Police Presence, Rapid Response Rates, and Crime Prevention[1]

Sarit Weisburd
Tel Aviv University

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Abstract

This paper estimates the impact of police presence on crime using a unique database that tracks the exact location of Dallas Police Department patrol cars throughout 2009. To address the concern that officer location is often driven by crime, my instrument exploits police responses to calls outside of their allocated coverage beat. This variable provides a plausible shift in police presence within the abandoned beat that is driven by the police goal of minimizing response times. I find that a 10 percent decrease in police presence at that location results in a 3.5 percent increase in crime. This result sheds light on the black box of policing and crime and suggests that routine changes in police patrol can significantly impact criminal behavior. *JEL* Codes: D29, K42.

1 Introduction

Does police presence deter crime? While it was once generally accepted that the role of police officers was apprehending criminals after they committed a crime, today there is a growing body of research that shows that increased investment in policing results in lower crime rates.[1] Specifically, previous papers have found that larger police forces and high doses of police presence in small areas result in lower crime rates (see Levitt (1997), Evans and Owens (2007), Di Tella and Schargrodsky (2004), and Draca et al. (2011)). However, the literature has largely ignored the fact that the rapid response philosophy where police officers are spread thinly throughout the city and much of an officer's time is dedicated to responding to emergency calls remains the dominant patrol strategy applied by police departments in the US and worldwide.[2] This paper examines the impact of this rapid response strategy on deterrence. More specifically, will adding additional officers to the current patrol system have any impact on crime?

Since the 1930s, police patrol in US cities has been dominated by the rapid response system. Simply stated police agencies have patrol cars drive around in police beats ready to respond rapidly to an emergency call. When they are not responding to such calls they spend their time in what has been termed random preventative patrol, showing their presence in the beats to deter offending (see Kelling & Moore, 1988). The random preventative patrol philosophy came under significant criticism after an experiment conducted over 4 decades ago, the Kansas City Policing Experiment, failed to find any impact of increased preventative patrol on crime.[3] While some argue that this

[1] See surveys of the literature conducted by Cameron (1988) , Marvell and Moody (1996), Eck and Maguire (2000), and Chalfin & McCrary (2017) and micro geographic interventions by Sherman & Weisburd (1995), Braga et al. (1999), Di Tella and Schargrodsky (2004), Gould and Stecklov (2009), Nagin (2013), Weisburd et al. (2015), and MacDonald et al. (2016).

[2] The different implications of thinly spreading police officers throughout a city versus focusing on specific locations is discussed theoretically in Galiani et al. (2016). They find that while focused policing in small areas is more effective for crime reduction, it results in segregation of "good" and "bad" areas throughout the city.

[3] This experiment took place between October 1972 and September 1973 in the South District of

could be a result of implementation as there is no evidence regarding the actual dosage of police presence received by treatment and control areas, there is no denying that this study left its mark on the literature.[4]

Today, innovative crime prevention programs tend to focus on high dosages of deterrence in small areas or over short time periods (e.g. hot spot policing, pulling-levers policing, police crackdowns), as well as community interventions via neighborhood policing or broken-windows policing.[5] These crime prevention techniques are often difficult to practice alongside a rapid response philosophy. Rapid response dictates a low dosages of police officers across the city, which makes officers unavailable for more concentrated crime prevention programs. My analysis, which uses a precise measure of the dosage of police presence throughout Dallas, Texas, suggests that we may have been too quick to embrace the conclusion that general shifts in patrol across a large city cannot significantly impact crime. Indeed, my analysis shows that preventative patrol in the context of a rapid response philosophy can provide significant deterrence of crime.

Analyzing the immediate impact of police presence on crime requires access to information on the location of police officers and crime over time. Such information has begun to be available because of the use of management information systems in policing that detail the exact locations (x y coordinates) of crime events, as well as Automobile Locator Systems (AVL) that track where police vehicles are when they patrol the city.

Kansas, Missouri. The experiment divided the 15 beats of this district into three areas: "reactive" where police only entered the area to respond to calls, "proactive" where police visibility was increased to 2 to 3 times its baseline level of patrol, and "control" areas where the baseline level of patrol from before the experiment was maintained.

[4] See Larson (1975) for a review of concerns regarding the implementation of the Kansas City Experiment.

[5] See Braga (2012) and Telep & Weisburd (2012) for a review of current deterrence strategies. Pulling-levers policing targets a small number of chronic offenders, while hot-spots policing focuses on a small number of chronically crime ridden geographic locations. Police crackdowns take place by shifting large groups of police to focused areas. Broken windows policing aims to reduce public disorders before actual crime occurs. Neighborhood policing is a strategy where specific officers conduct activities in designated neighborhoods in order to create a consistent relationship between these officers and residents of that area.

While most police agencies now analyze data on crime events, the use of AVL systems to analyze where police patrol is rare and seldom integrated with crime data. In Dallas, Texas, over the course of 12 months (throughout 2009), AVL systems were active in all 873 police patrol vehicles and data on their location was saved and stored.[6] I focus on the beat (a geographic patrol area averaging 1.7 square miles in size) each car was allocated to patrol as well as where these officers were actually present throughout the day. Information on incidents of crime was acquired from a separate database that tracks calls for service (911 calls) placed by local citizens to the police department.[7] Thus, the current project is not motivated by a specific policing experiment, or large change in routine police activity, but rather, takes advantage of a large amount of data (roughly 100 million pings of information) to provide an estimate of the social returns of an additional hour of police patrol in the current policing system.

A deterrence mechanism that is based on police interactions would imply that areas or times of day with higher levels of police presence will report less crime. However, this ignores the allocation of officers to riskier locations during riskier periods. An additional concern is simultaneity bias, as the occurrence of a crime is likely to increase police presence as officers are called to respond to the incident. These factors are illustrated in Figure (1), where areas and times with higher levels of allocated patrol tend to have higher levels of both police presence and crime.[8] Thus, while this dataset provides a unique picture of police presence across a city, the location of officers may be determined

[6]The AVL data does not include the location of officers on motorcycle and horseback (mounted division). The motorcycle patrol unit consists of 42 officers and the mounted division consists of 17 police officers.

[7]I separate calls that relate to crime into the following categories: violent crimes, burglaries, thefts, and public disturbances. I focus on 911 calls as they are less likely to suffer from reporting bias than reported crimes and are more likely to provide the exact time at which the incident occurred.

[8]While there are 873 Dallas patrol vehicles tracked in this study, on average there are 132 cars on active patrol per hour. These cars are allocated among 232 beats at the beginning of their shift. Thus, the most common allocation points are either 0 or 1 car allocated per hour. The reason that police presence (defined by the location of police vehicle throughout the shift) does not have a 1-1 relationship with police allocation is that officers often spend time outside of their allocated coverage beat.

by factors unobserved by the econometrician and correlated with crime.

My identification strategy stems from the two distinct responsibilities facing police patrol cars: proactive and reactive policing. While police may be allocated to a certain area (beat) in order to create a deterrence effect and lower the expected benefit of committing a crime, they are also responsible for answering emergency calls within their larger division quickly - generally, in under 8 minutes.[9] This introduces some degree of randomness into exact police presence at a given location and time. Specifically, the occurrence of an incident outside of a patrol officers assigned area can shift his location and provide an opportunity to identify a causal effect of police presence on crime. I therefore define an *Unrelated Outside Calls* instrument which is equal to a weighted sum of calls, unrelated to crimes, occurring within the division outside of the beat being currently patrolled. While the allocated level of presence can be determined by the perceived crime risk in that area, I argue that actual presence is impacted by exogenous factors.

The validity of this instrument requires that the incident that occurred at an outside beat is not correlated with crime at the given beat. I therefore focus on outside 911 calls reporting incidents of fire, mental health, child abandonment, animal attacks, dead people, suicides, and drug houses. My results are robust to controlling for beat, month, day of week, and weekend$\times$hour of day fixed effects. My results remain statistically significant, but are smaller, when defining a *Car Accident Outside Calls* instrument which is equal to the number of calls reporting car accidents occurring within the division outside of the beat being currently patrolled.

My results suggest that the number of officers patrolling a beat has a significant impact on the probability of crime. I first demonstrate that as reported in previous studies, there is a positive correlation in the data between police presence and crime.

[9] A complete summary of the Dallas Police Department goals as well as performance can be found in the "Dallas Police Department Management and Efficiency Study" conducted by Berkshire Advisors (2004).

This positive correlation remains significant even when controlling for beat and time fixed effects. This suggests that police departments may be able to quickly adjust police presence to changing crime risks within locations over time. It is only when instrumenting for actual police presence with out of beat calls that I can identify a deterrence effect. Using the *Unrelated Outside Calls* instrument, I estimate that a 10 percent decrease in police presence results in a 3.5 percent increase in crime. I provide evidence that this result cannot be explained by displacement of crime to neighboring beats or later hours.

While police departments often consider rapid response times (minimizing the elapsed time between receiving an emergency call and responding to that call) to be one of the most important tools for solving crimes, criminologists argue that no evidence exists to support that claim (Sherman, 2013).[10] Not only have few studies examined the impact of rapid response times on solving crimes, but also no attempt has been made to measure how rapid response tools impact the deterrence capacity of the police. My results provides an estimate of both the deterrence created by routine police activities and the possible community safety costs of police officers dividing their time between preventing future crimes and responding to past crimes.

These results join an empirical literature on measuring deterrence that focuses on applying techniques to mitigate simultaneity bias. My estimated elasticities of roughly -0.5 regarding the impact of a change in police presence on violent crime and -0.3 on property crime fall within the range of elasticities of between -0.4 and -1 (violent) -0.3 and -0.5 (property) reported in previous work (see Levitt (1997 & 2002) and Evans and Owens (2007)).[11] These studies applied instrumental variable strategies to estimate

[10] The general embracement of rapid response policing is evident in the summary of "best practices in police performance measurement" provided by the Rand Corporation (Davis, 2012). Using data from the Kansas City Preventative Patrol Experiment, Kelling et al. (1974) found no impact of response times on solving crimes. However, Blanes i Vidal & Kirchmaier (2017) find that faster response times increase the likelihood of detecting crimes when using an instrumenting strategy based on the distance of the incident from police headquarters. Mastrobuoni (2015) reaches a similar conclusion when analyzing the outcomes of quasi-experimental variations in police presence in the city of Milan.

