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 4.6 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. 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.[2] While some argue that this

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

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

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.[3]

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.[4] These crime prevention techniques are often difficult to practice along 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. 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,

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

[4] See Braga (2012) and Telep & Weisburd (2012) for a review of current deterrence strategies. Puling-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.

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.[5] I focus on the beat (a geographic patrol area averaging one square mile 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.[6] 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.[7] Thus, while this dataset provides a unique picture of police presence across a city, the location of officers may be determined by factors unobserved by the econometrician and correlated with crime.

My identification strategy stems from the two distinct responsibilities facing police

[5] 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.

[6] 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.

[7] 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. Thus, the most common allocation points are either 0 or 1 car allocated per hour. The reason that police presence does not have a 1-1 relationship with police allocation is that officers often spend time outside of their allocated coverage beat.

patrol cars: proactive and reactive policing. While police may be allocated to a certain area in order to create a deterrence effect and lower the expected benefit of committing a crime, they are also responsible for answering emergency calls quickly - generally, in under 8 minutes.[8] 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 *Outside Calls* instrument (OC) which is equal to the number of calls, unrelated to crimes, that officers assigned to a given beat are expected to answer outside of that beat. I show that beats and intervals of time with a higher OC have significantly lower levels of police presence and higher levels of crime (see Figure 2).[9] 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, abandoned properties, dead people, suicides, and drug houses. My results are robust to controlling for beat fixed effects, hour fixed effects, month fixed effects, and day of week fixed effects.

By construction, the *Outside Calls* instrument assumes that officers in all beats will be impacted similarly from assignment to out of beat calls. However, in reality this may not be the case, as certain beat characteristics (baseline level of police assignment, road

[8] 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).

[9] The *Outside Calls* instrument, focuses only on calls reporting incidents related to mental health, child abandonment, fire, animal attacks, abandoned properties, dead people, suicides, and drug houses. In order to allow a comparison between similar beats in this graphic illustration, I focus on those with 4 or less direct neighbors. Thus, for 95 percent of this sample, the probability of outside assignment falls below 20 percent.

density, traffic, etc.) may result in an increased time cost of *Outside Calls.* I therefore also present results for an alternative instrument, the *Outside Calls Shock (OCS)*, which measure the proportional increase in *Outside Calls* from the mean for that beat, day of week, and hour.

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. This positive correlation remains significant even when controlling for location 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 call assignments that I am able to identify a deterrence effect. Using the *Outside Calls* (*OC*) instrument, I estimate that a 10 percent decrease in police presence results in a 6.6 percent increase in crime. The *Outside Calls Shock* (*OCS*) yields a lower deterrence estimate of 4.6 percent for the same change in police presence.

This paper proceeds as follows. In the next section I present a general framework for analyzing the impact of police on crime and discuss the relevant literature. Section 3 introduces the data used for this project as well as my technique for measuring police presence. Section 4 discusses the empirical strategy and presents estimates of the impact of police presence on different types of crimes. Section 5 explores the mechanisms of deterrence that are driving my results. Section 6 concludes.

2 Does Police Presence Affect Behavior?

2.1 Framework

In his 1968 paper, Becker suggested that economists should analyze crime as they do any other major industry (Becker, 1968). Following this approach, I model crime as a specific type of job opportunity. A crime occurs whenever a crime opportunity is matched with an individual willing to accept the job. Burglaries and robberies provide for a cash salary while violent crime may provide alternative utility (e.g. respect, revenge, etc.). Thus, the number of crimes committed (C) will be a function of the the rewards from criminal success (r), expected sanctions from committing a crime (s), and the pool of individual available to commit crimes (N),[10]

$$C = f(r, s, N) \tag{1}$$

We would expect that rational criminals would be more likely to engage in a crime with a higher reward (r) and lower probability of sanction (s). However, it is unclear how potential criminals calculate the expected sanction from a crime. The focus of this paper is the geographic component of deterrence, where the presence of an officer (P) at a specific location at a specific time may impact the perceived probability of sanction (s) and the incidence of crime (C).

2.2 Previous Research

At the end of the 20th century, most studies failed to find a significant impact of policing on crime, whereas today studies often find that increased investment in policing decreases crime $\left(\frac{\partial f(r,s,N)}{\partial P} < 0 \text{ in equation (1)}\right)$.[11] While some of these earlier papers suggested that police are spread too thinly across cities to impact expected sanctions (s), the more recent literature focuses on techniques to mitigate simultaneity bias, a factor that could drive deterrence estimates towards zero. These techniques include time series analysis of aggregate measures of police presence and crime rates, difference-in-differences measures after an abrupt change in police presence, randomized experiments to identify a causal

[10] I assume that the rewards from criminal success (r) take into account losses from choosing not to be employed legally.

[11] See Cameron (1988), Marvell and Moody (1996), Eck & Maguire (2000), Nagin (2013), and Chalfin & McCrary (forthcoming).

effect of police presence on crime, as well as instrumenting techniques.[12] Most of these papers focus on the aggregate number of officers employed over a given period. Implicitly these papers assume that criminals calculate expected sanctions based on the number of officers employed in a given city (deterrence). Or alternatively, that as more officers are employed in a given city they are able to remove repeat offenders (incapacitation) and reduce N (see equation (1)). When more detailed information on police presence is available, it is usually constrained to a specific location in the city over a relatively short treatment period.

In this paper, I apply an instrumenting strategy to estimate the elasticity of crime with respect to police presence. This is inherently different than much of the previous literature which have produced estimates of crime elasticities in relationship to the number of officers employed. Corman and Mocan estimate the elasticity of robberies with respect to police force size to be -0.53 (Corman and Mocan, 2000). They use monthly data in NYC which reduces concerns regarding simultaneity bias as officers can only join the NYPD after a mandatory 6 month training course. Levitt addresses the endogeneity between states and over time regarding crime and police hiring in two separate papers. The first paper uses election year as an instrument for police force size, while the later paper uses the size of the fire department as an instrument for police hiring (Levitt, 1997 & 2002). He estimates an elasticity of -0.4 to -1 for violent crimes and -0.3 to -0.5 for property crimes.[13] Evans and Owens reach a similar conclusion in a cross state comparison using external funding for police hiring as an instrumental variable for police presence (Evans & Owens, 2007). However, Chalfin and McCrary (forthcoming) raise concerns regarding weak instruments and point out that these studies show a wide

[12] See works using Differencing Strategies (Corman and Mocan (2000), Di Tella & Schargrodsky (2004), Klick and Tabarrok (2005), Gould & Steklov (2009), Shi (2009), Draca et al. (2011), Machin and Marie (2011), Ater et al. (2014), MacDonald et al. (2015), Cohen & Ludwig (2003)), Randomized Experiments (Sherman and Weisburd (1995),Braga et al. (1999), Ratcliffe et al. (2011)), Instrumenting Strategies (Levitt (1997 & 2002), and Evans and Owens (2007)).

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

range of estimates that are often not statistically significant at conventional confidence intervals.

In separate papers, Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), Draca et al. (2011), and Gould and Stecklov (2009) measure the effect of an increase in police presence surrounding threats or actual acts of terrorism. Di Tella and Schargrodsky (2004) and Draca et al. (2011) estimate a smaller elasticity of crime with respect to police presence of between -0.3 and -0.4. It is interesting to note that randomized experiments measure a more modest impact of police presence on crime. As discussed in the introduction, the Kansas City Experiment failed to find a significant impact of shifts in police presence on crime (Kelling et al., 1974). 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 find that increasing police presence reduces crime, but only at high-crime micro locations. They examine the impact of alerting police commanders to the spread of patrol officers at treatment beats and hotspots in Dallas, Texas. This led to an increase in patrol throughout the beat, but a decrease in crime only at designated hotspots.

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, Draca et al. (2011) and Mastrobuoni (2016) are the only other paper that attempted to look at the geographic distribution of police officers throughout an entire city. Draca et al. (2011) focus on the allocation of police officers in London boroughs (population size ranging between 150,000 to 300,000) at the weekly level and consider the impact of a 35 percent increase in police presence after a large terrorist attack. One of the major concerns with this literature is that policy implications may be limited, as a 30 to 100 percent increase in police patrol is unlikely to be a feasible long term investment for any city. Mastrobuoni (2016) considers the impact of shift changes occurring at police headquarters in Milan on arrests and crime outcomes. During these shift changes, he finds a significantly lower clearance rates in areas that are farther away from police headquarters, but no effect on crime. He suggests that the lack of result, may be caused by the fact that police still remain visible except for the exact moment when the shift change takes place, actual police presence is not observed. I consider the actual presence of police at the hourly level within Dallas beats (average population of 5,000). Using more detailed data allows me to examine how the precise location of officers at a given time impacts the formation of individual expectations regarding the probability of sanctions (s) through crime outcomes (C) . My elasticity estimates carry with them important policy implications, regarding whether or not small changes in police behavior can have significant impacts on crime.

