaly 2014).[4] Note that there are 180,387 events coded as social disorder, and 91,031 events coded as physical disorder, across our years of data.

Police Stops

[4] As noted in Appendix B, we distinguish between similar-appearing events, like "Living in a Vehicle" and "Abandoned Vehicle", as part of our disorder coding process because different events imply different types of public concern. For example, an abandoned vehicle in and of itself is asocial: the vehicle may be left in a block for a variety of reasons (e.g., no insurance, mechanical issues, etc.). In this sense, the call regards a concern about the *vehicle*, rather than the person associated with the vehicle, and therefore we code it as physical disorder. In contrast, living in a vehicle implies social consequences: the call regards a concern about the *person* occupying the vehicle, rather than the vehicle's presence in the block itself, and therefore we code it as social disorder.

In order to capture the widest breadth of police stops, we generated a third index to represent public-police contacts that occurred outside of the realm of a specific call for service. This is a count variable that encompasses five different call-types that relate to both person and vehicle stops (see Appendix B for the full list of call-types).[5] There are 225,541 events coded as police stops across our years of data. Approximately 49% of these events are traffic stops.

Foot Patrol

The variable for foot patrol was provided by the SMPD. It is a count variable that represents the number of times police officers conducted a foot patrol in a block in question.[6] There are 6,722 events coded as foot patrols across our years of data.

Crime

In addition to calls for service data, we also examined data for the following five crime types: (1) aggravated assault, (2) burglary, (3) larceny, (4) motor vehicle theft, and (5) robbery (see Appendix C for the full list of events classified as each crime type). Individual count variables were created for each of these different crime types. There are 1,605 aggravated assaults, 3,131 burglaries, 21,041 larcenies, 2,795 motor vehicle thefts, and 1,400 robberies across our years of data. Note that these crime variables were generated from a records management system dataset, which is distinct from the calls for service dataset used to generate the disorder and police action variables.

ANALYTIC STRATEGY

We estimated two sets of longitudinal, block-level models to tease apart the bidirectional relationships between police actions and police incidents: one set of models use patrol strategies

[5] The correlation between the count and duration (i.e., length of stop) variables for police stops was 0.93, suggesting they provide similar information. We therefore use count variables.
[6] The correlation between the count and duration (i.e., length of patrol) variables for foot patrol was 0.87, suggesting they provide similar information. We therefore use count variables.

and calls for service in the preceding month(s) as covariates and levels of crime in the following month as the outcome variables, and the second set of models use calls for service and crime in the preceding month(s) as covariates and patrol strategies in the following month as the outcome variables. In order to identify the appropriate temporal scale of our variables, we estimated our models with sequentially increasing length lags: we continued to add monthly lags as long as they were statistically significant. Given that we are controlling for the level of the outcome variable in the prior month(s), our models are effectively capturing the *change* in the outcome variable over the subsequent month. We included month and year indicator variables to account for potentially unmeasured temporal changes across our months and years of data. We constructed dichotomous variables for all of our outcomes, except larceny and police stops, given that the counts of these events by month rarely exceeded one.

For our first set of models, which predict crime using patrol strategies and calls for service, we used the following model:

$$\hat{}[crimetype]_t = B_0 + B_1\,(lgfootpatrol)_{t-1} + B_2\,(lgwfootpatrol\_25)_{t-1} + B_3\,(lgpdstop)_{t-1} + B_4\,(lgwpdstop\_25)_{t-1} + B_5\,(lgsocdisorder)_{t-1} + B_6\,(lgwsocdisorder\_25)_{t-1} + B_7\,(lgphysdisorder)_{t-1} + B_8\,(lgwphysdisorder\_25)_{t-1} + B_9\,(lg[crimetype])_{t-1} + \Gamma_1 Z + \Gamma_2 M$$

Where $[crimetype]_t$ is crime incidents committed in the block (depending on the model) in the current month, $lgfootpatrol_{t-1}$ and $lgwfootpatrol\_25_{t-1}$ are the number of foot patrols conducted in the block and ¼ mile buffer of the block in the prior month(s), respectively, $lgpdstop_{t-1}$ and $lgwpdstop\_25_{t-1}$ are the number of police stops conducted in the block and ¼ mile buffer of the block in the prior month(s), respectively, $lgsocdisorder_{t-1}$ and $lgwsocdisorder\_25_{t-1}$ are the number of events classified as social disorder in the block and ¼ mile buffer of the block in the prior month(s), respectively, $lgphysdisorder_{t-1}$ and $lgwphysdisorder\_25_{t-1}$ are the number

of events classified as physical disorder in the block and ¼ mile buffer of the block in the prior month(s), respectively, $lg[crimetype]_{t-1}$ is the number of associated crime incidents committed in the block in the prior month(s), Z is a vector of indicator variables for year, and M is a vector of indicator variables for month. We included additional monthly lags when statistically significant. These models were estimated as logistic regression except for where *y* = larceny, which was estimated as ordinary least squares (OLS) regression.