[11] See McCrary (2002) for some concerns regarding estimates produced in the Levitt (1997) paper.

the elasticity of crime to police force size. Chalfin and McCrary (2017) raise concerns regarding weak instruments in these papers and point out that these studies show a wide range of estimates that are often not statistically significant at conventional confidence intervals. The instruments used in this research avoid this critique with first stage F statistics of 38.54 and 47.94 for the *Unrelated Outside Calls* and *Car Accident Outside Calls* instruments. The deterrence estimates reported in this paper also fall within much smaller confidence intervals.

An additional branch of the literature focuses on exogenous changes in police presence that are driven by threats or actual acts of terrorism (Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), Draca et al. (2011), and Gould and Stecklov (2009)). Di Tella and Schargrodsky (2004) and Draca et al. (2011) report smaller elasticities of crime with respect to police presence of between -0.3 and -0.4. Similarly, MacDonald et al. (2015) report an elasticity of crime with respect to police presence of -0.33 when examining an increase of 200 percent in police presence in the area surrounding the University of Pennsylvania campus. This estimate shrinks further when focusing on randomized experiments. Sherman & Weisburd (1995) found that doubling police patrol at hotspot locations in Minneapolis resulted in a 6 to 13 percent decrease in crime. Weisburd et al. (2015) also report that increasing police presence reduces crime, but only at high-crime micro locations.

This paper offers a bridge between the detailed location specific data that is analyzed in randomized experiments and the aggregate data that is usually available at the city level. To the best of my knowledge, Blanes i Vidal & Mastrobuoni (2017) is the only other paper that attempted to look at the geographic distribution of police officers throughout an entire city using precise GPS level data on police location. They take advantage of a natural experiment where police spent an extra 10 minutes per week in a 200 meter radius of an area where a burglary was reported for the week following a burglary. Interestingly, they find no effect of this change in weekly level police patrol on crime. I focus on police presence at the hourly level within Dallas beats (averaging 2.7 kms^2) and examine whether or not routine changes in police behavior can have significant impacts on crime. One important difference between these two studies is that this project focuses on moving police away from an area they have chosen to patrol, while Blanes i Vidal & Mastrobuoni (2017) focus on sending officers to patrol a specific location.

This paper proceeds as follows. In the next section I introduce the data used for this project as well as my technique for measuring police presence. Section 3 discusses the empirical strategy and presents estimates of the impact of police presence on different types of crimes. Section 4 explores the mechanisms of deterrence that are driving my results. Section 5 concludes.

2 The Data

Dallas, Texas is the ninth largest city in the US, with roughly 1.2 million residents and 3,266 sworn police officers spread over 385 square miles. I use two separate Dallas Police Department (DPD) databases that provide information on the precise location of both crime and police in 2009. The DPD call database records the time and location of each report of crime to the department. The Automated Vehicle Locator (AVL) database tracks the location of police cars throughout the day. Together they provide an opportunity to understand how police presence impacts crime.[12]

Dallas is an ideal location for research using AVL data since it is mostly flat and thus, is able to provide fairly precise latitude and longitude points with minimal missing data. Dallas police patrol is divided into 7 patrol divisions (Central, North Central, Northeast, Northwest, South Central, Southeast, Southwest) which are each commanded

[12] Using geographic mapping software I collect additional information on population size as well as miles of roads across different areas in Dallas. Census track data allow me to add in information on the characteristics of individuals living within these areas. These data are combined with information on daily temperature, visibility, precipitation, sunrise, and sunset times in order to control for variability in the probability of crime over time.

by a deputy chief of police. Figure 2 provides a map of the city divided into divisions and beats. There is some variation in the characteristics of beats across different divisions in the city as illustrated by Table 1. Beats in the Central division are smaller, averaging 0.6 square miles, while beats in other divisions average 1.8 square miles. Beats in the South Central division have a higher percentage of black residents, while beats in the Southwest have the highest percentage of Hispanic residents. Residents of the North Central division report higher incomes. These characteristics highlight the importance of focusing on crime outcomes at the beat level as different parts of the city may require different levels of police presence and face different crime risks.

The analysis is conducted on geographic beats at hour long time intervals. I use the call database to count the number of crimes called into 911 for each beat b and hour h. Focusing on 911 calls as opposed to crime reports is expected to lower concerns regarding selective reporting of incidents. While I cannot rule out the possibility that in certain beats crimes may not be called in to the police, this should not impact my results when controlling for beat fixed effects. A larger concern is whether the presence of a police car in an area may reduce calls to 911 as people can speak directly with the patrolling officer. Importantly, 911 is the generally accepted protocol for reporting crime. Beats average 1.7 square miles and roughly 40 minutes of patrol per hour, thus reporting via 911 will usually be significantly faster.[13]

The original database included 684,584 calls recorded throughout 2009 in Dallas, Texas. My final call database consists of 551,060 calls after removing duplicate calls and excluding calls that were classified as hang-ups. Details of the data cleaning process are in Appendix A. The main analysis focuses on 283,668 calls reporting incidents of crime. These crimes are classified into the following categories: public disturbances, burglaries,

[13] Using internal DPD data, a source from the Dallas Police Department estimated that roughly 90 percent of reported crimes are initiated via 911 calls. The remaining 10% are likely to be a combination of officer initiated calls (often related to traffic stops), sex assault victims (reporting from trauma centers, hospitals, colleges, and victims' advocates), as well as residents reporting both to patrol officers and arriving directly at the police station.

violent crimes, and theft.[14] Figure 3 illustrates how the number of crimes vary over time in different areas of Dallas. While crime in all areas tends to peak in May and plummet in December, there are also significant fluctuations in the crime rate throughout the year.

Beginning in the year 2000, Dallas police cars were equipped with Automated Vehicle Locators (873 tracked vehicles). These AVL's create pings roughly every 30 seconds with the latitudinal and longitudinal coordinates of these vehicles. Each ping includes the radio name of the vehicle which provides information on the allocation of the police vehicle. Thus, a ping with radio name A142 refers to a car that was allocated to patrol beat 142 during patrol A (during the $1st$ watch that takes place between 12 AM and 8 AM).[15]

The Automated Vehicle Locator Data also includes a report indicator for vehicles that are responding to a call for service. This indicator provides information on whether the vehicle is on general patrol or responding to a call. In contrast to an aggregate count of police officers per city, these data present an opportunity to map the activity of each individual squad car throughout the day.

The call database and Automated Vehicle Locator dataset are the actual data used by the Dallas police department to assign officers to 911 incidents. Thus, when a 911 call is placed in Dallas, the call taker records basic information on the incident (location, caller name, classification of incident, and time) and defines the severity of the incident. This information is loaded into the CAD (Computer Aided Dispatch) system which is the source for the call data. This incident then appears on the computer of the police dispatcher for the relevant division where the incident was reported.[16] The

[14] A crime is classified as a burglary if it involves entering a structure with the intent to commit a crime inside. Stabbings, shootings, robberies, assaults, kidnappings, and armed encounters are classified as violent crimes. Public intoxication, illegal parking, suspicious behavior, prostitution, loud music, gun fire, speeding, road rage, and panhandlers are classified as public disturbances.

[15] Cars are often allocated to more than one beat, therefore the radio name serves as a proxy for allocation to a given beat. While, it would be preferable to have data on the exact allocation, this can still provide insight into the general area of allocation.

[16] Each of the 7 divisions has its own set of dispatchers.

police dispatcher then assigns the incident to a patrol car based on priority (as recorded in call data) and distance of car (as tracked in AVL data). When possible the incident is assigned to the police officer allocated to the beat of the incident, but since this officer can be otherwise occupied and most calls require two officers, officers are often assigned to out of beat calls. While, it is possible during severe emergencies for police dispatchers to coordinate and allocate officers across divisions, police are generally dispatched to calls within their division.

To create a database of police location, I divide the city of Dallas into 232 geographic beats of analysis and map each ping from the Automated Vehicle Locator Database (AVL) into a beat.[17] The vehicle pings are then used to count the minutes of police presence over each hour long interval of 2009. I define minutes of presence for each car as the elapsed time between first entrance and first exit from the beat. If the car exited the beat and later returned, it is categorized as a new first entry and first exit. Thus, a car that is present in beat 142 between 6:50 and 7:20 will contribute 10 minutes of presence in hour 6 and 20 minutes of presence in hour 7. If that same car returns to the beat at 7:30 and exits at 7:50, it will contribute 40 minutes of presence in hour 7. Only cars that were in a beat for at least 5 minutes of that hour can contribute to minutes of presence.[18]

Figures 4 and 5 illustrate the levels of both police allocation and actual presence across different parts of the city over time. While beats in the South receive a higher allocation of police officers than beats in the North, it is clear from Figure 5 that actual presence is higher in the North. My identification strategy builds around the idea that actual police presence over time is not fully determined by the allocation of officers.

Table 1 summarizes the mean hourly values for crime, police allocation and police

[17]The study focuses on 232 out of 234 beats in Dallas. Two beats were excluded from the analysis as they are composed primarily of water.

[18]I set a lower bound of presence at 5 minutes in order to focus the analysis on cars that were likely to be patrolling the given beat and not simply driving through the area.

presence by beat at the division level. The majority of crimes occur in beats that are located in the Southwest side of the city (with an average crime rate of 0.194). On average police officers are allocated to cover beats for 60 to 80 percent of each hour. The highest level of police allocation is in the North Central division where on average each beat has an allocated officer for over 80% of each hour, while in the Northwest division, a patrol officer is allocated to a beat for only about 60% of every hour. However, police allocation only refers to whether or not there was an active patrol officer at this hour of the day whose radio name referred to the given beat. Actual police coverage varies significantly from allocated coverage, with the largest average difference observed in the Southeast division. While allocated coverage is determined at the start of an officers shift, police presence is a function of the events and crime concerns that develop throughout the day.

The simultaneous relationship between police presence and crime is already made apparent in Table 1. Beats in the Northeast division average 30 percent less police presence than beats in the Southwest division, yet beats in the Southwest division report a higher crime rate. In order to identify a causal effect of policing on crime, I focus on an instrument that impacts the level of police presence in a given beat, but should not directly impact crime.