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).[14] 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. The proposed project provides an estimate of 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.

3 The Data

In equation (1), I model crime as an outcome of rewards (r) , expected sanctions (s) , and the pool of individuals available to commit crimes (N). My empirical analysis will

[14] 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. (1976) found no impact of response times on solving crimes. However, Blanes i Vidal & Kirchmaier (2016) 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 (2016) reaches a similar conclusion when analyzing the outcomes of quasi-experimental variations in police presence in the city of Milan.

focus on the impact of changes in expected sanctions that are driven by changes in police presence in Dallas, Texas. Dallas 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.[15]

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 by a deputy chief of police. Figure 3 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) with a high population of young adults. 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 small geographic areas 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 reported for each beat b and hour

[15] Using geographic mapping software I collect additional information on population size as well as the types of roads and development (residential, business, etc.), along with number of schools, and parks 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.

h.[16] The original database included 684,584 calls recorded throughout 2009 in Dallas, Texas, my final call database consists of 551,073 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 304,851 calls reporting incidents of crime. These crimes are classified into the following categories: public disturbances, burglaries, violent crimes, and theft.[17] Figure 5 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).[18]

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. It can also be matched with call data, which specify the location and type of call being answered by the police officer. Thus, if car A142 is responding to a call reported in beat 133, I am able to identify that he/she is outside of his/her allocated beat. In contrast to an aggregate count of police

[16] Focusing on 911 calls as opposed to crime reports is expected to lower concerns regarding selective reporting of incidents, however, I cannot rule out the possibility that in certain areas crimes may not be called in to the police.

[17] 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.

[18] 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.

officers per city, these data present an opportunity to map the activity of each individual squad car throughout the day.

In order 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.[19] 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.[20]

Figures 6 and 7 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 7 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 2 summarizes the mean hourly values for crime, police allocation and police presence by beat at the division level. The majority of crimes occur in beats that are located in the Southwest side of the city. 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

[19]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.

[20]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.

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 differences observed in the Southeast and then Central and Northwest divisions. 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 2. Beats in the Southwest division average fifty percent more police presence than beats in the Southeast division and they exhibit a significantly 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.

Outside Calls (OC_{bh}) is calculated for each beat (b) and hour (h) as the number of calls officers assigned to beat b are expected to spend answering calls outside of the beat. Hour h is a time variable beginning at 0 at 12 AM on January 1st, 2009 and culminating at h =8759 at 11 PM on December 31st, 2009. The variable $Calls_{Db'h}$ is based on the number of 911 calls received in division D outside of beat b during hour h reporting incidents related to mental health, child abandonment, fire, animal attacks, abandoned properties, dead people, suicides, and drug houses. Importantly, instead of each call being counted equally for all beats in the division, $Calls_{Db'h}{=}\sum_{x\neq b\in D,h} w_{bx}$ is a weighted sum, where $w_{bx} = \frac{\max\_dist_b - dis\tan ce(b,x)}{\max\_dist_b}$.[21] I define PC_{ibh} as the number of minutes patrol car i was allocated to spend in beat b during hour h. $Patrol_{Db'h}$ is the sum of PC_{ixh} for all patrol cars in beats x within division D excluding beat b. I define Outside Calls (OC_{bh}) as,

[21] 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 am able to count the number of calls officers assigned to beat b are likely to answer based on their distance from the calls in that hour.

$$OC_{bh} = \frac{Calls_{Db'h}}{Patrol_{Db'h}} \tag{2}$$

It makes sense that higher levels of *Outside Calls* result in lower police presence. However, it may be that certain beats are better equipped than others to handle out of beat calls. In this case a positive shock in the amount of outside calls in a given hour for a given beat may be a more accurate predictor of changes in police presence for that beat.I address this concern by introducing an alternative instrument, the *Outside Calls Shock* (OCS_{bh}) as,

$$OCS_{bh} = \frac{OC_{bh} - \overline{OC}_{dbt}}{\overline{OC}_{dbt}} \tag{3}$$

The time of day t can be constructed for each hour h as $t = h \bmod 24$. $\overline{OC}_{dbt}$ is defined as the average number of *Outside Calls* for that beat at given time of day t and day of week d.

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.

4 Empirical Strategy and Results

In Section 2, I discussed a general framework for deterrence where police presence (P) is likely to impact crime (C) by increasing the expected sanctions (s) from involvement in criminal activity. In equation (4) I apply this framework to the Dallas data, modelling the occurrence of a crime (C_{bh}) as a function of its costs and benefits,

$$C_{bh} = x_{bh}\beta_0 + \beta_1 P_{bh} + \gamma_t + \eta_b + \varepsilon_{bh} \tag{4}$$

The variables included in x_{bh} capture time varying environment characteristics that could impact the costs and benefits of crime (weather, visibility, weekday/weekend, etc.). The focus of my analysis is P_{bh}, the level of police coverage in beat b and 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 $P_{bh} = 2$. The time and location 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 if 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},

$$P_{bh} = x_{bh}\alpha_0 + \alpha_1 OC_{bh} + \theta_t + \rho_b + \delta_{bh} \tag{5}$$

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 (2), or alternatively, OCS_{bh} as defined in equation (3). 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} or OCS_{bh}) should decrease police presence in the beat (P_{bh}).

Table (3) presents regression estimates for the first stage of my analysis. Part A examines the impact of the *Outside Calls* (OC) on police presence as defined in equation (5).[22] On average, a beat receives police coverage for 60 percent of each hour. In specification (1), I find that increasing *Outside Calls* does not have a statistically significant impact on police presence. Specification (1) cannot rule out the concern that beats that are more centrally located or hours with higher crime risks may have more *Outside Calls* and more police presence, as opposed to the expected negative relationship between OC and P.

The effect of *Outside Calls* on police presence becomes significant in specification (2) once I control for characteristics at the beat level as well as month and hour of the day fixed effects. I also introduce an interaction term between OC and beat centrality. A beat is defined as Centrality (High) if it shares a border with 7 or more beats in its division and Centrality (Medium) if it shares a border with 6 beats (Centrality(Low) is defined as sharing a border with 4 or less beats and is excluded from the regression). In specification (2), I find that increasing *Outside Calls* by 1 decreases police coverage by 0.485 ($60 \times 0.48 = 29$ minutes). Since average police presence in a given hour and beat is 0.6 this implies that the allocation of officers to calls outside of their beat results in an 80 percent decrease in police coverage. In the final specification which includes location fixed effects, along with hour fixed effects, month fixed effects, and controls for time

[22] The number of *Outside Calls* for each location and time is calculated using equation (2).

varying day characteristics, I find a one unit change in *Outside Calls* decreases police presence by 67 percent $\left(\frac{\widehat{\alpha}_1=0.397}{\overline{P_{bh}}=0.6}\times 100\right)$. Not surprisingly, the effect is even larger for more centrally located beats, where allocated police officers have easy access to multiple outside beats.

I also find significant effects when examining the impact of the *Outside Calls Shock* (OCS) in Part B of Table (3). I find that positive shocks in *Outside Calls* result in lower levels of police presence. Specifically, a 100% increase in *Outside Calls* from the baseline expected for that beat, hour and day of week results in a decrease in police presence of 0.035 (s.e. 0.007), implying a 6 percent change $\left(\frac{\widehat{\alpha}_1=0.035}{\overline{P_{bh}}=0.6}\times 100\right)$. Importantly, focusing on shocks in *Outside Calls,* lowers heterogeneity concerns regarding beats that may be different in multiple unobserved factors related to crime in addition to the number of *Outside Calls* that occur in their surrounding areas. Indeed, including beat fixed effects (in specification (3)) had little impact on the estimates resulting from specification (2). The impact of both instruments on police presence is significant at the one percent level and illustrates the strong impact of 911 calls on police coverage.

These instruments use incidents occurring in surrounding areas as an exogenous factor impacting presence in the given beat. Neither instrument would fall under the weak instrument category, as the F-statistic on the excluded instruments is above 20 for both specifications. While *Outside Calls* is a straightforward way to measure the number of calls occurring in surround beats, the *Outside Calls Shock* has the added benefit of being more uniformly defined across different beats. I therefore provide estimates of the deterrence effect using both *Outside Calls* and the *Outside Calls Shock* instruments in the subsequent tables.