For our second set of models, which predict patrol strategies using calls for service and crime, we estimated the following model:

$$\hat{}[patrolstrategy]_t = B_0 + B_1\,(lg[patrolstrategy])_{t-1} + B_2\,(lgw[patrolstrategy]\_25)_{t-1} + B_3\,(lgsocdisorder)_{t-1} + B_4\,(lgwsocdisorder\_25)_{t-1} + B_5\,(lgphysdisorder)_{t-1} + B_6\,(lgwphysdisorder\_25)_{t-1} + B_7\,(lgassaul)_{t-1} + B_8\,(lgburglr)_{t-1} + B_9\,(lglarcen)_{t-1} + B_{10}\,(lgmotveh)_{t-1} + B_{11}\,(lgrobber)_{t-1} + \Gamma_1 Z + \Gamma_2 M$$

Where $[patrolstrategy]_t$ is foot patrols *or* police stops conducted in the block (depending on the model) in the current month, $lg[patrolstrategy]_{t-1}$ *and* $lgw[patrolstrategy]\_25_{t-1}$ are the number of foot patrols *or* police stops conducted in the block and ¼ mile buffer of the block in the prior month(s), respectively, and $lgassaul_{t-1}$, $lgburglr_{t-1}$, $lglarcen_{t-1}$, $lgmotveh_{t-1}$, and $lgrobber_{t-1}$ are the number of aggravated assaults, burglaries, larcenies, motor vehicle thefts, and robberies in the block in the prior month(s). All other variables represent the same predictors as described in our first model. We again included additional monthly lags when statistically significant. The model where *y* = foot patrol was estimated as logistic regression whereas the model where *y* = logged police stops was estimated as OLS.[7]

[7] Although we would have preferred to estimate the models with larceny and police stops as negative binomial regression models, or zero-inflated negative binomial models, these models encountered estimation difficulties. We therefore estimated OLS models and log transformed our outcome for the police stops model. Note that as the mean of a count gets large enough the distribution will become normal.

Note that we do not include control variables of various neighborhood sociodemographic characteristics in these models. This is because (1) we are interested in *change* across months, (2) we do not have monthly or annual measures of these sociodemographic characteristics, and (3) given that the sociodemographic characteristics arguably change very slowly from month to month (and year to year), these models capturing change in the outcome variable given the level of our key variables of interest would not be impacted by such slow changing variables. Indeed, we tested time-invariant Census measures in some ancillary models, and they showed little significance.

RESULTS

PREDICTING CRIME FROM PATROL STRATEGIES AND CALLS FOR SERVICE

In our first set of models, we assess the relationship between patrol strategies and calls for service in the prior month(s) and levels of crime in the subsequent month. The results (displayed in Table 2) reveal a number of significant findings. First, we see a strong stasis effect for all three property crimes—burglaries, larcenies, and motor vehicle thefts—as the number of crime events of the same type in prior months is positively associated with the odds ratios (burglary and motor vehicle theft) and number (larceny) of crime events in the current month. The length of the effect for preceding crime, however, varies as a function of crime type: the effect holds twelve months for motor vehicle theft, ten months for burglary, and six months for larceny. This implies that the temporal scale remains important for our analyses and the effects that we detect for patrol strategies are independent of the effects of the number of associated crime incidents in the block in the prior month(s) (and thus we are capturing *change* in our outcome variable).

<<<Table 2 about here>>>

We see that the number of police stops in a block in the prior month is related to the odds of crime events in the same block in the current month. On the one hand, we find a negative relationship between the number of police stops in a block in the prior month and the odds of burglary in the block in the current month, suggesting that police stops within the block exhibit deterrent effects on this type of crime. For example, 4 additional police stops in a block in the prior month is expected to decrease the odds of a burglary in the block in the current month by 8% (exp(-0.02*4 = 0.923). On the other hand, we find a positive relationship between police stops and the odds of robbery, suggesting that police stops within the block do not exhibit deterrent effects on this type of crime. Larceny exhibits an unusual pattern, in which the existence of more police stops in one month has a positive relationship with the number of larcenies in the following month, but it reverses to a negative relationship the subsequent month.