Both *Unrelated Outside Calls* and *Car Accident Outside Calls* (OC_{bh}) are calculated for each beat (b) and hour (h) as a weighted average of the number of calls occurring in division D_b outside of beat b. Hour h is a time variable beginning at 0 at 12 AM on January 1st, 2009 and culminating at h =8736 at 11 PM on December 30th, 2009. Thus, for *Unrelated Outside Calls,* I sum the number of 911 calls received in division D_b outside of beat b during hour h reporting incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses. I apply the same strategy for out of beat car accident calls when calculating the *Car Accident Outside Calls* instrument. Importantly, instead of calls occurring in all k beats of the division being counted equally, OC_{bh} is a weighted sum,

$$OC_{bh} = \sum_{k \neq b \in D_b, h} n_{kh} w_{bk} \tag{1}$$

where n_{kh} is the number of incidents that occurred in beat k during hour h and $w_{bk} = \frac{\max\_dist_b - distance(b,k)}{\max\_dist_b}$ is the weight assigned to calls in beat k given its distance from beat b.[19]

In the next section I lay out my empirical strategy for estimating the deterrence effect of police presence on crime. I discuss unobserved factors that can create bias in estimating this effect and explain how the instruments address these concerns. My results illustrate that even with very detailed micro data, absent an exogenous shift in police presence, policing and crime remain positively correlated.

3 Empirical Strategy and Results

In equation (2) , I model the occurrence of a crime (C_{bh}) as a function of police presence (P_{bh}),

$$C_{bh} = x_{bh}\beta_0 + \beta_1 P_{bh} + \gamma_t + \eta_b + \varepsilon_{bh} \tag{2}$$

C_{bh} is a count of the number of 911 calls reporting incidents of crime (violent crimes, burglaries, thefts, and public disturbances) at beat b during hour h. The variables included in x_{bh} capture time varying environment characteristics that could impact the costs and benefits of crime (weather, visibility, etc.). The focus of my analysis is P_{bh}, a count of the amount of time police officers spent patrolling inside beat b at hour h. If one police vehicle was present for a full hour (h) at beat (b) then $P_{bh} = 1$. A single patrol car in the beat that was only present for 30 minutes will result in a P_{bh} value of 0.5, alternatively, 2 cars that were present over the entire hour will result in $P_{bh} = 2$.

[19] The variable $\max\_dist_b$ is defined as the maximum distance between beat b and any other beat in the division. In this way, I give larger weights to outside calls that officers patrolling beat b are more likely to be assigned to.

The time and beat fixed effects γ_t and η_b account for the differential probabilities in crime across different times and beats. If policing is uncorrelated with the remaining unobserved factors impacting crime (ε_{bh}), then $\widehat{\beta}_1$ estimates the amount of deterrence created when police coverage is increased by 1 car.

My main concern regards the endogeneity of policing P_{bh}. It has been well documented in the literature that police allocation is far from exogenous. In a well functioning police department officer allocation will be highly correlated with crime. Using detailed geographic data can further complicate the relationship as one would expect that when a crime occurs in a given hour more police will immediately enter the beat in response to the crime. Even after removing cars that are specifically assigned to respond to the call, I cannot rule out a situation where additional officers may be drawn to the location of the crime incident for backup purposes. An additional concern is that there may be seasonal differences in crime risks that are addressed by the police force by means of changing police allocation across beats and time.

The Dallas Police Department has a stated goal of answering all serious 911 calls (priority 1) within 8 minutes and priority 2 calls (e.g. potential for violence or past robbery) within 12 minutes (Eiserer, 2013). Thus, the pre-planned allocation of an officer to a beat can be disrupted by an influx of emergency calls. It is exactly this differentiation between the endogenous choice of sending officers to higher risk crime locations and the plausibly random timing of emergency calls in surrounding areas that provide a first stage for police presence P_{bh},

$$P_{bh} = x_{bh}\alpha_0 + \alpha_1 OC_{bh} + \theta_t + \rho_b + \delta_{bh} \tag{3}$$

While the allocated level of presence can be determined by the perceived crime risk in that area (δ_{bh}), actual presence is impacted by an exogenous factor OC_{bh} as defined in equation (1). The estimated coefficient on the instrument $(\widehat{\alpha}_1)$ is expected to be negative, since an increase in out of beat calls (higher OC_{bh}) should decrease police presence in the beat (P_{bh}). Figure (6) shows that beats and intervals of time with higher *Unrelated Outside Calls* (OC) have significantly lower levels of police presence and higher levels of crime.[20]

Table (2) presents regression estimates for the general impact of outside calls on police presence as defined in equation (3).[21] I find that increasing *Unrelated Outside Calls* by 1 decreases police coverage by 0.002 (s.e. 0.001) which is significant at the 1 percent level. The F statistic for the first stage when using the *Unrelated Outside Calls* instrument on its own is 9.99. The effect is much smaller and not statistically significant for *Car Accident Outside Calls.* One explanation for the smaller effect of *Car Accident Outside Calls* is that other officers will only be assigned to a car accident if a traffic patrol car is not available. Thus, in periods when traffic patrol cars are active, the distance to an outside car accident call may be a less precise predictor of outside assignment than distance to unrelated call.

To maximize the flexibility of these *Outside Calls* (OC) instruments, I interact them with quartile dummies for centrality of beat, an indicator for division, and an indicator for nighttime. This allows different divisions to follow different protocols or face different constraints at different times of day regarding between beat allocation, as well as heterogeneous impacts of *Outside Calls* on beats at varying levels of centrality. Centrality is determined based on the number of beats that share a border with the given patrol area. After including these interactions, the first-stage F-statistic is 38.54 for the *Unrelated Outside Calls* instrument and 47.94 for the *Car Accident Outside Calls* instrument in my main specification. The instrumental variable analysis conducted in this paper always include these interactions for both instruments.

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[20] The *Outside Calls* instrument, focuses only on calls reporting incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses. In order to allow a comparison between similar beats in this graphic illustration, I focus on those with 3 or less direct neighbors (the lowest quartile).

[21] The number of *Outside Calls* for each location and time is calculated using equation (1).

I estimate the impact of police presence on all crimes using equation (2) for fixed effects and 2SLS specifications. I compute heteroskedasticity and autocorrelation consistent standard errors for all specifications (see Conley (1999)). The focus of this paper is estimating β_1, the impact of an additional police vehicle in a given beat (b) and hour (h) on crime outcomes (C_{bh}). In the fixed effect model (column (1) of Table (3)) I find that an increase in police presence seems to imply an increase in crime even when controlling for weather as well as time fixed effects (month, day of week, and weekend$\times$hour) and beat fixed effects.[22] These results suggest that the presence of an additional police car at a given beat results in a significant 0.012 increase in crime (at an average crime rate of 0.15).

Two stage least squares estimates appear in columns (2) and (3) of Table (3) . The estimate in column (2) measures the deterrence effect when actual police presence (P_{bh}) is instrumented with *Unrelated Outside Calls*, column (3) provides an estimate of the effect when applying the alternative *Car Accident Outside Calls* instrument. These two stage least squares estimates provide an opportunity to measure deterrence without the simultaneity bias concerns in the OLS estimates (if more police are present at locations and times with increased crime risks this will result in a positive bias on the estimated deterrence effect $\left(\widehat{\beta}_1\right)$). The instrument allows me to focus on changes in police presence that were not a direct outcome of changes in perceived crime risks at the given beat and hour.

In specification (2) when instrumenting for police presence with *Unrelated Outside Calls*, I find a significant negative effect of police presence on crime equal to -0.087 (0.013). While β_1 in equation (2) represents the effect of an additional police vehicle (P_{bh}) on crime, what is driving the estimate is the reality that cars are often withdrawn from their patrol beat when assigned to an outside call. Accordingly, a real world inter-

[22] I control for weekend$\times$hour fixed effects in order to allow weekend hours to differ from weekday hours.

pretation of this effect is that removing 60 minutes of presence from a given beat at a given hour results in a 35 percent increase in crime $\left(100 \times \frac{0.087}{0.15}\right)$. If I focus on average police presence per hour (36 minutes), a 10 percent decrease in police presence implies a 3.5 percent increase in crime (elasticity of -0.35).[23] I estimate a smaller deterrence effect of -0.030 (0.011) when applying the *Car Accident Outside Calls* instrument. This estimate implies that a 10 percent decrease in police presence will results in a 1.2 percent increase in crime (elasticity of -0.12).

Table (3) also provides information on how different weather and time characteristics impact crime outcomes. I find that crime is more likely to occur on holidays. Higher temperatures increase the occurrence of crime, and bad weather lowers the probability of crime.

In Table (4) , I separately examine the impact of police on different types of crimes (violent crimes, public disturbances, theft, and burglaries). I first report the measured effect of police presence in an OLS model that controls for month, day of week, weekend×hour, and beat fixed effects, as well as temperature, precipitation, twilight, and holiday as well as division×centrality×dark interactions. In specifications (2) and (3), I report results when instrumenting for police presence with the *Unrelated Outside Calls* and *Car Accident Outside Calls* instruments used in Table (3) .[24]

All crime types exhibit a significant positive correlation between police presence and crime (see column (1)) that disappears when instrumenting for police presence with *Unrelated Outside Calls* and *Car Accident Outside Calls* (see columns (2)-(3)). It is interesting to note that for all crime types the OLS estimates suggest that increasing police presence by 1 vehicle results in a 10 percent increase in crime. If this estimate is being driven by backup officers responding to crime incidents it makes sense that the

[23] This is calculated as $\frac{3.6}{60} \times 100 \times \frac{0.087}{0.15}$.

[24] Unrelated incidents are defined in this paper as those reporting mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses

correlation between policing and crime is not impacted by the type of crime committed.

The estimated deterrence effect of police presence on crime when instrumenting for police presence with *Car Accident Outside Calls* is driven by violent crimes as the deterrence estimate is not statistically significant from zero for any of the other crime types (see column (3) of Table (4)). I find that police have the largest effect on violent crimes (see Row A), where a 10 percent increase in police presence, decreases violent crime by 2 to 4.7 percent.[25] The effect of police presence on both public disturbances and burglaries is significant when applying the *Unrelated Outside Calls* instrument, where a 10 percent increase in police presence reduces public disturbances by 2.9 percent and burglaries by 2.3 percent.[26]The effect of police presence on theft in Row D is no longer statistically significant when applying both *Outside Call* instruments, but still remains positive for *Unrelated Outside Calls*.