I estimate the impact of police presence on all crimes using equation (4) for OLS, fixed effects, and 2SLS specifications. 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 OLS model (column (1) of Table (4)) I find that an increase in police presence seems to imply an increase in crime even when controlling for observed location characteristics as well as time fixed effects. This estimate becomes more positive when controlling for location fixed effects as well as weather and day characteristics in specification (2). These results suggest that the presence of an additional police car at a given beat results in a significant 0.013 increase in crime (at an average crime rate of 0.148).

Two stage least squares estimates appear in columns (3) and (4) of Table (4) , these results measure the deterrence effect when actual police presence (P_{bh}) is instrumented with the *Outside Calls* (OC_{bh}) . In order to maximize the flexibility of the instrument in impacting police presence, *Outside Calls* is interacted with dummies for centrality of beat and division. This allows different divisions to follow different protocols, or face different constraints regarding between beat allocation, as well as heterogenous impacts of *Outside Calls* on beats at varying levels of centrality. 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 (3), I control for observed location characteristics and month and hour fixed effects and estimate a deterrence impact of -0.018 (0.024) using the *Outside Calls* instrument. The coefficient increases in size to 0.162 (0.022) and becomes significant after adding in location fixed effects, as well as weather, and time of day characteristics in specification (4). While β_1 in equation (4) represents the effect of an additional police vehicle (P_{bh}) on crime, what is driving the estimate is the reality that police cars are often withdrawn from beats because of being assigned to calls in other beats. Accordingly, a real world interpretation of this effect is that removing 60 minutes of presence from a given beat at a given hour results in a 110 percent increase in crime $\left(100 \times \frac{0.162}{0.148}\right)$. If I focus on average police presence per hour (36 minutes), a 10 percent decrease in police presence implies a 6.6 percent increase in crime (elasticity of -0.66).

Specifications (5) and (6) apply the *Outside Calls Shock* which has a more uniform interpretation across beats. I find a smaller deterrence effect when focusing on changes in police presence that are driven by the *Outside Calls Shock* (see column (6) versus column (4)). The estimated deterrence impact of -0.113 (0.020) when examining the impact of an additional police vehicle in a given beat b and hour h implies that a 10 percent decrease in police presence will results in a 4.6 percent increase in crime (elasticity of -0.46).

Table (4) also provides information on how different weather and time characteristics impact crime outcomes. I find that crime is 15 percent more likely to occur on weekends. Higher temperatures increase the occurrence of crime, and bad weather lowers the probability of crime.

In Table (5) , I separately examine the impact of police on different types of crimes (violent crimes, public disturbances, theft, and burglaries) following the same format as in Table (4). All crime types exhibit a significant positive correlation between police presence and crime (see columns (1) and (2)) that disappears when instrumenting for police presence with *Outside Calls* (see columns (3) and (4)). 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 correlation between policing and crime is not impacted by the type of crime committed.

The estimated deterrence effects from instrumenting for police presence with the *Outside Calls Shock* as reported in columns (5) and (6) of Table (5) are significantly smaller than those estimated when instrumenting with the *Outside Calls Shock* for all specifications. 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 5.6-7.2 percent.[23] In Row B, I find that this same change in police presence results in a 4.1-7

[23] I classify violent crimes as stabbings, shootings, robberies, assaults, kidnappings, and armed en-

percent decrease in public disturbances.[24] I also find a significant effect of police presence on theft in Row C, where a 10 percent increase in police presence is expected to reduce theft by 4.5 to 5 percent. I estimate that an increase in police presence will have the smallest effect on burglary (elasticity of 0.3-0.4).

In order to ensure the robustness of my results I run my analysis using an alternative *Outside Call Shock* which is driven by car accidents that occur outside of beat b, as opposed to general unrelated incidents.[25] In Table (6) I continue to find a significant impact of police presence on crime using this alternative instrument. Table (6) also provide an opportunity to examine whether or not crime types are impacted differently by changes in visibility and weather. I find that violent crimes, and public disturbances are more likely to occur in warmer weather. Additionally, burglaries and thefts tend to occur on weekdays while violent crimes and public disturbances are more likely on holidays and weekends. Not surprisingly, fewer public disturbances are reported in rainy weather, as these incidents usually occur outside.

As an additional check on this model, I show that these strong impacts of police presence on crime disappear when focusing on urgent non-crime related incidents, or beats that are known to have privately funded security patrol. In the first column of Table (7), I examine the impact of police presence on calls related to mental health, child abandonment, and suicide. These calls should not be sensitive to the probability of punishment and indeed, when instrumenting with the *Outside Call Shock* I find no sig-

counters. The deterrence impact was calculated by taking the estimate impact of an additional police vehicle on violent crime (-0.076 (using OC instrument) & -0.059 (using OCS instrument)) relative to the average violent crime rate of 0.063. Thus, the OC (OCS) estimate implies that an additional police car results in a 120 (94) percent decrease in 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.

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

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

nificant deterrence effect.[26] In columns (2)-(5), 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 it seems less likely that criminals would change behavior due to 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 related to public disturbances, theft, and burglary. However, I continue to find a significant impact of police presence on violent crimes within Public Improvement Districts.

5 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? Are police officers more effective when allocated to smaller 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* and the *Outside Calls Shock* instruments 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 (8), I find a significant impact of police presence on arrests when in-

[26] I focus on calls reporting mental health, child abandonment, and suicide as these incidents are unlikely to be deterred by police presence but still require immediate police assistance.

strumenting with both *Outside Calls* and the *Outside Calls Shock*. Thus, a 10 percent increase in police presence increases the probability of arrest by 3 to 5.5 percent, thereby doubling the average arrest rate per beat and hour. This suggests that police are creating deterrence, not only by being present in the area, but actively reminding individuals that there are repercussions for criminal behavior.[27]

If police presence impacts crime by providing a visual reminder of the costs of crime, I would expect smaller beats, where officers are more likely to be seen, to be more affected by losing a police vehicle than larger beats. In Table (9), I run my analysis separately for small beats (less than 4 miles of roads), midsize beats (4 to 8 miles of roads), and large beats (more than 8 miles of roads). I find that police vehicles have a larger impact on crime in smaller areas when using *Outside Calls* and the *Outside Calls Shock* instruments. When instrumenting for police presence with *OC*, I find that each additional car reduces crime by 0.191 (0.044) in the smaller beats versus 0.228 (0.043) in midsize beats and 0.102 (0.025) in the larger beats. This implies that a 10 percent increase in police presence in a small beat at a given hour results in a 3.9 percent decrease in crime $\left(100 \times 0.03 \times \frac{-0.191}{0.145}\right)$, versus a 6.5 percent decrease in large beats $\left(100 \times 0.09 \times \frac{-0.102}{0.141}\right)$.

It is interesting to note that while smaller 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.[28] This is driven by the significant difference in average police presence between small and large beats, where small (large) beats average 20 (57) minutes of police presence per hour. I estimate a slightly larger impact of police presence on small beats and significantly smaller impact on large beats

[27] When examining hourly data it seems reasonable that arrests impact crime by increasing awareness of police presence as opposed to incapacitation. An incapacitation effect would only make sense in this case if the individual arrested had planned to commit a crime at that exact unit of time.

[28] My estimates represent the impact of an additional police vehicle on crime. As discussed previously since what is driving these estimates is the reality that officers are being withdrawn from their allocated beats, it is relevant to discuss the impact of a decrease in police presence.

when instrumenting with the *Outside Calls Shock* instrument. Specifically, a 10 percent increase in police presence in a small beat at a given hour results in a 4.7 percent decrease in crime $\left(100 \times 0.03 \times \frac{-0.226}{0.145}\right)$, versus a 2.5 percent decrease in large beats $\left(100 \times 0.09 \times \frac{-0.039}{0.141}\right)$.This baseline rate of police presence per beat may also contribute to the size of the deterrence effect. In other words, taking an officer away from a beat that averages little to no police presence may be more detrimental to crime control than taking an officer from a beat with relatively high levels of police presence.

Throughout this paper I have focused on estimating the immediate impact of police presence on crime. In Table (10), I consider how police presence in previous hours impacts crime in hour h. A positive coefficient on previous police presence would suggest a displacement effect, where the location of officers impacts the timing of crime as opposed to the occurrence of crime. In specifications (1)-(3), I consider the impact of police presence in the previous hour, previous 2 hours, and previous 3 hours on total crime. In all specifications and time periods I instrument for actual police presence with the *Outside Calls Shock*. The impact of past presence on current crime is not statistically significant from zero in any of these specifications.