There is an additional impact on the change in crime in the focal block in the current month from the number of police stops conducted in the ¼ mile buffer surrounding a block in the prior month. The direction of this effect varies again by crime type. For example, as the number of police stops in the surrounding area of a block increase, property crime in the focal block—burglary, larceny, and motor vehicle theft—decreases: providing more evidence to suggest that police stops are particularly receptive to burglary (given the preceding within-block negative relationship between burglary and police stops). In contrast, as the number of police stops in the surrounding area of a block increase, the odds of violent crime in the focal block—aggravated assault and robbery—increases. In this respect, our findings provide no evidence to suggest that more police stops in the surrounding area of a block translate into reduced odds of aggravated assault or robbery in the block; in fact, it appears that higher numbers of nearby police stops in one month are associated with greater odds of these types of crime in the following month.

The relationship between foot patrol and crime is weaker than the relationship between police stops and crime. Indeed, we find only three statistically significant relationships for within-block effects, and all suggest no deterrence: more foot patrol in a block increases the odds of aggravated assault and robbery as well as the number of larcenies (the larceny pattern takes two months to take effect). Moreover, we only find two significant relationships for nearby-block effects, although both of these effects suggest deterrence: blocks with more foot patrol in their surrounding area have reduced odds of aggravated assault and fewer numbers of larcenies. Foot patrols nearby a block thus appear to be more effective for crime reduction than foot patrols within a block: for example, 5 additional foot patrols nearby a block in the prior month is expected to decrease the odds of an aggravated assault in the block in the current month by 7% (exp(-0.014*5)=0.932).

Transitioning to disorder, we find positive relationships between social disorder and all five crime types within the block. This is a robust temporal effect, as higher levels of social disorder have a positive relationship with crime events two and three months into the future. We also find additional effects for social disorder surrounding blocks in the prior month and crime within blocks in the current month: positive relationships exist for all crime types except larceny, which exhibits a negative relationship. For example, 10 additional social disorder events nearby a block in the prior month is expected to increase the odds of a robbery in the block in the current month by 6% (exp(0.006*10)=1.062). More social disorder within and surrounding a block therefore appears to translate into more crime in that block in subsequent months, with the exception of larceny.

In terms of physical disorder, we find positive, within-block relationships for all five crime types. The temporal scale, however, remains important, given that this positive effect

spans longest for burglary (three months) and shortest for aggravated assault (one month). In terms of nearby physical disorder, positive relationships exist for the property crimes of motor vehicle theft and larceny (the effect for larceny spans two months), and negative relationships exist for the violent crimes of aggravated assault and robbery. Thus, similar to social disorder, we find that more physical disorder within a block generally translates into more crime in the block; however, unlike social disorder, we find that more nearby physical disorder translates into less violent crime in the block.

PREDICTING PATROL STRATEGIES FROM CRIME AND CALLS FOR SERVICE

We now turn to our final set of models, whereby we identify factors that help to explain the spatial and temporal distribution of foot patrol and police stops. All results are displayed in Table 3.

<<<Table 3 about here>>>

Foot Patrol

First, we see the expected result that blocks with more foot patrol in the prior three months are more likely to experience foot patrol in the current month. Moreover, we find that blocks with more foot patrol in their surrounding area in the prior month are more likely to experience foot patrol in the current month as well. Our results are thus capturing the *change* in foot patrol across months: with each additional foot patrol in the block in the prior month increasing the odds that the block will experience foot patrol in the current month by 260% (exp(1.293) = 3.643) and each additional foot patrol in the nearby area increasing such odds by 1.5% (exp(0.015)=1.015).

Turning to the effects of disorder, we find that blocks with more social disorder in the prior three months are more likely to experience foot patrol in the current month. In contrast,

blocks with more social disorder in their surrounding area in the prior month are less likely to experience foot patrol in the current month. For example, 10 additional social disorder events in the surrounding area of a block in the prior month decrease the odds of foot patrol in the block in the current month by 2% (exp(-0.002*10)=0.98). Interpreting these within- and nearby-block effects, together, suggest that police may be accurately deploying their foot patrol resources to areas where their benefits may arguably be most realized.