Many of the call categories included in the *Unrelated Outside Calls* instrument are not only unrelated to crime, but also, to police presence. These call categories provide an opportunity for a placebo test to ensure that the deterrence estimates reported in Table (3) and Table (4) are driven by changes in police presence. Table (5) illustrates that unrelated calls that should not be sensitive to police officer patrol (fires, suicides, abandoned children, and drug houses) are not significantly impacted by police presence when applying both instruments. There are two categories used in the *Unrelated Outside Calls* instrument: mental health reports and animal attack reports that are affected

[25] I classify violent crimes as stabbings, shootings, robberies, assaults, kidnappings, and armed encounters. I classify public intoxication, illegal parking, suspicious behavior, prostitution, loud music, gun fire, speeding, road rage, and panhandlers as public disturbances. The deterrence impact on violent crimes was calculated by taking the estimated impact of an additional police vehicle on violent crime (-0.051 (using unrelated *OC* instrument) & -0.021 (using car accident *OC* instrument)) relative to the average violent crime rate of 0.065. Thus, the unrelated (car accident) *OC* instrument estimate implies that an additional police car results in a 78 (32) percent decrease in violent crime. Since the average amount of police presence is 0.6, a 10 percent increase in police presence requires dividing the full hour impact (a 167% increase in police presence) by 16.7. This calculation is also applied to all other crime types.

[26] I classify public intoxication, illegal parking, suspicious behavior, prostitution, loud music, gun fire, speeding, road rage, and panhandlers as public disturbances.

by police presence. As mental health reports often involve the homeless, and both homelessness and dog walking without a leash can result in citations from the Dallas Police Department these activities may be less common when police are present. In Table (9) of the appendix, I re-run the analysis in Table (3) instrumenting for police presence with the subset of unrelated calls that are not sensitive to police officer patrol and find a very similar deterrence effect.

4 A Closer Look at the Mechanisms of Deterrence

My estimates suggest that police presence at the beat level can significantly impact crime. The next step is to understand the mechanism by which police presence changes behavior. What are patrol officers doing to prevent crime? Does police presence also impact non-crime related incidents? Are police officers more/less effective when allocated to certain areas? Does an increase in police presence this hour displace crime to the next hour or alternatively, to a neighboring beat?

Police officers engage in both active patrol (e.g. stops, questioning, frisks) and passive patrol (e.g. car patrol, paperwork) when working a beat. In order to correctly interpret my deterrence results, it is relevant to understand the extent to which *Outside Calls* impact active police patrol. This differentiation is important for gaining insight into whether or not an empty patrol car (or an officer who is simply filling out paperwork in his/her car) can have the same deterrence effect as an officer actively patrolling the streets. I therefore use arrests as a proxy for active police presence and examine how they are impacted by changes in police presence that are driven by out of beat calls.

In Table (6), I find a significant impact of police presence on arrests when instrumenting with both *Unrelated Outside Calls* and the *Car Accident Outside Calls*. Thus, a 10 percent increase in police presence increases the probability of arrest by 8 to 12 percent.[27] One interpretation of these results is that police are creating deterrence, not

[27] An additional police car increases the arrest rate by $100 \times \frac{0.047}{0.034} - 100 \times \frac{0.069}{0.034}$ percent. This number

only by being present in the area, but actively reminding individuals that there are repercussions for criminal behavior. An alternative explanation could be that part of the deterrence effects presented in this paper may be a result of incapacitation, where the individual arrested had planned to commit multiple crimes in that beat at that exact unit of time but due to police presence was arrested after the first attempt. If this is the mechanism through which incapacitation immediately impacts crime, then it is possible to measure a deterrence effect that is separate from incapacitation by estimating equation (2) focusing on how police presence (P_{bh}) impacts the probability of a crime as opposed to the number of crimes. In this specification, I continue to find a significant deterrence effect such that a 10 percent increase in police presence results in a 1 to 2.7 percent decrease in the probability of crime.[28]

In Table (7), I run my analysis separately on 17 beats in Dallas, Texas that included a public improvement district (PID) in 2009. Since these beats have additional privately paid security patrols, they may be impacted differently by a DPD officer's presence (or lack thereof). Indeed, my analysis suggests that public improvement districts show little sensitivity to decreases in police presence on crime.

If police presence affects crime by providing a visual reminder of the costs of crime, I would expect smaller beats, where officers are more visible, to be more affected by losing a police vehicle than larger beats. Another factor affecting deterrence could be light versus darkness. While police officers may be more visible in the daylight, squad cars with flashing lights may be more visible in the dark. In Table (8), I both split the data into three groups of roughly equal sizes: small beats (less than 4.6 miles of roads), midsize beats (4.6 to 8 miles of roads), and large beats (more than 8 miles of roads) and

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is divided by 16.7 to estimate the impact of a 10 percent increase in police presence.

[28]The estimated coefficient on P_{bh} is -0.068 (s.e. 0.011) when applying the *Unrelated Outside Calls* instrument and -0.024 (s.e. 0.007) when applying the *Car Accident Outside Calls* instrument. The average probability of crime per beat and hour is 0.15 (s.d. 0.4) and the average amount of police presence is 0.605 (s.d. 1.078).

differentiate between daylight and night patrol hours. I find that police vehicles generally have a larger impact on crime during night patrol hours using both the *Unrelated Outside Calls* and the *Car Accident Outside Calls* instruments. However, it is relevant to note that the first stage F statistics during daylight hours are significantly smaller and even fall under the weak instrument category for small beats.

In part B, when examining deterrence during night patrol hours and instrumenting for police presence with *Unrelated OC*, I find that each additional car reduces crime by 0.006 (0.017) in the smaller beats versus 0.113 (0.029) in midsize beats and 0.074 (0.014) in the larger beats. This implies that a 10 percent increase in police presence in a mid-sized beat during a night patrol hour results in a 3.5 percent decrease in crime $\left(100 \times 0.049 \times \frac{-0.113}{0.161}\right)$, versus an 4.9 percent decrease in large beats $\left(100 \times 0.089 \times \frac{-0.074}{0.134}\right)$. It is interesting to note that while mid-size beats are more affected than larger beats by a given level of police presence, at the margin large beats benefit more from a 10 percent increase in police presence. This is driven by the significant difference in average police presence between mid-size and large beats, where small beats average 29 minutes of presence and large beats average 53 minutes of presence per hour.

When instrumenting for police presence with *Car Accident Outside Calls*, I find a smaller deterrence effect of 0.071 (0.023) on mid-sized beats and a similar estimate of 0.084 (0.013) for large beats. I measure a statistically significant positive effect of police presence on crime for the smallest beats when using this instrument. One possible explanation for this positive effect and the generally noisy effects measured in other specifications for small beats is that in a small beat the interpretation of "out of beat" presence is less concrete, as an officer in a neighboring beat can still be very close by.

Throughout this paper I have focused on estimating the immediate impact of police presence on crime. In Figure (7), I examine how police presence impacts crime dynamically over time when applying the *Unrelated Outside Calls* instrument. If the instrument is uncorrelated across time, we would not expect $\widehat{P}_{b(h+k)}$ to have any effect on crime at time h (C_{bh}).[29] If $\widehat{P}_{b(h-k)}$ increases crime at time h (C_{bh}) this would suggest a displacement effect, where the location of officers impacts the timing of crime as opposed to the occurrence of crime. It is also possible that police presence in previous periods ($\widehat{P}_{b(h-k)}$) would create an expectations effect for more police which would reduce crime.

In a 7 hour period, beats average 8.5 unrelated outside calls, with the highest incidence rate recorded at 28 calls. To measure the impact of police presence across periods, I focus on locations where outside calls are more spread out and thus, less correlated. Patrol officers located in very central beats may often find themselves responding to outside call after outside call in neighboring beats. Thus, an outside call in this hour, combines with an outside call in the previous hour or post hour, making it very difficult to separately identify the effects of police presence across time. In Figure (7), I run the iv analysis across time at non-central beats with 3 or less direct neighbors in the division (the lowest quartile). These beats average 20 percent less unrelated outside calls per hour than the mean. I find that the deterrence effect at hour=0 is driven by police presence at hour=0. The effects of police presence in previous periods and post periods are not statistically significant from zero and much smaller in size.[30]

The question of deterrence versus geographic displacement is an important issue. My findings suggest that increasing the size of the patrol force would decrease crime (as this could hypothetically allow an increase in police presence in all locations). However, if increasing police presence in one location simply shifts crime to the next location, it could raise significant concerns about increasing police presence in a specific beat. I therefore consider the impact of police presence at larger geographic levels, where I would expect to find a smaller impact of police presence on crime if criminals are shifting their

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[29] $\widehat{P}_{b(h+k)}$ refers to the predicted level of police presence after applying the *Unrelated Outside Calls* instrument.

[30] Generally, these results do not point at either a substantial time displacement effect or expectations effect. However, it is relevant to note that its possible these effects are cancelling each other out.

activities to neighboring beats. In Dallas, beats are grouped into sectors, with each sector comprised of roughly 7 beats. I estimate elasticities of between 0.3 to 0.7 when analyzing the deterrence effect of police on crime at the sector level.[31] These estimates are very similar to those found at the beat level, suggesting that crime does not easily displace to neighboring areas.

5 Conclusion

While there exists an abundance of research and views regarding the deterrent effects of policing on crime, there has yet to be a detailed analysis using information on how the exact location of police officers affects behavior. In a survey conducted in May 2010, 71 percent of city officials reported decreases in the number of police personnel in order to deal with budget cuts resulting from the economic downturn.[32] With lower budgets, police departments are being forced to make tough decisions regarding police activities and deployment. Understanding how these deployment techniques impact crime is key for optimizing outcomes given the current budgets.

Police department performance measures are often a function of crime rates, arrests, response times, and clearance rates (the proportion of crimes reported that are cleared by arrests). Some deterrence programs may take time to develop and see results. Thus, a police department that is very involved in neighborhood based crime reduction activities may get little reward for its effort in terms of decreased crime rates. Additionally, as crime rates and clearance rates are influenced by outside factors and their outcomes are an imprecise reflection of investment, departments may prefer to focus on shortening response times, an easily measured police activity.[33] Indeed, The Dallas

[31] See Table (10) in appendix for estimates of the deterrence effect by crime type at the sector level.

