Police Presence, Rapid Response Rates, and Crime Prevention

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Abstract: This paper estimates the impact of police presence on crime. To address the concern that officer location is often driven by crime, our instrument exploits police responses to calls outside of their allocated coverage beat. This variable provides a plausible shift in police presence within the given beat that is driven by the police goal of minimizing response times. We find that a 10 percent decrease in police presence at that location results in a 1.2 to 2.5 percent increase in crime.

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Abstract

This paper estimates the impact of police presence on crime. To address the concern that officer location is often driven by crime, our instrument exploits police responses to calls outside of their allocated coverage beat. This variable provides a plausible shift in police presence within the given beat that is driven by the police goal of minimizing response times. We find that a 10 percent decrease in police presence at that location results in a 1.2 to 2.5 percent increase in crime.

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] This deterrence effect is often credited to specific policing strategies such as neighborhood and hot spots policing. However, the literature has largely ignored the fact that much of an officer's time is still dedicated to responding to emergency calls. While fast response times may help to lower the expected benefit of committing a crime (see Becker, 1968) it can also disrupt preemptive police activity. We examine the possible trade-off that occurs when a police department must divide its time between responding to incidents that have already occurred and deterring future crimes.

A positive correlation between the size of the police department and crime incidents has been shown to give way to a deterrence effect when focusing on exogenous shifts in police hiring.[2] However, a larger police force does not necessarily imply a higher level of street level patrol, and even when patrol is increased the mechanism of deterrence is unclear. If more police officers allow for more behind the scenes work this could create a crime decrease without any observed change in police presence. When more officers are patrolling the streets this could both increase police visibility and reduce response times to emergency calls. While these mechanisms all decrease crime, differentiating between them has important policy implications for creating optimal deterrence.

If people react to police presence then the exact location of officers is essential for deterring crime. Alternatively, if the mechanism of deterrence is faster response times

[1] See surveys of the literature conducted by Cameron (1988) , Marvell and Moody (1996), and Eck and Maguire (2000) and micro geographic interventions by Weisburd and Sherman (1995), Braga et al. (1999), Di Tella and Schargrodsky (2004), Gould and Stecklov (2009), Nagin (2013), and Chalfin & McCrary (2014).

[2] See works by Marvell and Moody (1996), Corman and Mocan (2000), Evans & Owens (2007), Levitt (1997), and Chalfin & McCrary (2014).

then a police car's location is less important than how quickly it arrives at the scene of the crime. Analyzing the impact of police presence at a given location and time on crime at that same place requires access to information on the location of police officers and crime over time. Such information has begun to become 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 that track where police vehicles are when they are patrolling the city. Where 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, during the period of our study AVL systems were installed in all 873 police patrol vehicles and data on their location was saved and stored. We focus on the beat 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 placed by local citizens to the police department.[3]

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 more risky locations during more risky 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. This is 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. Thus, while this dataset provides a unique picture of police presence across a city, the location of officers may still be determined by factors unobserved by the econometrician and correlated with crime.

Our identification strategy stems from the two distinct responsibilities facing police patrol cars: proactive and reactive policing. While police may be allocated to a certain

[3] We separate crime into the following categories: violent crimes, burglaries, thefts, and general disturbances.

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. Using patrol officers to respond to calls outside of their area of patrol introduces some degree of randomness into whether or not police are present at a given location and time.

In order to identify a causal effect of police presence on crime, we introduce an instrument called response ratio (RR) equal to the fraction of time officers assigned to a given beat spend answering calls outside of that beat. We show that beats and intervals of time with a higher RR have significantly lower levels of police presence and higher levels of crime (see Figure 2). While the allocated level of presence can be determined by the perceived crime risk in that area, we argue that actual presence is impacted by exogenous factors.

The validity of this instrument requires that both the incident that occurred at an outside beat and the assignment of an officer to this outside incident are not correlated with crime at the given beat. The first assumption seems reasonable as long as crimes occurring in the same hour at different areas in Dallas are uncorrelated. Indeed, our estimated deterrence effect remains significant even when using only outside incident types that should be unrelated to the types of crime examined within the specific beat (e.g. car accidents). The concern regarding assumption 2 is that if a crime occurs in a given beat this may directly lower RR and increase police presence at that beat as the allocated officers have less time to spend answering outside calls. In order to address this concern, we also consider an alternative instrument based on the intention to assign cars to outside beats.[4]

The city of Dallas is divided into seven police divisions, where each division includes

[4] We estimate a statistically significant impact of police presence on crime when instrumenting with the response ratio (RR) and the intention to assign (expected response ratio).The lower estimate from the response ratio instrument can be explained by the possible correlation between crimes occurring internally at the beat and the probability of being allocated to an outside call.

roughly 30 beats. We define the expected response ratio (ERR) as the number of outside incidents patrol cars in this beat are expected to answer divided by the amount of allocated patrol time.[5] By construction the expected response ratio (ERR) is higher when more outside incidents occur and lower when there are more officers allocated at the division level. This instrument can be thought of as intention to assign, where on days with more outside incidents and less division level patrol, officers are more likely to be assigned outside of their beat.