Physical disorder within and nearby blocks exhibits unilaterally positive relationships with foot patrol. One additional physical disorder event in a block in the prior month increases the odds that the block will experience foot patrol in the current month by 4.6% (exp(0.045) = 1.046). Moreover, 10 additional physical disorder events surrounding a block in the prior month increase the odds that the block will experience foot patrol in the current month by 5% (exp(0.005*10)=1.051).

Lastly, we find that the number of crimes in a block in prior months also has some impact on the likelihood of foot patrol in the block in the current month. For example, a larger number of aggravated assaults in a block in the prior month increases the odds of foot patrol in the block in the current month: each additional assault increases the odds that the block will experience foot patrol by 53% (exp(0.427) = 1.533). A larger number of burglaries in the prior three months also increase the odds that the block will experience foot patrol in the current month and into the future for the subsequent two months.

Police Stops

Similar to foot patrol, we see the expected effect that blocks with more police stops in the prior month are likely to experience more police stops in the current month. Unlike foot patrol, however, the temporal effect of stops in prior months spans upwards of twelve months. For

example, each additional police stop in the block in the prior month increases the number of police stops in the block in the current month by 2% (exp(0.022)=1.022), and there are smaller increases in subsequent months as well. There is an additional positive relationship between police stops in the surrounding area of a block in the prior month and police stops in the block in the current month.

In terms of disorder, we find positive relationships between social disorder in a block and its surrounding area in prior months and police stops in the block in the current month. The temporal effects for both geographic scales of social disorder are robust: an additional social disorder event is associated with an increased number of police stops in the block for the subsequent four months. Physical disorder in a block and its surrounding area also impact the number of police stops in a block. Specifically, more physical disorder in the block in each of the prior four months predicts more police stops in the block in the current month; and more nearby physical disorder in the preceding two months predicts fewer police stops in the block in the current month. Similar to foot patrol, there appears to be a strong relationship between disorder in prior months and where police conduct stops in the current month.

Transitioning to crime, we find that the numbers of aggravated assaults, burglaries, and motor vehicle thefts in a block in prior months are positively associated with the number of police stops in the block in the current month. Whereas the effect for assault spans only two months, the effects for burglary and motor vehicle theft span twelve months. Finally, we find that the number of larcenies in a block in the prior twelve months, controlling for the other crime types as well as disorder, is negatively associated with the number of police stops in the block in the current month. Crime events, therefore, have particularly strong predictive effects for police

actions, although the direction of their effects varies by crime type. Indeed, police may be targeting changes in different types of crime with different types of responses.

DISCUSSION

The present research explores the long-term, bidirectional relationships between calls for service, crime, and police patrol strategies in Santa Monica, California. By analyzing block-level, monthly data over a nine-year period, we examine the longitudinal relationships between these events at fine-grained spatial and temporal scales over an extended period of time. In doing so, we supplement previous research which has primarily used experimental, quasi-experimental, and/or cross-sectional designs to test the effectiveness of patrol strategies over shorter periods of time (and sometimes at larger units of analysis). Indeed, our results reveal a number of significant findings.

We find that patrol strategies not only impact future crime, but also vary as a function of space: police respond to higher levels of certain types of crime by increasing the frequency of certain patrol strategies, and certain patrol strategies themselves are associated with lower levels of certain types of crime. For example, burglary seems particularly responsive to (and important for) police stops: blocks with more burglaries receive greater numbers of police stops and blocks with more police stops have reduced odds of experiencing burglary. Blocks with more motor vehicle thefts also receive greater numbers of police stops and blocks with more police stops in their surrounding area have reduced odds of experiencing motor vehicle theft. In these cases, our findings provide evidence to suggest that police use incident information to guide their patrol practices, and that these practices can exhibit some deterrent effect on crime over the long-term.

Parsimonious relationships, however, do not exist for all patrol strategies and all crime types. For example, although burglary is receptive to police stops, it does not appear to be

receptive to foot patrol: blocks with more burglaries are more likely to receive foot patrol, but blocks with more foot patrol do not have reduced odds of burglary. This particular set of findings suggests a potential mismatch between event type and police response: officers may be responding to increases in burglary with a non-effective strategy. Indeed, much theory would suggest that foot patrol, for example, might not be the most effective means to reduce burglary, given the types of locations and environments in which burglaries often occur.