[32] Information released in "The Impact of The Economic Downturn on American Police Agencies" by the US Department of Justice, October 2011.

[33] See Davis (2012) for a more in depth discussion regarding police outcomes and outputs (police investment).

Morning News reported in 2013 that after criticism of rising response times to 911 calls the Dallas Police Department "temporarily reassigned dozens of officers who normally spend much of their time targeting drug activity to duties where they respond to 911 calls" (Eiserer, 2013).

The results presented in this paper raise concerns that frequently assigning officers to out of beat 911 calls may have significant costs in terms of deterring future crimes. I estimate that a 10 percent decrease in police presence at a given beat and hour increases crime at that location by 3.5 percent. These estimates are especially relevant to 911 calls as my instruments focus on shifts in police presence that are created because officers are assigned to incidents outside of their beat. This paper asks the question, what happens when a police car leaves its allocated area to fulfill other departmental duties? I find that shortening response times may directly impact the deterrence effect of patrol officers. This problem will only increase as the number of hired police officers decreases in size.

Despite the concern that deterrence is negatively impacted by the assignment of officers to out of beat calls, the flip side of this finding, is that the thin allocation of officers across large areas (which is driven by the rapid response philosophy) can have crime prevention benefits. The prevalent assumption that there is a tension between the rapid response philosophy and deterrence is not borne out of my research. In other words, the fact that the movement of these allocated officers impacts crime, implies that allocating officers in an effort to provide fast response times can be wedded to a deterrence policy. While the allocation of officers to beats may be driven by the demands of providing fast response times, in reality, the presence of these cars reduce the probability of crime. While this implies that it may be possible for police executives "to have your cake and eat it too," it also highlights the caution that must be taken in order to maximize the deterrence benefits of a rapid response system. While arriving quickly at the scene of an incident may help to lower the expected benefit of committing a crime (see Becker (1968), Blanes i Vidal & Kirchmaier (2017), and Mastrobuoni (2015)), it can also disrupt preemptive police activity. My results suggest that optimizing the impact of policing on crime requires weighing the costs and benefits of assigning officers to out of beat calls.

In addition to providing a measure of the crime costs of decreasing police force size throughout the US, this paper provides insight into the mechanism through which police reduce crime. My outcomes are particularly interesting given recent studies that imply that policing is only effective when focused at specific high crime locations.[34] One interpretation of my results is that police do not need to be micro managed and simply assigning them to a fairly large geographic area (beats average 1.7 square miles) will reduce crime. However, the Dallas Police Department is known to follow a directed patrol data driven strategy that attempts to direct patrol specifically to hotspot areas (street blocks with very high crime rates). Thus, within the beat, allocated police may be focused on specific hot spot areas that they are forced to abandon when answering a call.

This paper attempts to shed light on what police are doing in order to lower crime. My results show that their geographic presence alters crime outcomes. The next natural step is to understand how the activities of patrol officers create these crime impacts. I find that assigning officers to out of beat calls, not only reduces police presence, but also lowers arrest rates. Thus, it is plausible that part of the deterrence effect discussed in this paper is driven by an incapacitation effect, where crime decreases because a criminal is arrested before he/she can commit multiple offenses.[35] However, as this effect occurs immediately (within the same hour) it also suggests a separate deterrence channel where increased police visibility has a direct impact on crime outcomes.

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[34]See works by Weisburd et al. (2015) and Koper & Mayo-Wilson (2012).

[35]See work by Ater et al. (2014) that find a significant impact of arrests on crime that they attribute to an incapacitation effect.

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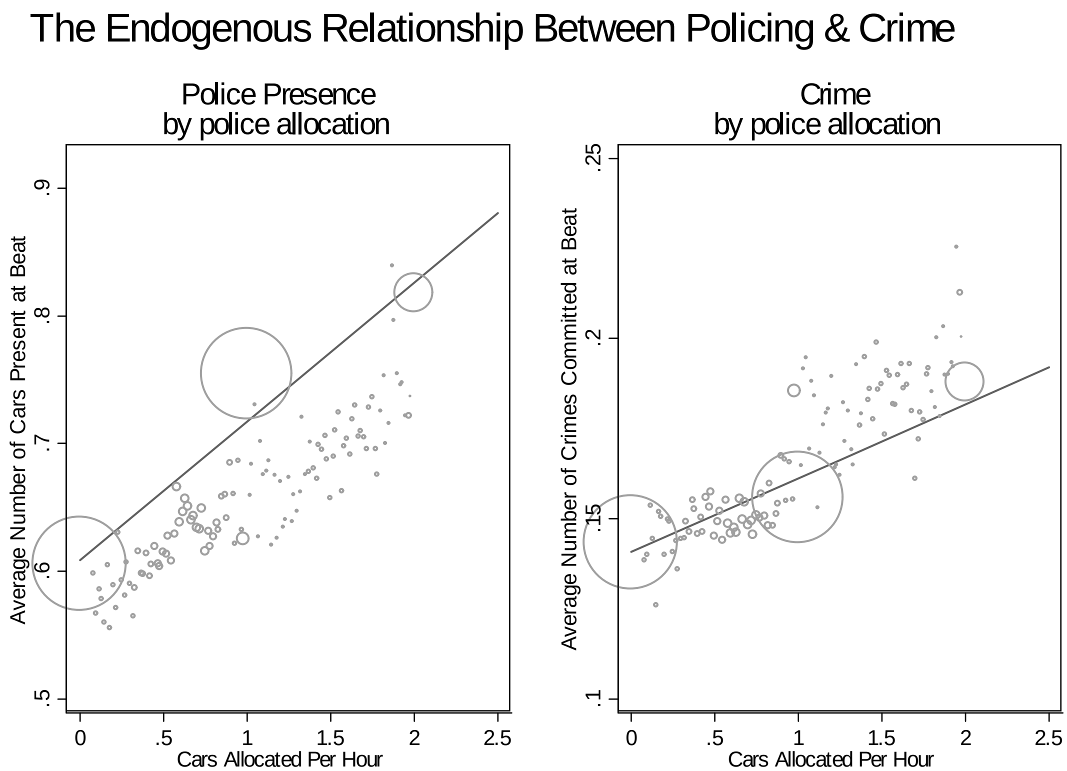
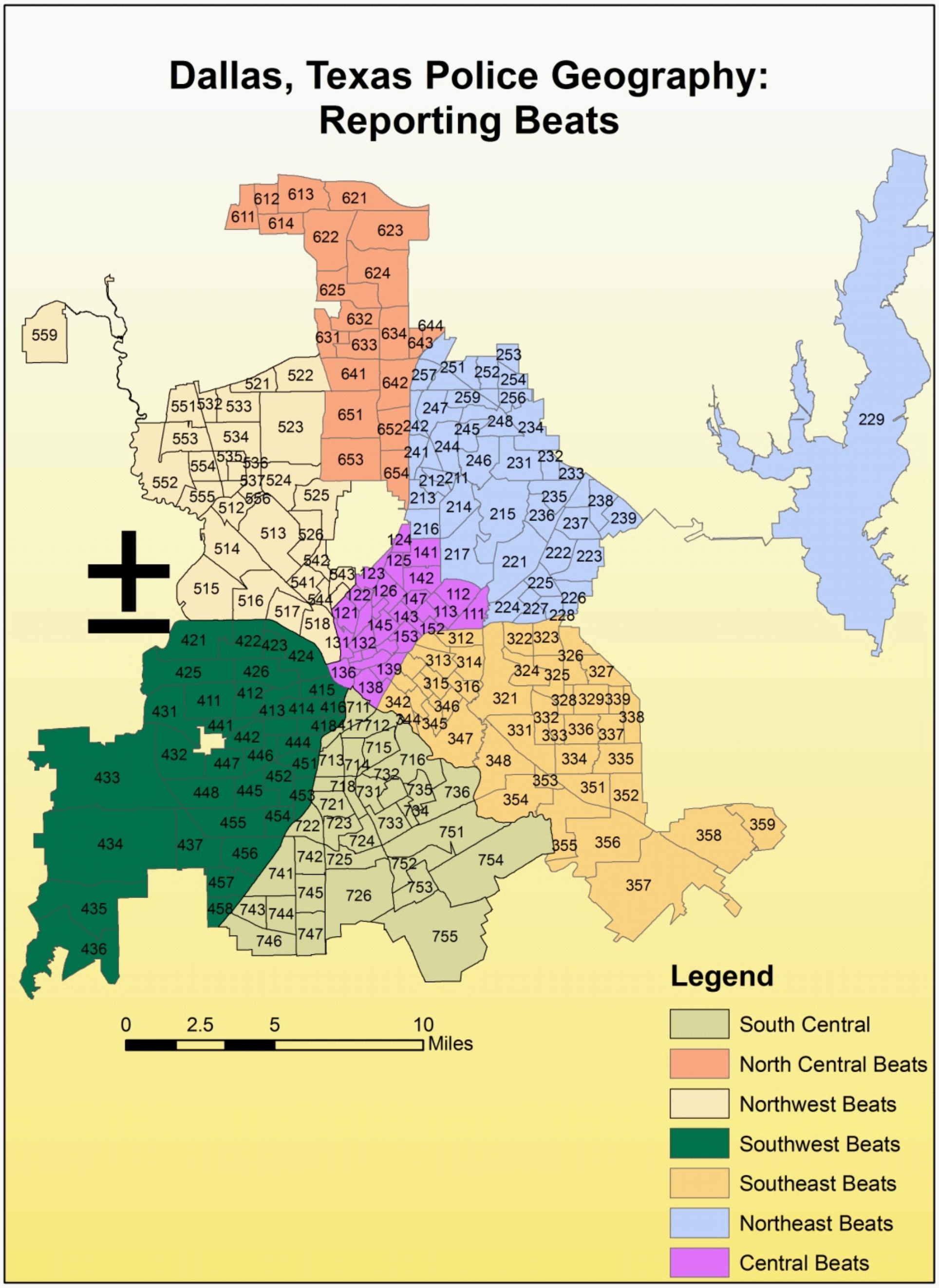


Figure 1: The data was collapsed at each vehicle allocation point. Generally either 0,1, or 2 cars are allocated to patrol a given beat at a given hour. However, if a car did not begin or end patrol on the hour this results in a fraction of car allocation. The size of the circle relates to the density of observations at that car allocation point.