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 activities to neighboring beats. In Dallas, beats are grouped into sectors, with each sector comprised of roughly 7 beats. Table (11) summarizes how changes in police presence at the sector level impact crime. I instrument for police presence using the average *Outside Calls Shock* for beats in that sector during that hour long period. My estimated deterrence results are very similar to those found when running the analysis at the beat level (see Table (6)). If crime were displacing to neighboring beats, I would expect a decrease in crime at the beat where the police car was located, combined with an increase in crime at neighboring beats. These results suggest that crime does not easily displace to neighboring areas.

6 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.[29] 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 a more noisy reflection of investment, departments may prefer to focus on shortening response times, an easily measured police activity.[30] Indeed, The Dallas Morning News reported in 2013 that after criticism of rising response times to 911 calls

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

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

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 each 10 percent decrease in police presence at a given beat and hour increases crime at that location by 4.6 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) and Blanes i Vidal & Kirchmaier (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.[31] 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 square mile) 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 impact crime outcomes. I find that assigning officers to out of beat calls, not only reduces police presence, but also lowers arrest rates. Since the analysis in this paper focuses on the immediate impact of police at a given hour on crime, these results suggest that this decrease in arrests (as police presence decreases) could be increasing crime. This effect is different from a long term incapacitation effect that is often attributed to arrests, where crime decreases because more criminals are being taken off the streets.[32]

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

[32] 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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6.1 Appendix A: The Data Cleaning Process

6.1.1 The Call Data

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

2. 551,073 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. 304,851 calls reporting incidents of crime: public disturbances, burglaries, violent crimes, and theft.

4. 246,222 remaining calls record car accidents, fires, child abandonment, mental health related incidents, animal attacks, alarms, calls for officer assistance, abandoned property, drug house, suicides, blockage, etc.

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.

6.1.2 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
- master incident id

6.1.3 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.

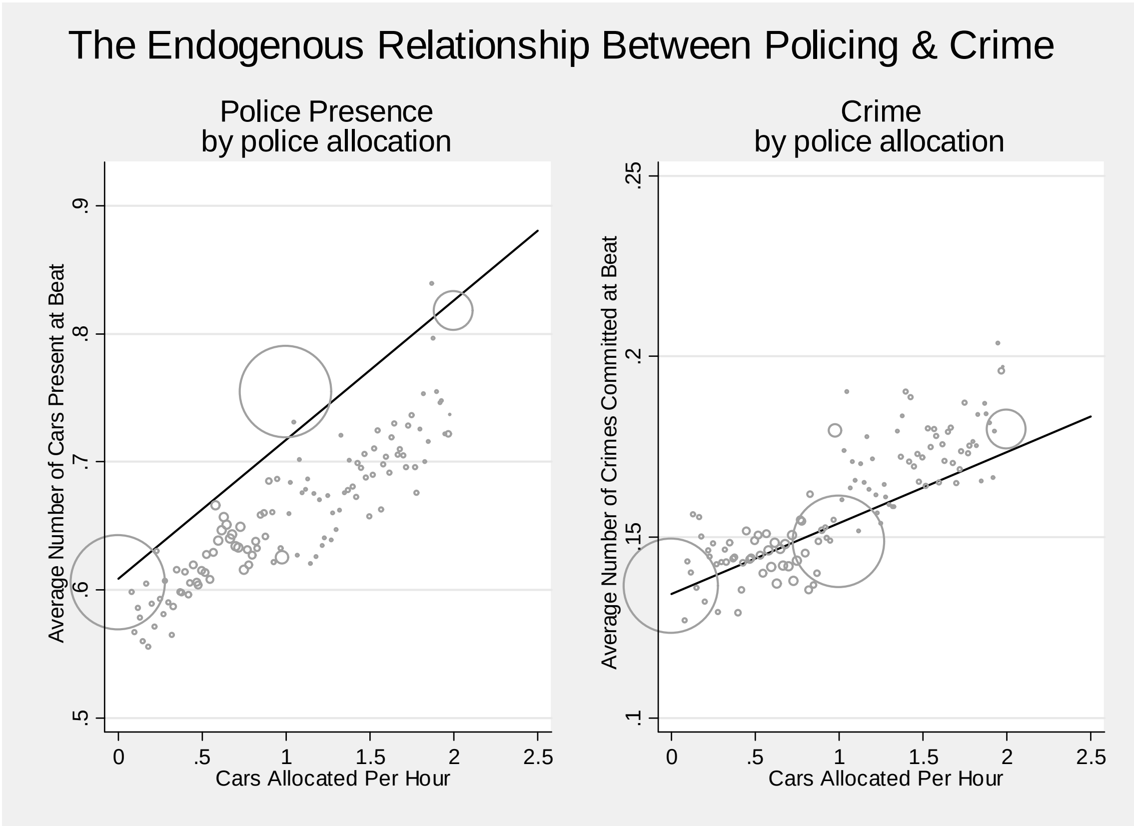

Figure 1: The data was collapsed at each vehicle allocation point. Generally either 0,1, or 2 cars are allocated to patrol a given beat at a given hour. However, if a car did not begin or end patrol on the hour this results in a fraction of car allocation. The size of the circle relates to the density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

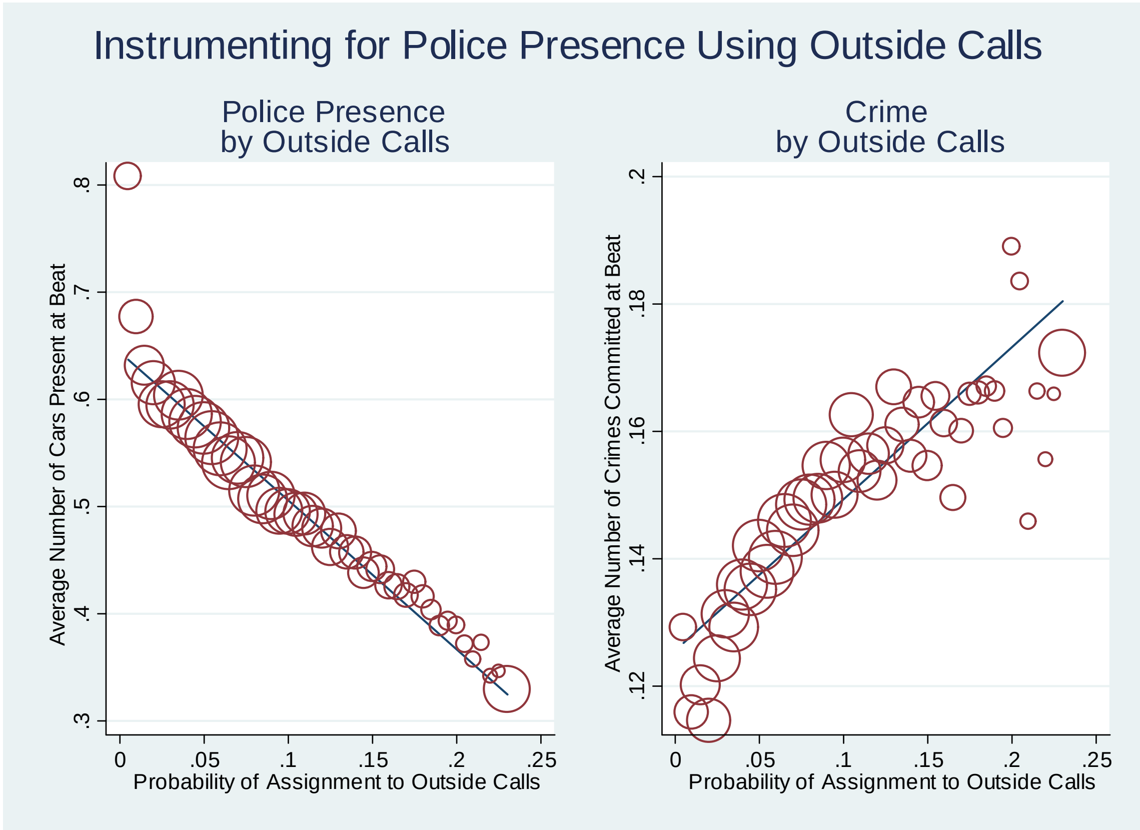

Figure 2: The data was collapsed at each fraction of hour allocated to out of beat calls. The size of the circle relates to the density of observations at that fraction of time allocated to out of beat calls.