These more complex findings are not limited to burglary. We also observe somewhat peculiar effects for aggravated assault: blocks with more assault are more likely to receive foot patrol, but more foot patrol within-blocks predicts more assault, and more foot patrol nearby blocks predicts fewer assaults. Although these particular findings may superficially suggest that police stops exert little deterrent effect on aggravated assault, it is important to consider two potential alternative explanations: (1) police may simply be responding to increasing levels of crime in these locations by increasing their patrol activity (although we used monthly lags to minimize this possibility) and (2) increases in police activity may translate into increases in reporting and/or documenting of crime in these areas. If these alternatives are true, then the directions of these relationships must be interpreted with some caution. Future research should attempt to dissect these relationships in the context of onview versus citizen-reported calls for service.

Finally, we observe a third set of findings whereby changes in police incidents appear to follow changes in police actions but not vice-versa. For example, we find that more foot patrol in the surrounding area of a block exhibits a negative effect on larceny in the focal block, but we do not find that more larceny in a block systematically predicts greater foot patrol in the block. In

these particular instances, police activity targeted at one particular issue at one location may inadvertently impact other types of incidents in that same location.

Together, these findings suggest a number of important implications. First, the long-term effects of patrol strategies must be evaluated within the context of the place where they are being employed: levels and types of crime and disorder should be considered when examining the police-crime nexus. Second, temporal scales must be explicitly evaluated as part of these analyses: predictors exhibit immense variation in their cumulative effects on police actions and police incidents. For example, burglary exhibits longer-lasting effects on police actions than other crime types; however, burglary itself exhibits lengthier effects on police stops than foot patrol. In this respect, tailoring temporal scales to predictor variables reduces the risk of obscuring the effects of such variables on outcomes of interest. Third, longitudinal analyses can be used to derive insight into the bidirectional relationships between these ongoing, interrelated processes.

In sum, our findings provide evidence to suggest that foot patrol and police stops are not conducted equally across space, but rather appear to be systemically deployed across the city landscape. Levels of crime and disorder impact foot patrol and police stops, and levels of foot patrol and police stops impact certain types of crime. The nature of these relationships, however, is complex and contingent on an array of place-based factors. The role of the police as capable guardians should continue to be negotiated within a place-based framework. Although practitioners' attempts to propel proactivity may be grounded in optimistic assumptions (e.g., preventing a spiral of disorder and decay), their reality may be clouded by greater uncertainty. Applying a capable guardianship framework absent consideration of place dampens the potential utility of this theory in the context of crime prevention.

LIMITATIONS

We note some limitations of our study. First, and foremost, we did not analyze the dispositions of police actions.[8] Instead, we assumed that uniform effects exist for all foot patrols and police stops. Second, we could not control for unobserved departmental changes that could have impacted police actions during our study period (e.g., the formation of specific foot patrol teams). Although there may have been various directives over this period, it is notable that we detected remarkably similar numbers of foot patrols and police stops across our years of data. Third, although pseudo r-square values are a rough approximation of variance explained in linear models and therefore should be treated with caution, we nonetheless note that our models were only able to explain a small amount of the variance explained based on this measure. As a consequence, future research will wish to assess whether variables we could not measure may improve the models. Fourth, we only analyzed data from one city: Santa Monica, California. It is possible that different effects may have been observed had data from a different city been used for our analyses. Indeed, denser and/or higher crime urban cities with greater police activity may allow for testing of these bidirectional relationships at smaller temporal scales, given that small spatial units in these types of cities would likely have larger numbers of events at smaller temporal units than observed in Santa Monica. Fifth, and finally, our definitions of disorder were strictly theoretical: we did not employ factor analysis and/or any other statistical techniques to derive our measures. Although this decision may have altered the clustering of calls for service included in our aggregations, we believe that our approach was best suited for our analyses because we were primarily interested in the *theoretical* links between different *types* of police action and different *types* of police incidents.

[8] We did not include disposition data in our analyses given that (1) approximately half of these data were missing for foot patrol (and approximately 83% of events *with* data were coded as "Checks Okay") and (2) there was little variance in the disposition data for police stops (approximately 74% of events resulted in an "Advisal" or "Citation/Other Enforcement").