Figure 2: Dallas Beats



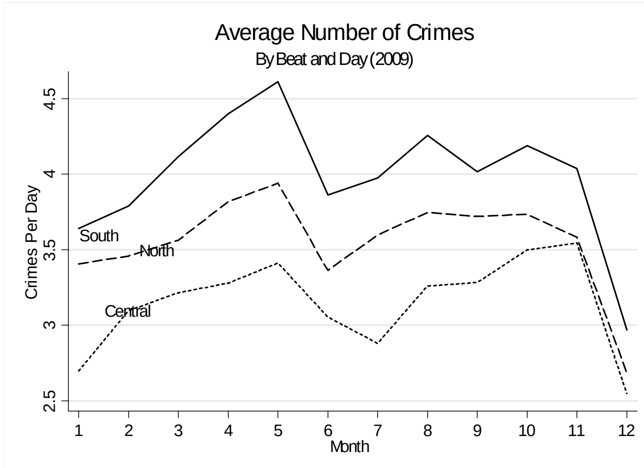


Figure 3: The data was collapsed at each beat and day of year. The South line is the average number of crimes commited per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of crimes commited per beat and day in the Northeast, Northwest, and North Central Divisions.

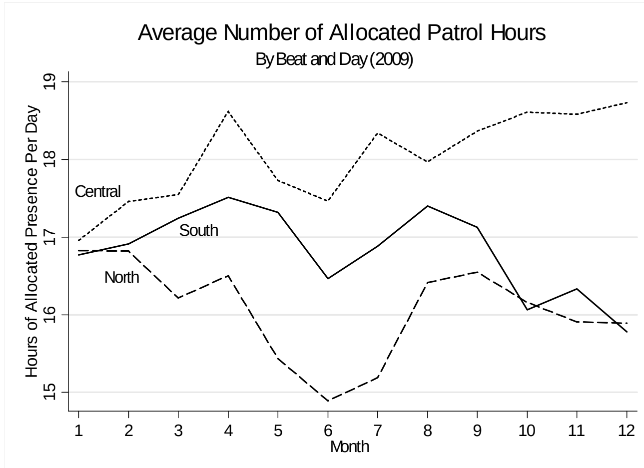


Figure 4: The data was collapsed at each beat and day of year. The South line is the average number of allocated patrol hours per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of allocated patrol hours per beat and day in the Northeast, Northwest, and North Central Divisions.

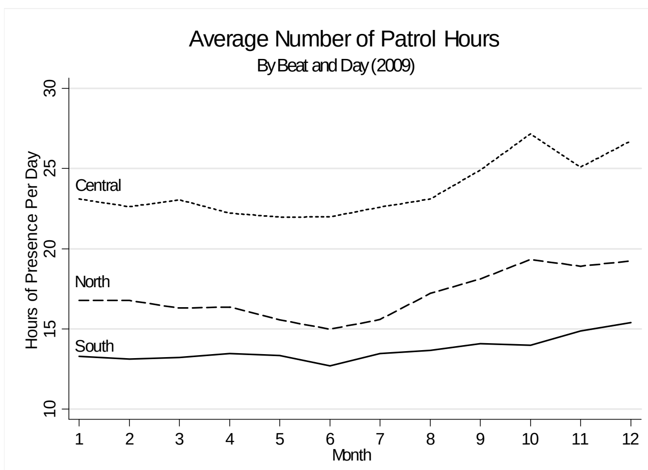


Figure 5: The data was collapsed at each beat and day of year. The South line is the average hours of actual police presence per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average hours of actual police presence per beat and day in the Northeast, Northwest, and North Central Divisions.

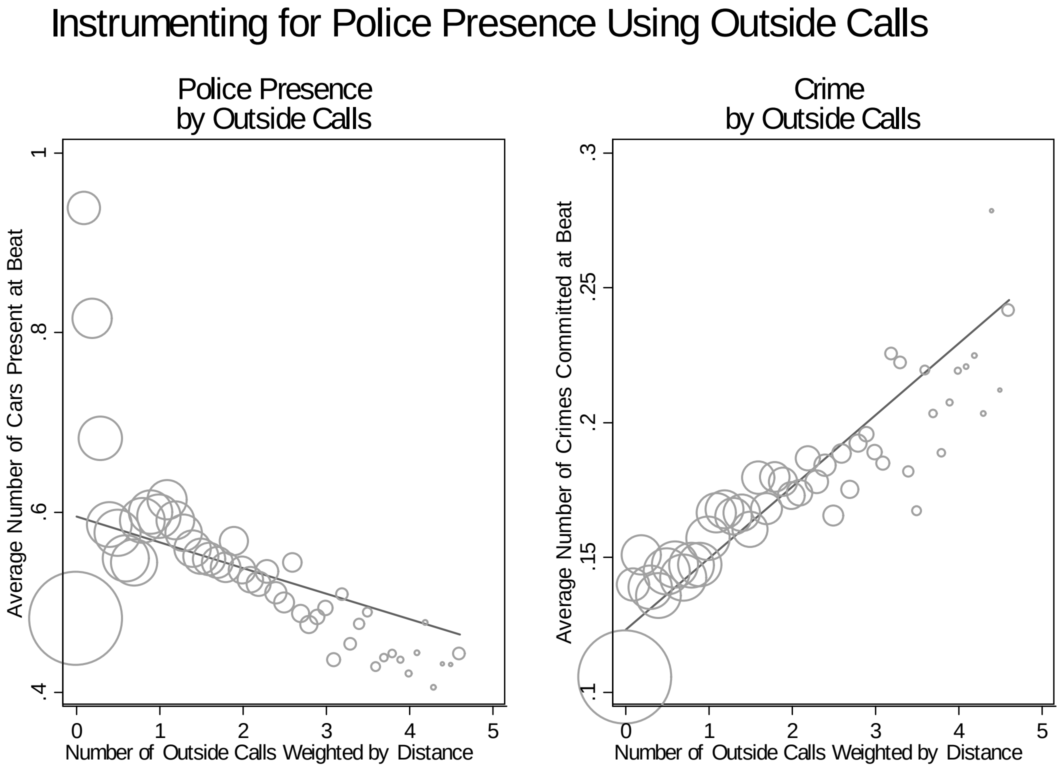


Figure 6: The data was collapsed at each weighted count of out of beat calls unrelated to crime (e.g. calls related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses). The size of the circle relates to the density of observations at that count of out of beat calls. In order to allow a comparison between similar beats in this graphic illustration, I focus on patrol areas that share a border with 3 or less neighboring beats (first quartile of "Centrality").

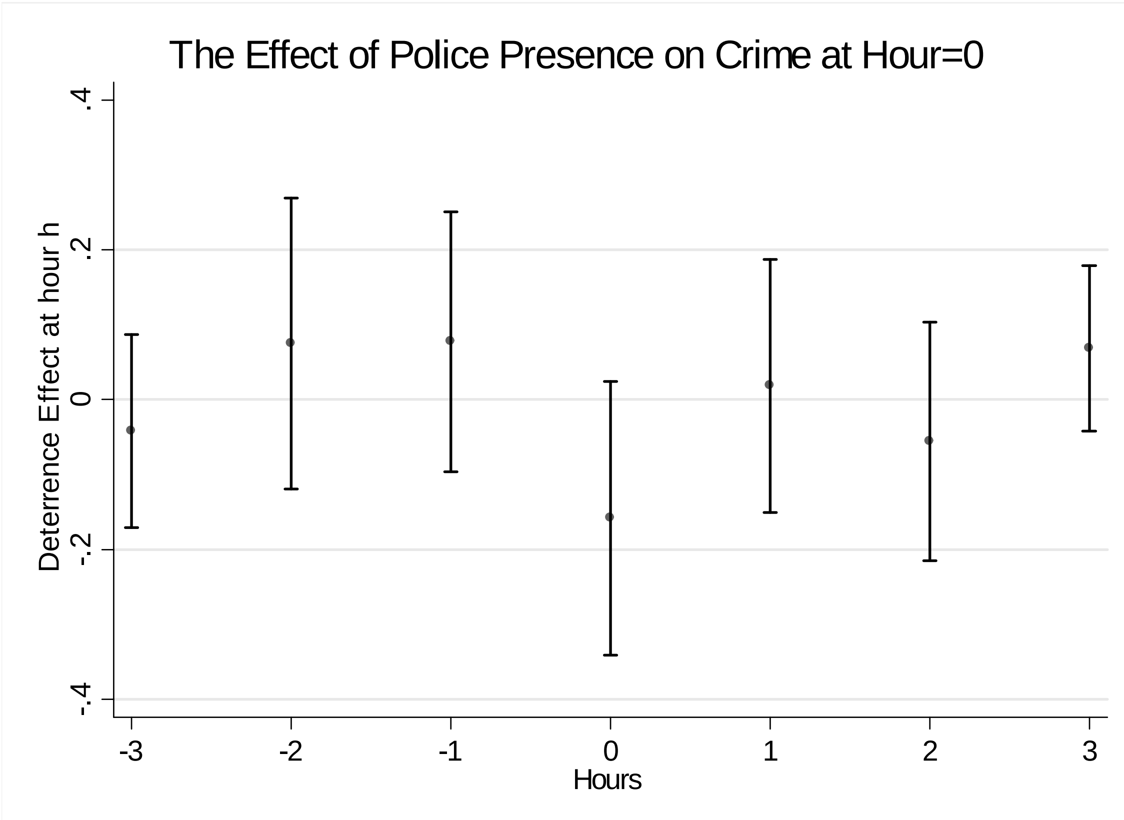


Figure 7: This is an event study plot examining the impact of police presence in previous hours and future hours on crime at hour=0 at non-central beats (the lowest quartile - with 3 or less direct neighbors). The figure maps the estimated coefficients and 95 percent confidence intervals for the impact of police presence in: current hour (hour=0), the 3 previous hours, and 3 post hours on crime at hour=0. I instrument for police presence with unrelated outside calls interacted with quartile dummies for centrality of beat, an indicator for division, and an indicator for nighttime. I include controls for temperature, precipitation, twilight, holiday, and darkness by centrality and division. I also include month, day of week, hour of day x weekend, and beat fixed effects.