Our findings suggest that the number of officers patrolling a beat has a significant impact on the probability of crime. We 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. It is only when instrumenting for actual police presence with out of beat call assignments that we are able to identify a deterrence effect. Using the response ratio (RR) instrument, we estimate that a 10 percent increase in police presence results in a 1.2 percent decrease in crime. The expected response ratio (ERR) yields a higher deterrence estimate of 2.5 percent for the same change in police presence.

This paper proceeds as follows. In the next section we review relevant research on the impact of police on crime. Section 3 introduces the data used for this project as well as our technique for measuring police presence. Section 4 discusses our 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 our results. Section 6 concludes.

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[5] The expected number of outside incidents is the number of calls occurring in the division patrol area outside of the given beat divided by the number of cars allocated to those areas. This number is multiplied by 30 minutes (the average amount of time a patrol car spends on an a call)

2 Does Police Presence Affect Behavior?

At the end of the 20th century, many believed that police had no impact on reducing crime, whereas today studies often find that increased investment in policing decreases crime.[6] The methodological change that resulted in this reversal in finding is a focus on techniques that correct for simultaneity bias, thereby measuring a deterrence impact with a causal interpretation. 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 effect of police presence on crime, as well as instrumental variable techniques.[7] Most of these papers focus on the aggregate number of officers employed over a given period. When more detailed information is available it is usually constrained to a specific location in the city over a relatively short treatment period.

Corman and Mocan estimate the elasticity of robberies with respect to police force size to be -0.53. They use monthly data in NYC and claim that police hiring cannot respond immediately to crime due to a mandatory 6 month training course for new officers in the NYPD. 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. More specifically, doubling police patrol at hotspot locations in Minneapolis

[6] See Cameron (1988), Marvell and Moody (1996), Eck & Maguire (2000), Nagin (2013), and Chalfin & McCrary (2014).

[7] See works by Marvell and Moody (1996), Corman and Mocan (2000), Di Tella & Scharrgrodsky (2004), Klick and Tabarrok (2005), Draca et al. (2011), Gould & Steklov (2009), Shi (2009), Machin and Marie (2011), Sherman and Weisburd (1995), Braga et al. (1999), Levitt (1997), and Evans and Owens (2007).

resulted in a 6 to 13 percent decrease in crime (Sherman & Weisburd, 1995). Weisburd et al. (forthcoming) 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 (Weisburd et al., forthcoming).

The papers closest to our identification strategy apply instrumental variable analysis to examine the impact of police hiring on crime. Levitt addresses the endogeneity between states regarding crime and police hiring in two separate papers. First, by instrumenting for police force size with election years, and later by instrumenting with the size of the fire department (Levitt, 1997 & 2002). He estimates an elasticity of -0.4 to -1 for violent crimes and -0.3 to -0.5 for property crimes.[8] 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 (2014) raise concerns regarding weak instruments and point out that these studies show a wide range of estimates that are often not statistically significant at conventional confidence intervals.

Our paper can be seen as 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 our knowledge, Draca et al. is the only other paper that attempted to look at the geographic distribution of police officers throughout an entire city (Draca et al. (2011)). They 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. We consider the presence of police at the hourly level within Dallas beats (average population of 5,000). Our analysis provides an estimate of the deterrence

[8] See Justin McRary (2002) for some concerns regarding estimates produced in the 1997 paper.

created by every-day policing and the possible community safety costs of the dual role police officers must uphold.

3 The Data

We focus our analysis on two databases that provide information on the precise location of both crime and police in 2009. The Dallas Police Department call database records the time and location of each report of crime to the department. The Automated Vehicle Locator database tracks the location of police cars throughout the day. Together they provide an opportunity to understand how police presence impacts crime. Using geographic mapping software we collect additional information on the types of roads, as well as number of schools, parks and type of development (residential, business, etc.) across different areas in Dallas. Census track data allow us to add in information on the characteristics of individuals living within these areas. This data is 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. We may think that crimes are more likely to occur at times with lower visibility, or alternatively, that bad weather could reduce crime.

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 largest percentage of Hispanic residents. Residents of the North Central division tend to 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.

We conduct our analysis on geographic beats at hour long time intervals. We use the call database to count the number of crimes reported for each beat b, day d, and hour h. Figure 4 illustrates how the number of crimes vary throughout the year within the 7 divisions of Dallas. While crime in all areas tends to peak in May and plummet in December, most divisions also show fluctuations in the crime rate throughout the year.

Beginning in the year 2000 most 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 (1st watch 11 PM to 8 AM).[9]

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 provides information on the location and type of call being answered by the police officer. Thus, if car A142 is responding to a call reported at beat 133, we are able to identify that he is outside of his allocated beat. In contrast to an aggregate count of police officers per city, these data allow us to map the activity of each individual squad car throughout the day.