Figure 3: Dallas Beats

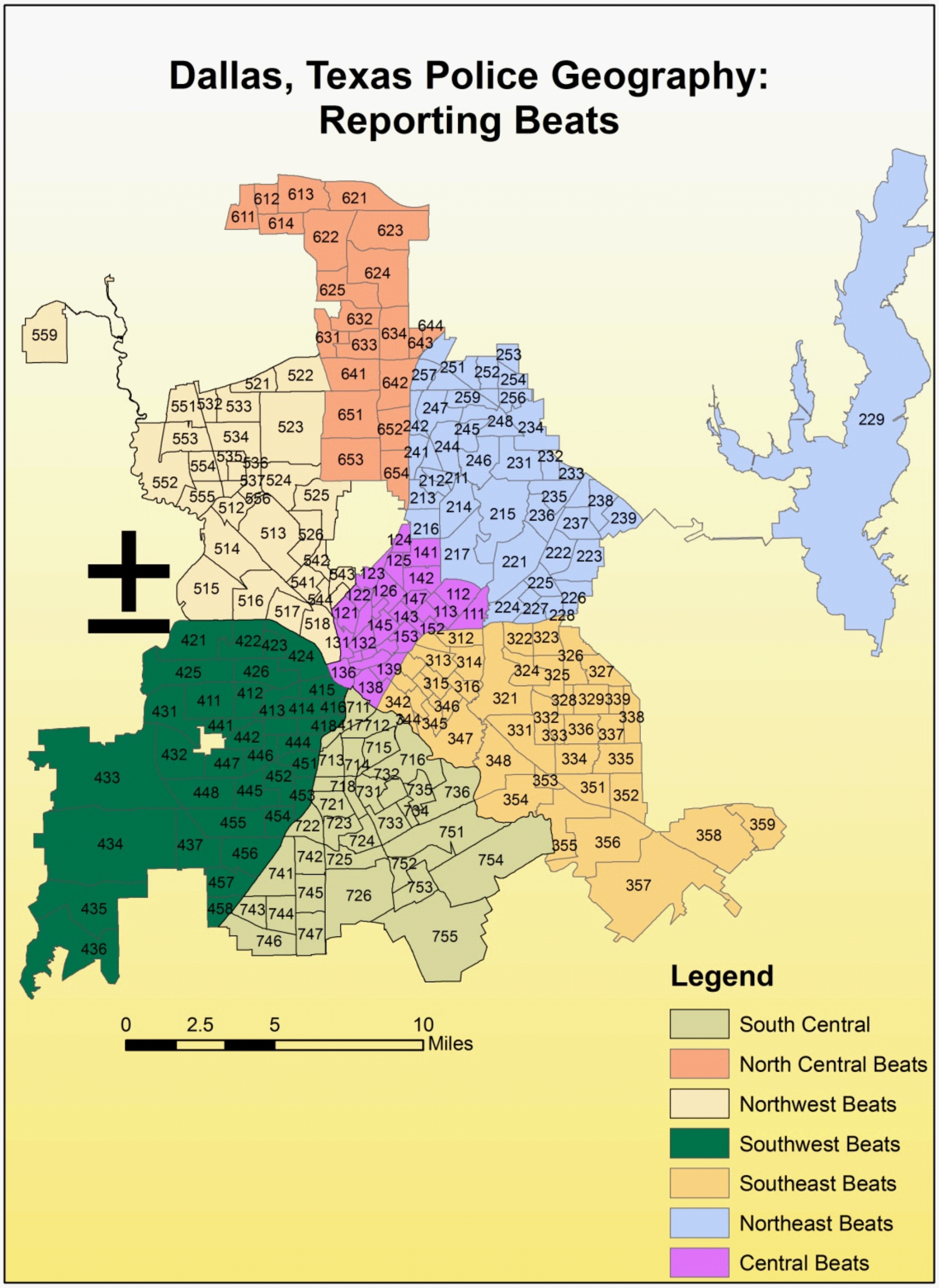

Figure 4: The Distribution of Crime in 2009

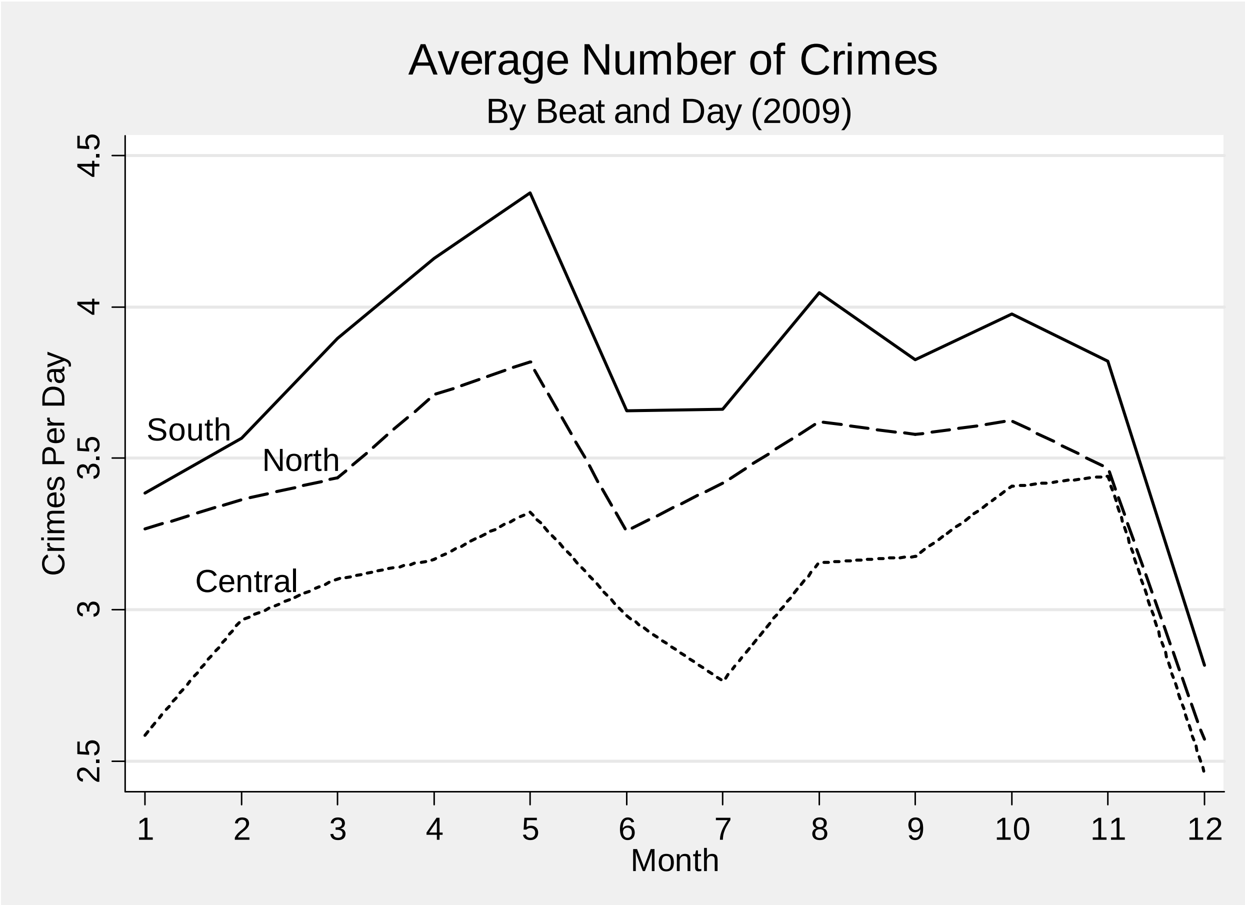

Figure 5: The data was collapsed at each beat and day of year. The South line is the average number of crimes commited per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of crimes commited per beat and day in the Northeast, Northwest, and North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

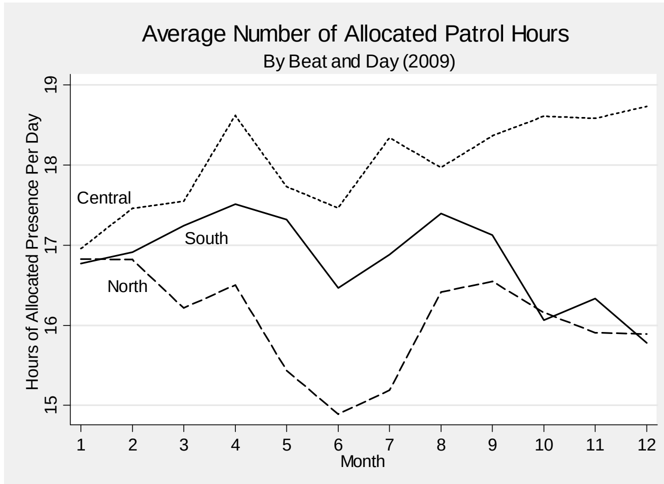

Figure 6: The data was collapsed at each beat and day of year. The South line is the average number of allocated patrol hours per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of allocated patrol hours per beat and day in the Northeast, Northwest, and North Central Divisions.