CONCLUSION

Our study finds evidence to suggest that foot patrol and police stops are in fact related to calls for service and crime over the long-term. Although our results present a more complex relationship than typically argued by many proponents of these strategies, they nonetheless provide valuable insight into the reciprocal nature of these events. While changes in calls for service and crime often precede changes in police action, changes in crime also tend to follow them. Police actions must be neatly tailored to police incidents at micro-spatial levels if long-term deterrent effects at these levels are to be achieved. Future research should continue to use longitudinal data at precise spatial and temporal scales to further unravel the relationship between police actions and police incidents.

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Table 1. Descriptive statistics for key variables of interest.

Variable	Mean	Std. Dev.	Minimum	Maximum
Block Social Disorder	1.1	2.4	0	82
Social Disorder ¼ Mile Buffer	39.5	36	0	345
Block Physical Disorder	0.6	1.3	0	33
Physical Disorder ¼ Mile Buffer	19.5	15.6	0	184
Block Foot Patrol	0.04	0.7	0	49
Foot Patrol ¼ Mile Buffer	1.4	5.5	0	108
Block Police Stops	1.4	3.9	0	256
Police Stops ¼ Mile Buffer	47.8	56.3	0	660
Block Aggravated Assault	0.01	0.1	0	3
Block Burglary	0.02	0.1	0	5
Block Larceny	0.1	0.5	0	22
Block Motor Vehicle Theft	0.02	0.1	0	4
Block Robbery	0.01	0.1	0	3

Table 2. Regression models where *y* = crime type; month and year indicator variables not presented.

	Dependent Variable (In Current Month)				
Independent Variable (In Prior Month[s])	Aggravated Assault (S.E.)	Burglary (S.E.)	Larceny (S.E.)	Motor Vehicle Theft (S.E.)	Robbery (S.E.)
Block Foot Patrol					
T-1	0.041*	-0.01	0.001	0.003	0.052**
	(0.018)	(0.022)	(0.003)	(0.022)	(0.017)
T-2	--	--	0.016***	--	--
			(0.003)		
Foot Patrol ¼ Mile Buffer					
T-1	-0.014*	-0.003	-0.001***	-0.009	-0.002
	(0.006)	(0.004)	(0.0002)	(0.005)	(0.005)
Block Police Stops					
T-1	0.009	-0.02***	0.008***	-0.008	0.023***
	(0.005)	(0.005)	(0.001)	(0.005)	(0.005)
T-2	--	--	-0.002**	--	--
			(0.001)		
Police Stops ¼ Mile Buffer					
T-1	0.003***	-0.003***	-0.0001**	-0.002**	0.003***
	(0.001)	(0.001)	(0.00004)	(0.001)	(0.001)
Block Social Disorder					
T-1	0.067***	0.035***	0.018***	0.023*	0.048***
	(0.01)	(0.01)	(0.001)	(0.01)	(0.01)
T-2	0.038***	0.035**	0.007***	0.045***	0.03**
	(0.01)	(0.011)	(0.001)	(0.009)	(0.01)
T-3	--	0.028**	0.002*	--	--
		(0.01)	(0.001)		
Social Disorder ¼ Mile Buffer					
T-1	0.005***	0.006***	-0.0002**	0.006***	0.006***
	(0.001)	(0.001)	(0.0001)	(0.001)	(0.001)
Block Physical Disorder					
T-1	0.072***	0.03*	0.01***	0.062***	0.039*
	(0.011)	(0.015)	(0.001)	(0.014)	(0.016)
T-2	--	0.034*	0.004***	0.03*	0.036*
		(0.016)	(0.001)	(0.014)	(0.016)
T-3	--	0.03*	--	--	--
		(0.015)			
Physical Disorder ¼ Mile Buffer					
T-1	-0.008***	-0.002	0.001***	0.004*	-0.007**

	(0.002)	(0.002)	(0.0002)	(0.002)	(0.002)
T-2	--	--	0.001**	--	--
			(0.0002)		
Crime					
T-1	0.241	0.492***	0.173***	0.634***	0.175
	(0.137)	(0.089)	(0.003)	(0.093)	(0.146)
T-Longest	--	0.411***	0.086***	0.278**	--
		(0.092) [1]	(0.003) [2]	(0.1) [3]	
Constant	-4.768***	-4.151***	-0.023***	-4.821***	-4.787***
	(0.13)	(0.154)	(0.006)	(0.102)	(0.135)
# Observations	155502	143766	149634	140832	155502
Pseudo R2	0.083	0.031	--	0.06	0.102
R-Squared	--	--	0.35	--	--

*$p < 0.05$ **$p < 0.01$ ***$p < 0.001$

[1] T-Longest =10 months
[2] T-Longest = 6 months
[3] T-Longest = 12 months

Table 3. Regression models where *y* = patrol strategy; month and year indicator variables not presented.