Table 1: Beat Characteristics Summarized by Division

Average Time Constant Beat Characteristics						Average Hourly Beat Characteristics				
Population	Road Miles	Size (Miles^2)	HH Income	Percent Black	Percent Hispanic	Total Crimes	Allocated Police	Police Presence	Unrelated Calls (Out)	Accident Calls (Out)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Division=Central (29 Beats)						**Division=Central (N=252,387)**				
3258.00	6.22	0.61	38409.59	0.15	0.29	0.132	0.754	0.932	1.437	3.304
(2695.87)	(3.77)	(0.32)	(13329.34)	(0.12)	(0.2)	(0.375)	(0.714)	(1.733)	(1.141)	(2.052)
Division=North Central (22 Beats)						**Division=North Central (N=191,532)**				
8613.86	9.53	1.68	75819.55	0.12	0.25	0.148	0.815	0.821	0.900	2.321
(4148.73)	(6.3)	(1.18)	(18981.49)	(0.08)	(0.21)	(0.4)	(0.607)	(1.055)	(0.868)	(1.72)
Division=Northeast (41 Beats)						**Division=Northeast (N=356,249)**				
6252.76	5.97	2.25	44423.30	0.23	0.33	0.156	0.654	0.460	1.337	3.089
(2986.75)	(3.88)	(7.22)	(14233.6)	(0.15)	(0.16)	(0.411)	(0.664)	(0.761)	(1.07)	(1.941)
Division=Northwest (31 Beats)						**Division=Northwest (N=269,700)**				
4913.36	8.97	1.52	38770.48	0.15	0.45	0.139	0.595	0.745	1.235	3.102
(3381.12)	(5.45)	(1.09)	(21082.2)	(0.16)	(0.26)	(0.385)	(0.582)	(1.229)	(1.024)	(1.974)
Division=South Central (37 Beats)						**Division=South Central (N=321,567)**				
3081.38	6.37	1.49	28069.28	0.72	0.25	0.144	0.636	0.440	1.209	2.493
(1445.97)	(5.37)	(1.6)	(8138.18)	(0.17)	(0.16)	(0.39)	(0.621)	(0.79)	(1.034)	(1.74)
Division=Southeast (39 Beats)						**Division=Southeast (N=339,378))**				
3997.67	6.32	1.63	27410.70	0.44	0.47	0.166	0.770	0.430	1.393	2.918
(1832.93)	(3.63)	(1.79)	(8372.98)	(0.27)	(0.24)	(0.423)	(0.741)	(0.782)	(1.123)	(1.903)
Division=Southwest (33 Beats)						**Division=Southwest (N=287,166)**				
5842.94	8.97	2.27	34301.05	0.26	0.62	0.194	0.702	0.615	1.314	2.959
(3087.18)	(7.3)	(3.32)	(8708.15)	(0.23)	(0.24)	(0.459)	(0.658)	(0.997)	(1.089)	(1.944)

Table 2: Outside Calls as Predictors of Police Presence

A. Instrumenting for Police Presence with *Unrelated Outside Calls*	
Unrelated Outside Calls[1]	-0.002***
	(0.001)
B. Instrumenting for Police Presence with *Car Accident Outside Calls*	
Car Accident Outside Calls[2]	-0.0002
	(0.0004)
Month Fixed Effects	Yes
Day of Week Fixed Effects	Yes
Weekend x Hour of Day Fixed Effects	Yes
Beat Fixed Effects	Yes
Observations	2,017,979

Notes: Each observation is a beat and hour in 2009. Average police presence is 0.6 (s.d. 1.1). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All Specifications also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

[1]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls are defined as those reporting incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.

[2]Number of calls reporting car accidents occurring at outside beats weighted by distance to given beat.

[3]For the instrumental variable analysis in this paper the outside calls instrument is interacted with division, centrality of beat (split by quartiles of number of borders), and nighttime hours. These interactions strengthen the predictive capabilities of the outside call instrument resulting in F statistics of 38.54 when applying the *Unrelated Outside Calls* instrument and 47.94 when applying the *Car Accident Outside Calls* instrument.

*Significant at 10%; **significant at 5%; ***significant at 1%

Table 3: The Effect of Police Presence on Crime

	OLS (1)	IV= *Unrelated Outside Calls* (2)	IV= Car Accident Outside Calls (3)
Police Vehicles[1]	0.012***	-0.087***	-0.030***
	(0.0002)	(0.013)	(0.011)
Temperature	0.002***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)
Precipitation	-0.001***	-0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0003)
Twilight	0.007***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)
Holiday	0.013***	0.003	0.009*
	(0.004)	(0.005)	(0.005)
Time FE's	Yes	Yes	Yes
Beat FE's	Yes	Yes	Yes
IV Interactions	Yes	Yes	Yes
1st Stage F Stat		38.54	47.94
Observations	2,017,979	2,017,979	2,017,979

Notes: Each observation is a beat and hour in 2009. The average crime rate is 0.15 (s.d. 0.4), average police presence is 0.6 (s.d. 1.1). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All specifications include IVXDivisionXCentralityXDark interactions, allowing the impact of out of beat calls to vary across different policing divisions, light/darkness, as well as the centrality of the beat (split by quartiles of number of borders). All Specifications include fixed effects for month, weekendxhour, and day of week. I also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

[2]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.

[3]Number of calls reporting car accidents occurring at outside beats weighted by distance to given beat.

*Significant at 10%; **significant at 5%; ***significant at 1%

Table 4: The Effect of Police Presence on Different Types of Crimes

	OLS	*Instrumenting for Police Vehicles with IV:* *Unrelated Outside Calls*[2]	*Car Accident Outside Calls*[3]
	(1)	(2)	(3)
A. Dependent Variable = Violent Crimes (mean of dependent variable 0.065, s.d. 0.258)			
Police Vehicles[1]	0.005***	-0.051***	-0.021***
	(0.0003)	(0.007)	(0.006)
B. Dependent Variable = Public Disturbances (mean of dependent variable 0.053, s.d. 0.234)			
Police Vehicles[1]	0.004***	-0.025***	-0.004
	(0.0002)	(0.007)	(0.005)
C. Dependent Variable = Burglaries (mean of dependent variable 0.032, s.d. 0.181)			
Police Vehicles[1]	0.003***	-0.012***	-0.005
	(0.0002)	(0.004)	(0.003)
D. Dependent Variable = Theft (mean of dependent variable 0.012, s.d. 0.109)			
Police Vehicles[1]	0.001***	0.0001	-0.002
	(0.0001)	(0.003)	(0.002)
Time FE's	Yes	Yes	Yes
Beat FE's	Yes	Yes	Yes
IV Interactions	Yes	Yes	Yes
1st Stage F Statistic		38.54	47.94
Observations	2,017,979	2,017,979	2,017,979

Notes: Each observation is a beat and hour in 2009. The average number of police vehicles patrolling a beat is 0.6 (s.d. 1.1). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All IV specifications include IVXDivisionXCentralityXDark interactions, allowing the impact of out of beat calls to vary across different policing divisions, light/darkness, as well as the centrality of the beat (split by quartiles of number of borders). All Specifications include fixed effects for month, weekendxhour, and day of week. I also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

[2]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.

[3]Number of calls reporting car accidents occurring at outside beats weighted by distance to given beat.

*Significant at 10%; **significant at 5%; ***significant at 1%

Table 5: Analyzing the Unrelated Outside Calls Instrument

	Instrumenting for Police Vehicles with IV:	
	Unrelated Outside Calls	*Car Accident Outside Calls*
	(1)[2]	(2)
Placebo Categories (Fire, Suicide, Abandoned Children, Drug Houses)		
A. Dependent Variable = Fire Reports (mean of dependent variable 0.004, s.d. 0.065)		
Police Vehicles[1]	-0.001	0.0003
	(0.001)	(0.001)
B. Dependent Variable = Suicide Reports (mean of dependent variable 0.001, s.d. 0.037)		
Police Vehicles[1]	0.0004	-0.001*
	(0.001)	(0.001)
C. Dependent Variable = Abandoned Children (mean of dependent variable 0.001, s.d. 0.027)		
Police Vehicles[1]	0.0001	-0.001
	(0.0004)	(0.001)
D. Dependent Variable = Drug House Reports (mean of dependent variable 0.001, s.d. 0.037)		
Police Vehicles[1]	0.0002	-0.0001
	(0.001)	(0.001)
Dependent Variable = Placebo Categories A-D (mean of dependent variable 0.005, s.d. 0.071)		
Police Vehicles[1]	-0.0005	-0.001
	(0.002)	(0.001)
Additional Categories in Unrelated Calls (Mental Health, Animal Attacks)		
E. Dependent Variable = Mental Health (mean of dependent variable 0.004, s.d. 0.065)		
Police Vehicles[1]	-0.004***	-0.004***
	(0.001)	(0.001)
F. Dependent Variable = Animal Attack (mean of dependent variable 0.001, s.d. 0.024)		
Police Vehicles[1]	-0.001***	-0.001*
	(0.0004)	(0.0003)
Dependent Variable = All Unrelated Calls (mean of dependent variable 0.01, s.d. 0.099)		
Police Vehicles[1]	-0.006***	-0.005***
	(0.002)	(0.002)
1st Stage F Statistic	38.54	47.94
Observations	2,017,979	2,017,979

Notes: Each observation is a beat and hour in 2009. Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All IV specifications include IVXDivisionXCentralityXDark interactions and fixed effects for beat, month, weekendxhour, and day of week. I also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark.
[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).
[2]Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 6: The Impact of Police Presence on Arrests

	IV=*Unrelated Outside Calls*[2] (1)	IV= *Car Accident Outside Calls*[3] (2)
Police Vehicles[1]	0.047***	0.069***
	(0.010)	(0.009)
Temperature	0.0003***	0.0003***
	(0.0001)	(0.0001)
Precipitation	-0.001***	-0.001***
	(0.0003)	(0.0002)
Twilight	-0.002**	-0.002**
	(0.001)	(0.001)
Holiday	0.002	0.004**
	(0.002)	(0.002)
Time FE's	Yes	Yes
Beat FE's	Yes	Yes
1^{st} Stage F Statistic	38.54	47.94
Observations	2,017,979	2,017,979

Notes: Each observation is a beat and hour in 2009. The average number of police vehicles patrolling a beat in each hour is 0.6 (s.d. 1.1), the average number of arrests is 0.03 (s.d. 0.29). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All specifications include IVXDivisionXCentralityXDark interactions, allowing the impact of out of beat calls to vary across different policing divisions, light/darkness, as well as the centrality of the beat (split by quartiles of number of borders). All Specifications include fixed effects for month, weekendxhour, and day of week. I also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

[2]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.