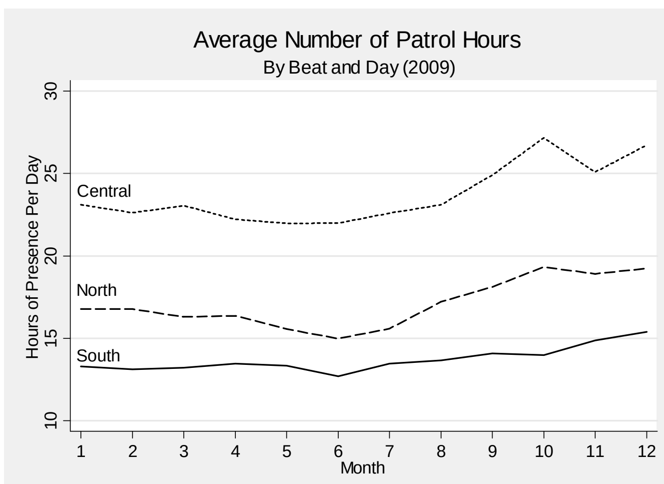

Figure 7: The data was collapsed at each beat and day of year. The South line is the average hours of actual police presence per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average hours of actual police presence per beat and day in the Northeast, Northwest, and North Central Divisions.

Table 1: Beat Characteristics Summarized by Division

	Central (1)	North Central (2)	North East (3)	North West (4)	South Central (5)	South East (6)	South West (7)
Schools	1.10	1.95	1.46	1.35	1.30	1.15	1.91
	(1.35)	(1.70)	(1.60)	(1.85)	(1.24)	(0.93)	(1.63)
Acres	390.06	1074.18	1440.65	973.95	954.49	1041.23	1454.32
	(206.87)	(754.57)	(4619.66)	(700.51)	(1022.06)	(1143.44)	(2127.89)
Population	3258.00	8613.86	6252.76	4913.35	3081.38	3997.67	5842.94
	(2695.87)	(4148.73)	(2986.74)	(3381.12)	(1445.97)	(1832.93)	(3087.18)
Miles of roads	6.22	9.53	5.97	8.97	6.37	6.32	8.97
	(3.77)	(6.30)	(3.88)	(5.45)	(5.37)	(3.63)	(7.30)
Household size	1.92	2.23	2.49	2.45	2.91	3.24	3.21
	(0.54)	(0.38)	(0.37)	(0.58)	(0.25)	(0.58)	(0.52)
Percent Black	0.15	0.12	0.23	0.15	0.72	0.44	0.26
	(0.12)	(0.08)	(0.15)	(0.16)	(0.17)	(0.27)	(0.23)
Percent Hispanic	0.29	0.25	0.33	0.45	0.25	0.47	0.62
	(0.20)	(0.21)	(0.16)	(0.26)	(0.16)	(0.24)	(0.24)
Percent Asian	0.03	0.06	0.05	0.05	0.003	0.003	0.01
	(0.02)	(0.04)	(0.05)	(0.05)	(0.01)	(0.005)	(0.01)
Percent young[1]	0.42	0.26	0.27	0.32	0.20	0.22	0.24
	(0.12)	(0.12)	(0.09)	(0.10)	(0.02)	(0.02)	(0.04)
Household income	38409.6	75819.6	44423.3	38770.5	28069.3	27410.7	34301.1
	(13329.34)	(18981.49)	(14233.60)	(21082.19)	(8138.17)	(8372.98)	(8708.15)
Number of beats	29	22	41	31	37	39	33

Notes: Standard deviations are presented in parenthesis.
[1]Percent young refers to the average percent of young adults (age 20 to 34) residing in beats.

Table 2: Hourly Means for Beats Summarized by Division

	Central (1)	North Central (2)	North East (3)	North West (4)	South Central (5)	South East (6)	South West (7)
Public Disturbances[1]	0.049	0.058	0.053	0.051	0.040	0.053	0.071
	(0.225)	(0.243)	(0.233)	(0.229)	(0.201)	(0.235)	(0.273)
Burglaries	0.016	0.024	0.022	0.020	0.018	0.020	0.024
	(0.126)	(0.156)	(0.148)	(0.141)	(0.136)	(0.143)	(0.156)
Violent Crimes[2]	0.052	0.050	0.063	0.051	0.068	0.074	0.074
	(0.231)	(0.228)	(0.255)	(0.229)	(0.265)	(0.275)	(0.276)
Theft	0.011	0.013	0.012	0.014	0.010	0.011	0.014
	(0.104)	(0.112)	(0.109)	(0.120)	(0.100)	(0.104)	(0.117)
Total Crimes	0.127	0.144	0.149	0.136	0.136	0.157	0.182
	(0.367)	(0.393)	(0.400)	(0.378)	(0.379)	(0.410)	(0.443)
Allocated Police Coverage[3]	0.754	0.815	0.654	0.595	0.636	0.770	0.702
	(0.714)	(0.607)	(0.664)	(0.582)	(0.621)	(0.741)	(0.658)
Police Presence[4]	0.992	0.912	0.527	0.825	0.519	0.508	0.713
	(1.761)	(1.110)	(0.813)	(1.280)	(0.867)	(0.865)	(1.065)
Outside Calls (OC)[5]	0.121	0.085	0.088	0.122	0.100	0.092	0.101
	(0.091)	(0.073)	(0.066)	(0.090)	(0.073)	(0.073)	(0.074)
OC Shock (OCS)[6]	0.216	0.244	0.216	0.221	0.227	0.214	0.222
	(0.387)	(0.433)	(0.386)	(0.394)	(0.403)	(0.388)	(0.394)
Beats	29	22	41	31	37	39	33
Observations	252,386	191,530	356,247	269,699	321,567	339,375	287,166

Notes: Standard deviations are presented in parenthesis.

[1] Public intoxication, illegal parking, suspicious behavior, prostitution, loud music, gun fire, speeding, road rage, and panhandlers are classified as public disturbances.

[2] Stabbings, shootings, robberies, assaults, kidnappings, and armed encounters are classified as violent crimes.

[3] Police vehicles allocated to beat per hour (60 minutes = 1 vehicle)

[4] Police vehicles present in beat per hour (60 minutes = 1 vehicle)

[5] Number of calls unrelated to crime that officers allocated to this beat are expected to answer at outside beats. Unrelated calls are defined as those reporting incidents related to mental health, child abandonment, fire, animal attacks, abandoned properties, dead people, suicides, and drug houses.

[6] The proportional increase in outside unrelated calls from the mean for that beat, day of week, and hour (OCS=1 implies a 100 percent increase in outside calls).

Table 3: Outside Calls and Outside Calls Shock as Predictors of Police Presence

	(1)	(2)	(3)
A. Instrumenting for Police Presence with Unrelated Outside Calls (mean police presence=0.6)			
Outside Calls[1]	-0.187	-0.485***	-0.397***
	(0.164)	(0.143)	(0.050)
Outside Calls X Centrality (Medium)		0.186	-0.209**
		(0.213)	(0.100)
Outside Calls X Centrality (High)		0.079	-0.275**
		(0.301)	(0.130)
Holiday		-0.090***	-0.087***
		(0.011)	(0.011)
Weekend		-0.101***	-0.097***
		(0.012)	(0.012)
B. Instrumenting for Police Presence with a Shock in Outside Calls (mean police presence=0.6)			
Outside Calls Shock[2]	-0.093***	-0.027***	-0.035***
	(0.014)	(0.008)	(0.007)
Outside Calls Shock X Centrality (Medium)		-0.041**	-0.036*
		(0.017)	(0.019)
Outside Calls Shock X Centrality (High)		-0.057**	-0.049**
		(0.022)	(0.021)
Holiday		-0.092***	-0.091***
		(0.011)	(0.011)
Weekend		-0.118***	-0.118***
		(0.013)	(0.013)
Time Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	2,017,970	2,017,970	2,017,970