	Dependent Variable (In Current Month)	
Independent Variable (In Prior Month[s])	Foot Patrol (S.E.)	Police Stops (S.E.)
Block Patrol Strategy		
T-1	1.293***	0.022***
	(0.053)	(0.001)
T-2	0.401***	0.01***
	(0.051)	(0.001)
T-3	0.583***	0.007***
	(0.046)	(0.001)
…	--	…
T-12	--	0.013***
		(0.001)
Patrol Strategy ¼ Mile Buffer		
T-1	0.015***	0.001***
	(0.003)	(0.0001)
Block Social Disorder		
T-1	0.075***	0.009***
	(0.011)	(0.001)
T-2	0.056***	0.008***
	(0.011)	(0.001)
T-3	0.038***	0.004***
	(0.011)	(0.001)
T-4	--	0.003***
		(0.001)
Social Disorder ¼ Mile Buffer		
T-1	-0.002*	0.001***
	(0.001)	(0.0001)
T-2	--	0.001***
		(0.0001)
T-3	--	0.0004**
		(0.0001)
T-4	--	0.0004**
		(0.0001)
Block Physical Disorder		
T-1	0.045***	0.007***
	(0.011)	(0.001)
T-2	--	0.006***
		(0.001)
T-3	--	0.003*
		(0.001)
T-4	--	0.003*

			(0.001)	
Physical Disorder ¼ Mile Buffer				
T-1	0.005*		-0.001***	
	(0.002)		(0.0002)	
T-2	--		-0.001***	
			(0.0002)	
Aggravated Assault				
T-1	0.427**		0.029*	
	(0.134)		(0.013)	
T-Longest			0.032*	T-2
			(0.013)	
Burglary				
T-1	0.281*		0.05***	
	(0.124)		(0.009)	
T-Longest	0.385**	T-3	0.036***	T-12
	(0.119)		(0.009)	
Larceny				
T-1	0.039		-0.012***	
	(0.029)		(0.003)	
T-Longest			-0.013***	T-12
			(0.003)	
Motor Vehicle Theft				
T-1	0.212		0.046***	
	(0.131)		(0.01)	
T-Longest			0.042***	T-12
			(0.009)	
Robbery				
T-1	-0.013		0.025	
	(0.164)		(0.014)	
Constant	-5.258***		0.125***	
	(0.14)		(0.006)	
# Observations	154035		140832	
Pseudo R2	0.339		--	
R-Squared	--		0.565	

*$p < 0.05$ **$p < 0.01$ ***$p < 0.001$

Appendix A

Table 1A. Correlation table for key variables of interest.

Variable	Social Disorder	Physical Disorder	Police Stops	Foot Patrol	Aggr. Assault[1]	Burglary	Larceny	MVT[2]	Robbery
Social Disorder	1								
Physical Disorder	0.401	1							
Police Stops	0.667	0.392	1						
Foot Patrol	0.213	0.09	0.216	1					
Aggr. Assault[1]	0.163	0.08	0.148	0.048	1				
Burglary	0.073	0.056	0.058	0.021	0.02	1			
Larceny	0.439	0.284	0.41	0.138	0.102	0.059	1		
MVT[2]	0.095	0.101	0.094	0.023	0.022	0.016	0.072	1	
Robbery	0.157	0.089	0.158	0.054	0.058	0.026	0.134	0.034	1

[1] Aggr. Assault = Aggravated Assault
[2] MVT = Motor Vehicle Theft

Appendix B

Social Disorder:

The full-list of call-types includes: (1) “Alcohol & Beverage Code Violation”, (2) “Disturbance at a Business”, (3) “Disturbance of the Peace”, (4) “Disturbance of the Peace Report”, (5) “Drinking in Public”, (6) “Family Disturbance”, (7) “Fight”, (8) “Illegal Weapon”, (9) “Indecent Exposure Just Occurred”, (10) “Indecent Exposure Now”, (11) “Indecent Exposure Report”, (12) “Juvenile Annoying Investigation”, (13) “Lewd Activity”, (14) “Living in a Vehicle”, (15) “Loitering”, (16) “Loud Music”, (17) “Overdose”, (18) “Panhandling”, (19) “Party Complaint”, (20) “Person with a Gun”*, (21) “Prostitution”, (22) “Public Intoxication”, (23) “Report of Shots Fired”, (24) “Smoking Violation”, (25) “Suspicious Activity”, (26) “Suspicious Circumstances”, (27) “Suspicious Person”, (28) “Suspicious Vehicle”, (29) “Trespassing”, (30) “Truant Juvenile”, and (31) “Urinating/Defecating in Public”.