[3]Number of calls reporting car accidents occurring at outside beats weighted by distance to given beat.

*Significant at 10%; **significant at 5%; ***significant at 1%

Table 7: Examining The Impact of Policing in Public Improvement Districts

	Instrumenting for Police Vehicles with IV:	
	Unrelated Outside Calls[2]	*Car Accident Outside Calls*[3]
	(1)	(2)
A. Dependent Variable = Violent Crimes (mean of dependent variable 0.054, s.d. 0.234)		
Police Vehicles[1]	-0.008	-0.002
	(0.006)	(0.005)
B. Dependent Variable = Public Disturbances (mean of dependent variable 0.052, s.d. 0.231)		
Police Vehicles[1]	-0.007	-0.001
	(0.006)	(0.005)
C. Dependent Variable = Burglaries (mean of dependent variable 0.029, s.d. 0.170)		
Police Vehicles[1]	-0.006	0.001
	(0.005)	(0.004)
D. Dependent Variable = Theft (mean of dependent variable 0.010, s.d. 0.102)		
Police Vehicles[1]	0.0004	0.003
	(0.003)	(0.002)
Time FE's	Yes	Yes
Beat FE's	Yes	Yes
IV Interactions	Yes	Yes
1st Stage F Statistic	38.29	56.12
Observations	147,845	147,845

Notes: Each observation is a beat and hour in 2009. The average number of police vehicles patrolling a beat is 0.60 (s.d. 1.078). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All specifications include IVXDivisionXCentralityXDark interactions, allowing the impact of o of beat calls to vary across different policing divisions, light/darkness, as well as the centrality of the beat (split by quartiles of number of borders). Due to the smaller sample size, I limit the controls to shiftxweekend (a shift is defined as 0-8 AM, 8 AM- 5 PM, and 5 PM- midnight), winter, temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

[2]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and dru houses.

[3]Number of calls reporting car accidents occurring at outside beats weighted by distance to given beat.

*Significant at 10%; **significant at 5%; ***significant at 1%

Table 8: The Deterrence Effect of Police on Crime by Beat Size

	IV= *Unrelated Outside Calls*[2]			IV= *Car Accident Outside Calls*[3]		
	Small	Medium	Large	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)
A. Examining Deterrence During Daytime Hours						
Police Vehicles[1]	-0.064	0.006	-0.041**	-0.002	-0.074***	-0.015
	(0.060)	(0.026)	(0.018)	(0.067)	(0.030)	(0.017)
Mean Level of Police Presence	0.341	0.556	0.991	0.341	0.556	0.991
	[0.565]	[0.890]	[1.509]	[0.565]	[0.890]	[1.509]
Mean Level of Crime	0.154	0.173	0.156	0.154	0.173	0.156
	[0.401]	[0.427]	[0.404]	[0.401]	[0.427]	[0.404]
First Stage F Statistic	6.22	16.87	23.95	4.9	15.55	24.15
Observations	367,111	367,158	371,991	367,111	367,158	371,991
B. Examining Deterrence During Nighttime Hours						
Police Vehicles[2]	-0.006	-0.113***	-0.074***	0.041***	-0.071***	-0.084***
	(0.017)	(0.029)	(0.014)	(0.013)	(0.023)	(0.013)
Mean Level of Police Presence	0.342	0.492	0.886	0.342	0.492	0.886
	[0.670]	[0.810]	[1.429]	[0.670]	[0.810]	[1.429]
Mean Level of Crime	0.15	0.161	0.134	0.15	0.161	0.134
	[0.407]	[0.426]	[0.384]	[0.407]	[0.426]	[0.384]
First Stage F Statistic	24.38	27.57	36.97	34.26	40.57	43.18
Observations	302,564	302,586	306,569	302,564	302,586	306,569
Beat & Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. Standard deviations appear in brackets. All specifications include IVXDivisionXCentralityXDark interactions, allowing the impact of out of beat calls to vary across different policing divisions, light/darkness, as well as the centrality of the beat (split by quartiles of number of borders). All Specifications also include controls for temperature, precipitation, twilight, dark (=1 after sunset), and holiday as well as month, weekend×hour, day of week, and beat fixed effects. Small, medium, and large beats were split equally into 3 groups based on the miles of roads included within the beat (small beats contain less than 4.6 miles of roads and large beats contain more than 8 miles of roads).

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

[2]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.

[3]Number of calls reporting car accidents occurring at outside beats weighted by distance to given beat.

*Significant at 10%; **significant at 5%; ***significant at 1%

5.1 Appendix A: The Data Cleaning Process

5.1.1 The Call Data

1. 684,584 calls recorded by DPD in Dallas, Texas in 2009

2. 551,060 calls after removing duplicate calls and hang-up calls. Calls are defined as duplicates if they are coded as duplicate or false, or if the same problem with the same priority is reported in the same reporting area (the smallest geographic unit used by DPD) within 1.2 hours of each other, or alternatively, if 2 calls are placed reporting incidents that occurred at the exact same geographic coordinates (latitude longitude points) within a 2.4 hour period.

3. 283,668 calls reporting incidents of crime: public disturbances, burglaries, violent crimes, and theft.

4. 44,565 calls reporting car accidents.

5. 19,784 calls reporting fires, child abandonment, mental health related incidents, animal attacks, drug houses, suicides, dead person.

Each call is identified by a unique master incident id and mapped to a beat. Time of incident is determined by the time the call was made to the police department.

5.1.2 The Automated Vehicle Locator Data (AVL)

1. I map 91,975,620 vehicle pings of information (defined by radio name, latitude longitude points, date, and time) into DPD beats using geographic mapping software.

2. In order to differentiate between shifts for a car with the same radio name - I assign a new shift if the car has not been active for at least 2 hours.

3. Collapse data so each observation includes:

    - radio name (includes name of beat allocated to patrol)

- beat
- entrance time to beat
- exit time from beat

5.1.3 The Final Dataset

1. Organized by beat, day, and hour
2. Minutes of actual presence - as defined by latitude & longitude location of police vehicles.
3. Minutes of allocated presence - as defined by radio name and patrol time.

5.2 Appendix B: An Alternative Unrelated Outside Calls Instrument

Table 9: The Impact of Police Presence on Crime (IV=Subset of Unrelated Calls)

	IV= *Unrelated Outside Calls Subset*[2] *(Excluding Mental Health and Animal Attack Calls)* (2)
Police Vehicles[1]	-0.080***
	(0.022)
Temperature	0.002***
	(0.0001)
Precipitation	-0.001***
	(0.0003)
Twilight	0.006***
	(0.002)
Holiday	0.004
	(0.005)
Time FE's	Yes
Beat FE's	Yes
IV Interactions	Yes
1st Stage F Stat	22.63
Observations	2,017,979

Notes: Each observation is a beat and hour in 2009. The average crime rate is 0.15 (s.d. 0.4), average police presence is 0.6 (s.d. 1.1). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. The instrument includes IVXDivisionXCentralityXDark interactions, allowing the impact of out of beat calls to vary across different policing divisions, light/darkness, as well as the centrality of the beat (split by quartiles of number of borders). Time FE's include month, weekendxhour, and day of week controls. I also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

[1]The number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle).

[2]Number of calls unrelated to crime occurring at outside beats weighted by distance to given beat. Unrelated calls include incidents related to child abandonment, fire, dead people, suicides, and drug houses.

*Significant at 10%; **significant at 5%; ***significant at 1%

5.3 Appendix C: Does Police Presence Shift Crime to Neighboring Beats?

Table 10: The Impact of Police Presence on Crime at the Sector Level

	Y=All Crime (1)	Y=Violence (2)	Y=Disturbances (3)	Y=Burglary (4)	Y=Theft (5)
A. Examining Displacement Across Beats (Instrument = *Unrelated Outside Calls*)					
Police Vehicles[1]	-0.222***	-0.107***	-0.075***	-0.040***	-0.009*
	(0.050)	(0.021)	(0.018)	(0.009)	(0.005)
B. Examining Displacement Across Beats (Instrument= *Car Accident Outside Calls*)					
Police Vehicles[1]	-0.074**	-0.044***	-0.010	-0.020***	-0.005
	(0.031)	(0.014)	(0.012)	(0.006)	(0.006)
Mean [Y]	1.029	0.428	0.387	0.214	0.079
	[1.194]	[0.707]	[0.689]	[0.478]	[0.284]
Observations	304,465	304,465	304,465	304,465	304,465

Notes: Each observation is a sector and hour in 2009. The average number of police vehicles patrolling a sector in each hour is 4.013 (s.d. 3.194). Standard errors in parenthesis account for geographic clustering within a 10 km radius, and serial correlation of 5 hours. All specifications include IVXDivisionXDark interactions, allowing out of sector calls to have different effects in different policing divisions and during light/darkness.). All Specifications include fixed effects for sector, month, weekendxhour, and day of week. I also control for temperature, precipitation, twilight, and holiday as well as DivisionXCentralityXDark interactions.

In Part A, Outside calls are defined as the number of calls unrelated to crime occurring at outside sectors weighted by distance to sector (first stage F statistic=63.52). Unrelated calls include incidents related to mental health, child abandonment, fire, animal attacks, dead people, suicides, and drug houses.

In Part B, Outside calls are defined as the number of calls reporting car accidents occurring at outside sectors weighted by distance to given sector (first stage F statistic=81.37).

[1]The number of police vehicles patrolling the sector at given hour (60 minutes of presence = 1 vehicle).

*Significant at 10%; **significant at 5%; ***significant at 1%