Notes: Each observation is a beat and hour in 2009. Standard errors account for clustering at the beat level. Degree of Centrality is defined by the number of neighboring beats within the given division. The interaction term for Centrality (Low) which is defined as having less than 5 beats is excluded from regression. I report results for interaction term with Centrality (Medium)= 6 neighbors, and Centrality (High)=7 or more neighbors. Time Fixed Effects refer to including 11 month dummies and 23 hour dummies.
Specification (2) interacts number of outside calls with beat centrality and includes additional controls: percent Black, percent Hispanic, percent Asian, average household size, average individual income, average household income, size of beat, miles of road within beat, percent children, percent teens, and percent vacant homes.
Specification (3) includes additional controls: temperature, precipitation, twilight, and dark.
[1]Number of calls unrelated to crime that officers allocated to this beat are expected to answer at outside beats. Unrelated calls are defined as those reporting incidents related to mental health, child abandonment, fire, animal attacks, abandoned properties, dead people, suicides, and drug houses. [2]The proportional increase in outside-unrelated-calls from the mean for that beat, day of week, and hour.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 4: The Effect of Police Presence on Crime

	OLS		IV=Outside Calls[2]		IV=Outside Calls Shock[3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Police Vehicles[1]	0.009***	0.013***	-0.018	-0.162***	-0.107***	-0.113***
	(0.003)	(0.002)	(0.024)	(0.022)	(0.026)	(0.020)
Individuals in household	-0.017		-0.023		-0.043*	
	(0.014)		(0.014)		(0.015)	
Percent Hispanic	0.093***		0.083**		0.049	
	(0.035)		(0.037)		(0.061)	
Percent Asian	-0.226***		-0.237***		-0.274	
	(0.077)		(0.087)		(0.177)	
Percent Teens	0.294		0.540*		1.345*	
	(0.208)		(0.291)		(0.790)	
Temperature		0.001***		0.001***		0.001***
		(0.0001)		(0.0001)		(0.0001)
Precipitation		-0.001***		-0.001***		-0.001***
		(0.0003)		(0.0003)		(0.0003)
Twilight		0.008***		0.008***		0.008***
		(0.002)		(0.002)		(0.002)
Holiday		0.010***		0.008***		0.003
		(0.002)		(0.002)		(0.002)
Weekend		0.037***		0.016***		0.022***
		(0.002)		(0.003)		(0.003)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2,017,970	2,017,970	2,017,970	2,017,970	2,017,970	2,017,970

Notes: Each observation is a beat and hour in 2009. The average crime rate is 0.148 (s.d. 0.398), average police presence is 0.605 (s.d. 1.079). Standard errors in parenthesis account for clustering at the beat level. Time Fixed Effects refer to including 11 month dummies and 23 hour dummies. All specification includes IVXDivisionXCentrality interactions, this allows out of beat calls to have different effects in different policing divisions and for beats that are more centrally located to be more affected by out of beat calls. Specifications (1),(3) and (5) include additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, percent children, and percent vacant homes. Specifications (2), (4) and (6) also control for darkness.

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

[2]The number of calls unrelated to crime that officers allocated to this beat are expected to answer at outside beats. Unrelated calls are defined as those reporting incidents related to mental health, child abandonment, fire, animal attacks, abandoned properties, dead people, suicides, and drug houses.

[3]The proportional increase in outside-unrelated-calls from the mean for that beat, day of week, and hour.

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

Table 5: The Effect of Police Presence on Different Types of Crimes

	OLS		IV=Outside Calls[1]		IV=Outside Calls Shock[2]	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent Variable = Violent Crimes (mean of dependent variable 0.063, s.d. 0.255)						
Police Vehicles	0.004***	0.006***	-0.007	-0.076***	-0.057***	-0.059***
	(0.001)	(0.001)	(0.007)	(0.010)	(0.011)	(0.010)
B. Dependent Variable = Public Disturbances (mean of dependent variable 0.053, s.d. 0.235)						
Police Vehicles	0.003***	0.005***	-0.014*	-0.062***	-0.035***	-0.036***
	(0.001)	(0.001)	(0.007)	(0.011)	(0.009)	(0.009)
C. Dependent Variable = Theft (mean of dependent variable 0.012, s.d. 0.109)						
Police Vehicles	0.001**	0.001***	0.002	-0.010***	-0.007**	-0.009***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
D. Dependent Variable = Burglaries (mean number of dependent variable 0.020, s.d. 0.144)						
Police Vehicles	0.002***	0.002***	0.001	-0.014***	-0.009**	-0.010***
	(0.000)	(0.000)	(0.002)	(0.003)	(0.004)	(0.004)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2,017,970	2,017,970	2,017,970	2,017,970	2,017,970	2,017,970

Notes:
Each observation is a beat and hour in 2009. Police vehicles refer to the number of police vehicles patrolling the beat at given hour (60 minutes of presence = 1 vehicle). Standard errors in parenthesis account for clustering at the beat level. Time Fixed Effects refer to including 11 month dummies and 23 hour dummies. All specification includes IVXDivisionXCentrality interactions, this allows out of beat calls to have different effects in different policing divisions and for beats that are more centrally located to be more affected by out of beat calls.
Specifications (1),(3) and (5) include additional controls: percent black, percent hispanic, percent asian, average household size, average individual income, average household income, size of beat, miles of road within beat, percent teens, percent children, percent vacant homes. Specifications (2), (4), and (6) also include controls for temperature, precipitation, twilight, dark (=1 after sunset), holiday, and weekend.
[1]The number of calls unrelated to crime that officers allocated to this beat are expected to answer at outside beats. Unrelated calls are defined as those reporting incidents related to mental health, child abandonment, fire, animal attacks, abandoned properties, dead people, suicides, and drug houses.
[2]The proportional increase in outside-unrelated-calls from the mean for that beat, day of week, and hour.

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

Table 6: Estimating Crime Impacts when Instrumenting with Car Accident OCS

	All Crime (1)	Violence (2)	Disturbances (3)	Theft (4)	Burglary (5)
Police Vehicles[1]	-0.168***	-0.077***	-0.064***	-0.014***	-0.013***
	(0.022)	(0.010)	(0.011)	(0.003)	(0.005)
Temperature	0.001***	0.001***	0.001***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.001***	-0.000	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Twilight	0.008***	0.003***	0.003***	0.001*	0.001**
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Dark	0.002	0.000	0.000	0.001*	0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Holiday	-0.009***	0.000	-0.000	-0.004***	-0.005***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Weekend	0.016***	0.007***	0.016***	-0.002***	-0.005***
	(0.003)	(0.001)	(0.002)	(0.000)	(0.001)
Mean of Dependent Variable	0.148	0.063	0.053	0.012	0.02
	[0.398]	[0.255]	[0.235]	[0.109]	[0.144]
Time FE's	Yes	Yes	Yes	Yes	Yes
Location FE's	Yes	Yes	Yes	Yes	Yes
Observations	2,017,970	2,017,970	2,017,970	2,017,970	2,017,970

Notes:
Standard errors in parenthesis account for clustering at the beat level. Standard deviations are presented in brackets. OCS is calculated as the proportional increase in outside-car-accident-calls from the mean for that beat, day of week, and hour. Time Fixed Effects refer to including 11 month dummies and 23 hour dummies. All specifications include OCSXDivisionXCentrality interactions, this allows out of beat calls to have different effects in different policing divisions and for beats that are more centrally located to be more affected by out of beat calls. Mean police presence is equal to 0.605 (s.d. 1.079).

[1]Police vehicles per beat within given hour (60 minutes = 1 vehicle).