* Note that social disorder includes “Person with a Gun” because the mere possession of a firearm is not necessarily considered a crime (unless specific criteria are met), and therefore including it fits with our theoretical definition of social disorder.

Physical Disorder:

The full list of call-types includes: (1) “Abandoned Vehicle”, (2) “Failure to Pay Parking Fee”, (3) “General Parking Problem”, (4) “Handicap Zone Violation”, (5) “Malicious Mischief Just Occurred”, (6) “Malicious Mischief Now”, (7) “Malicious Mischief Report”, (8) “Mark & Tag Abandoned Vehicle”, (9) “Oversize Vehicle Violation”, (10) “Red Zone Violation”, (11) “Trash Dumping”, (12) “Valet Zone Violation”, (13) “Vehicle Blocking Driveway”, (14)

“Vehicle Out of Space”, (15) “Vehicle Parked in Alley”, (16) “Vehicle Parked on Sidewalk”, (17) “Violation of Posted Sign”, and (18) “Violation of Preferential Parking Zone”.

Police Stops:

The full list of call-types includes: (1) “Citizen Flag”, (2) “Exhibition of Speed”, (3) “Expired Registration”, (4) “Pedestrian Stop”, and (5) “Traffic/Vehicle Stop”.

Appendix C

Aggravated Assault:

The full list of event-types includes: (1) “Aggravated Assault – Firearm”, (2) Aggravated Assault – General”, (3) “Aggravated Assault – Hands”, (4) “Aggravated Assault – Knife”, and (5) “Aggravated Assault – Other Weapon”.

Burglary:

The full list of event-types includes: (1) “Burglary – General”, (2) “Burglary Attempt – Non-Residential”, (3) “Burglary Attempt – Residential”, (4) “Burglary – Force Non-Residential”, (5) “Burglary – Force Residential”, and (6) “Possess Burglary Tool”.

Larceny:

The full list of event-types includes: (1) “Larceny – Bicycle”, (2) “Larceny – From Building”, (3) “Larceny – From Coin Machine”, (4) “Larceny – From Vehicle”, (5) “Larceny – General”, (6) “Larceny – Other”, (7) “Larceny – Pickpocket”, (8) “Larceny – Purse-snatch”, (9) “Larceny – Shoplift”, and (10) “Larceny – Vehicle Parts/Accessories”.

Motor Vehicle Theft:

The full list of event-types includes: (1) “GTA – Commercial Vehicle”, (2) “GTA – Other Vehicle”, (3) “GTA – Passenger Car”, and (4) “GTA – Recovery”.

Robbery:

The full-list of event-types includes: (1) “Robbery – General”, (2) “Robbery – Strongarm – Bank”, (3) “Robbery – Strongarm – Commercial”, (4) “Robbery – Strongarm – Gas Station”, (5) “Robbery – Strongarm – Other Location”, (6) “Robbery – Strongarm – Residential”, (7) “Robbery – Strongarm – Store”, (8) “Robbery – Strongarm – Street/Hwy”, (9) “Robbery – Firearm – Bank”, (10) “Robbery – Firearm – Commercial”, (11) “Robbery – Firearm – Gas Station”, (12) “Robbery – Firearm – Other Location”, (13) “Robbery – Firearm – Residential”, (14) “Robbery – Firearm – Store”, (15) “Robbery – Firearm – Street/Hwy”, (16) “Robbery – Knife – Commercial”, (17) “Robbery – Knife – Other Location”, (18) “Robbery – Knife – Residential”, (19) “Robbery – Knife – Store”, (20) “Robbery – Knife – Street/Hwy”, (21) “Robbery – Other Weapon – Bank”, (22) “Robbery – Other Weapon – Commercial”, (23) “Robbery – Other Weapon – Gas Station”, (24) “Robbery – Other Weapon – Other Location”, (25) “Robbery – Other Weapon – Residential”, (26) “Robbery – Other Weapon – Store”, and (27) “Robbery – Other Weapon – Street/Hwy”.