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

Table 7: Examining Situations Where Deterrence Should Play a Less Significant Role

	Non-Crime Calls (1)	Violence in PID (2)	Disturbances in PID (3)	Theft in PID (4)	Burglary in PID (5)
Police Vehicles[1]	-0.002	-0.042***	-0.009	0.005	-0.007
	(0.002)	(0.013)	(0.012)	(0.005)	(0.007)
Temperature	0.0001***	0.001***	0.0004***	-0.000	-0.000
	(0.00001)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.000	0.000	-0.002***	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Twilight	-0.000	-0.010***	-0.002	0.002	-0.005***
	(0.000)	(0.003)	(0.003)	(0.001)	(0.002)
Dark	-0.001**	0.005**	0.006**	0.003***	-0.001
	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)
Holiday	-0.001**	-0.006	0.004	-0.003*	-0.006***
	(0.0004)	(0.004)	(0.004)	(0.002)	(0.002)
Weekend	-0.000	0.007**	0.019***	0.000	-0.004**
	(0.000)	(0.003)	(0.003)	(0.001)	(0.002)
Mean of Dependent Variable	0.006 [0.080]	0.053 [0.232]	0.048 [0.224]	0.01 [0.102]	0.018 [0.135]
Time FE's	Yes	Yes	Yes	Yes	Yes
Location FE's	Yes	Yes	Yes	Yes	Yes
Observations	2,017,970	147,845	147,845	147,845	147,845

Notes: Standard errors in parenthesis account for clustering at the beat level. Standard deviations are presented in brackets. OCS is calculated as the proportional increase in outside-unrelated-calls from the mean for that beat, day of week, and hour. Specification (1) measures the impact of a change in police presence on calls reporting child abandonment, mental health issues, and suicide. Specifications (2)-(5) focus on a subset of the data (17 beats) that include public improvement districts. For these specifications, I am unable to include both month and hour fixed effects, instead I control for summer and winter months as well as Shift FE's (0-8 AM, 8 AM-5PM, and 5 PM-Midnight). Time Fixed Effects refer to including 11 month dummies and 23 hour dummies. All specifications include OCSXDivisionXCentrality interactions, this allows out of beat calls to have different effects in different policing divisions and for beats that are more centrally located to be more affected by out of beat calls. Mean police presence is equal to 1.033 (s.d. 2.076).

[1]Police vehicles per beat within given hour (60 minutes = 1 vehicle).

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

Table 8: The Impact of Police Presence on Arrests

	IV=Outside Calls		IV=Outside Calls Shock	
	(1)	(2)	(3)	(4)
Police Vehicles[1]	0.013*	0.031***	0.016**	0.017**
	(0.008)	(0.007)	(0.007)	(0.007)
Individuals in household	-0.013**		-0.012**	
	(0.005)		(0.006)	
Percent Hispanic	0.043***		0.044***	
	(0.014)		(0.014)	
Percent Asian	-0.027		-0.026	
	(0.057)		(0.057)	
Percent Vacant Houses	0.129***		0.134***	
	(0.047)		(0.046)	
Temperature		0.0003***		0.0003***
		(0.000)		(0.000)
Precipitation		-0.001***		-0.001***
		(0.000)		(0.000)
Twilight		-0.002**		-0.002**
		(0.001)		(0.001)
Dark		-0.004***		-0.004***
		(0.001)		(0.001)
Holiday		0.002		0.000
		(0.001)		(0.001)
Weekend		0.011***		0.010***
		(0.002)		(0.002)
Time FE's	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes
Observations	2,017,970	2,017,970	2,017,970	2,017,970

Notes:
Standard errors account for clustering at the beat level.
Specifications (1) and (3) include additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, percent children, and percent teenagers. Time Fixed Effects refer to including 11 month dummies and 23 hour dummies. All specifications include OCSXDivisionXCentrality interactions, this allows out of beat calls to have different effects in different policing divisions and for beats that are more centrally located to be more affected by out of beat calls.
[1]Police vehicles per beat within given hour (60 minutes = 1 vehicle).
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 9: The Deterrence Effect of Police on Crime by Beat Size

	Outside Calls			Outside Calls Shock		
	Small	Medium	Large	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Police Vehicles[1]	-0.191***	-0.228***	-0.102***	-0.226***	-0.201***	-0.039**
	(0.044)	(0.043)	(0.025)	(0.038)	(0.044)	(0.016)
Temperature	0.002***	0.002***	0.001***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.002***	-0.002***	0.000	-0.002***	-0.002***	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Twilight	0.014***	0.005	0.006***	0.014***	0.005*	0.007***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Dark	0.005	0.002	-0.002	0.005	0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Holiday	0.005	-0.008*	-0.018***	0.003	-0.006	-0.008**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)
Weekend	0.027***	0.017***	0.008	0.025***	0.020***	0.020***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Mean Police Vehicles	0.336	0.502	0.952	0.336	0.502	0.952
	[0.619]	[0.824]	[1.480]	[0.619]	[0.824]	[1.480]
Mean Crime Rate	0.145	0.157	0.141	0.145	0.157	0.141
	[0.393]	[0.410]	[0.386]	[0.393]	[0.410]	[0.386]
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	Yes	Yes	Yes	Yes	Yes	Yes
Observations	556,599	791,516	669,855	556,599	791,516	669,855

Notes:
Standard errors in parenthesis account for clustering at the beat level. Standard deviations are presented in brackets. Small beats are defined as beats with less than 4 miles of roads. Medium beats are defined as beats with 4-8 miles of roads. Large beats are beats with over 8 miles of roads. Time Fixed Effects refer to including 11 month dummies and 23 hour dummies. All specifications include IVXDivisionXCentrality interactions, this allows out of beat calls to have different effects in different policing divisions and for beats that are more centrally located to be more affected by out of beat calls.

[1]Police vehicles per beat within given hour (60 minutes = 1 vehicle).

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

Table 10: The Impact of Previous Police Presence on Crime (Instrument=OCS)

	All Crimes			Violent Crimes		
	(1)	(2)	(3)	(4)	(5)	(6)
Police Vehicles[1]	-0.158***	-0.167***	-0.158***	-0.082**	-0.075***	-0.073***
	(0.053)	(0.039)	(0.033)	(0.034)	(0.024)	(0.020)
Police Vehicles Previous Hour	0.033			0.023		
	(0.051)			(0.033)		
Police Vehicles Previous 2 Hours		0.051			0.017	
		(0.035)			(0.022)	
Police Vehicles Previous 3 Hours			0.045			0.017
			(0.029)			(0.018)
Temperature	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.001***	-0.001***	-0.001***	-0.0003*	-0.0003*	-0.0003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Twilight	0.008***	0.008***	0.008***	0.003***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Dark	0.003	0.003	0.003	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Holiday	-0.013***	-0.013***	-0.013***	-0.002	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Weekend	0.021***	0.022***	0.022***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,015,913	2,013,886	2,011,890	2,015,913	2,013,886	2,011,890

Notes:
Standard errors in parenthesis account for clustering at the beat level. Police vehicles in previous hour is the number of cars that patrolled this beat in the previous hour, I instrument for this variable with OCS, the proportional increase in outside-unrelated-calls from the mean in the previous hour. Police vehicles in previous 2 (3) hours is the average number of police cars patrolling per hour in the previous 2 (3) hour period, I instrument for this variable with OCS, the proportional increase in outside-unrelated-calls from the mean in the previous 2 (3) hours.

[1]Police vehicles per beat within given hour (60 minutes = 1 vehicle).

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

Table 11: The Impact of Police Presence on Crime at the Sector Level (Instrument=OCS)

	All Crime (1)	Violence (2)	Disturbances (3)	Theft (4)	Burglary (5)
Police Vehicles[1]	-0.166***	-0.081***	-0.055***	-0.011***	-0.019***
	(0.021)	(0.010)	(0.009)	(0.004)	(0.004)
Temperature	0.010***	0.004***	0.005***	0.000	0.000**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.008***	-0.002	-0.007***	0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Twilight	-0.104***	-0.052***	-0.033***	-0.006**	-0.014***
	(0.012)	(0.007)	(0.005)	(0.003)	(0.003)
Dark	-0.027	-0.010	-0.006	-0.003	-0.007
	(0.027)	(0.012)	(0.011)	(0.002)	(0.004)
Holiday	-0.055**	-0.001	0.006	-0.023***	-0.037***
	(0.022)	(0.013)	(0.009)	(0.004)	(0.006)
Weekend	0.106***	0.041***	0.114***	-0.011***	-0.039***
	(0.031)	(0.013)	(0.019)	(0.003)	(0.005)
Mean of Dependent Variable	0.982	0.418	0.35	0.079	0.135
	[1.147]	[0.697]	[0.643]	[0.284]	[0.377]
Shift FE's	Yes	Yes	Yes	Yes	Yes
Location FE's	Yes	Yes	Yes	Yes	Yes
Observations	304,465	304,465	304,465	304,465	304,465

Notes:

Standard errors in parenthesis account for clustering at the sector level. Standard deviations are presented in brackets. OCS is calculated as the proportional increase in outside-unrelated-calls from the mean for that beat, day of week, and hour. Mean police presence in the sector is equal to 4.013 (s.d. 3.194). Shift FE's control for different times of day: shift 1 (12 AM - 8 AM), shift 2 (8 AM - 4 PM), and shift 3 (4 PM - 12 AM).

[1]Police vehicles per sector within given hour (60 minutes = 1 vehicle).

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