The Automated Vehicle Locator database for 2009 consists of almost half a billion pings of information. We divide the city of Dallas into 234 geographic beats of analysis and map each ping into a beat. The vehicle pings are then used to count the minutes of police presence over each hour long interval of 2009. We define minutes of presence for each car as the elapsed time between first entrance and first exit from the beat. If the

[9] 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, we believe this still can provide insight into the general area of allocation.

car exited the beat and later returned it is counted 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.[10]

Figures 5 and 6 illustrate the changes in both police allocation and actual presence across divisions and time. While beats in the Southeast division (red line) receive a higher allocation of police officers than beats in the Northwest division (orange line), it is clear from Figure 6 that actual presence is significantly higher in the Northwest division. Our identification strategy builds around this idea that actual police presence over time is not fully determined by the allocation of officers.

Table 2 presents the mean hourly values for crime, police allocation and police presence by beat, summarized 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 and presence is in the Central division.

The simultaneous relationship between police presence and crime is already made apparent in Table 2. While beats in the Southwest division average fifty percent more police coverage than beats in the Southeast division, they have a significantly higher crime rate. In order to identify a causal effect of policing on crime we introduce an instrument that impacts the level of police presence in a given beat, but should not directly impact crime.

The response ratio (RR_{bdh}) is calculated for each beat (b) , day (d) and hour (h) as the fraction of time police cars allocated to the given beat (A_{bdh}) spend answering calls

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

outside of the beat. Let $mcalls_{ibdh}$ be number of minutes patrol car i spends answering calls outside of allocated beat b during day d, and hour h. We define $mpatrol_{ibdh}$ to be the number of minutes patrol car i was allocated to spend in beat b during that time period. Let $APatrol_{bdh} = \sum_{i \in A_{bdh}} mpatrol_{ibdh}$ be the total amount of allocated patrol. We calculate the response ratio (RR_{bdh}) as,

$$RR_{bdh} = \frac{\sum_{i \in A_{bdh}} mcalls_{ibdh}}{APatrol_{bdh}} \tag{1}$$

When considering the same beat over time it seems unlikely that incidents occurring in other areas should directly impact crime at this location. However, we would expect that when more officers are called away from their allocated beat (higher RR_{bdh}) this would result in lower police presence.

In Figure 7 we map out the average police coverage at 8 PM across months for beats with both low response ratios ($RR_{bd20} < 0.1$) and high response ratios ($RR_{bd20} > 0.9$). Areas with high response ratios, where allocated officers are spending much of their time answering outside calls, consistently have lower levels of presence. This figure also maps the expected response ratio (ERR_{bdh}) which is the expected time officers allocated to beat (b), on day (d) and hour (h) spend responding to outside calls, divided by the allocated minutes of presence at given location and time. Thus, the numerator is equal to 30 minutes times the number of calls for assistance received within the larger division D of beat b divided by the minutes of allocated police officer patrol at the division level (excluding beat b).[11] The denominator remains the number of minutes of allocated patrol at that beat (see equation (1)),

$$ERR_{bdh} = \max\left(0, \frac{\sum_{x \neq b \in D} incidents_{xdh}}{\sum_{x \neq b \in D} APatrol_{xdh}} \frac{1}{APatrol_{bdh}}, 1\right) \tag{2}$$

The added strength of the expected response ratio (ERR_{bdh}) is that it is determined

[11] The numerator is multiplied by 30 minutes, the average amount of time an officer spends on an allocated call.

only by activity outside of the beat, whereas a lower response ratio (RR_{bdh}) may result from internal incidents.[12]

In the next section we lay out our empirical strategy for estimating the deterrence effect of police presence on crime. We discuss unobserved factors that can create bias in estimating this effect and explain how our instruments address these concerns. Our 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

Our analysis focuses on crimes 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_{bdh}) will be a function of the costs and benefits of the crime job,

$$C_{bdh} = x_{bdh} f3_0 + f3_l P_{bdh} + r_h + r;_b + E_{bdh} \tag{3}$$

The variables included in x_{bdh} capture time varying environment characteristics that could impact crime (e.g. weather, light/darkness, weekend/holiday). The focus of our analysis is P_{bdh}, the level of police coverage in beat b, day d, and hour h. If one police vehicle was present for a full hour (h) at beat (b) on day (d) then $P_{bdh} = 1$, if the car left after 30 minutes then $P_{bdh} = 0.5$, if 2 cars were present over the entire hour then $P_{bdh} = 2$. The time and location fixed effects r_h and $r;_b$ account for the differential probabilities in crime across hours and beats. If policing is uncorrelated with the remaining unobserved factors impacting crime (E_{bdh}) then $f3_l$ estimates the amount of deterrence created when police coverage is increased by 1 car.

[12] See Appendix A for a calculation of the expected response ratio when zero vehicles were allocated to patrol at given day d, time h, and location b ($APatrol_{bdh} = 0$).

Our main concern regards the endogeneity of policing P_{bdh}. Generally, when a crime occurs in a given hour we would expect more police to enter the beat in response to the crime. Even when we remove cars that are specifically allocated to respond to the call from P_{bdh}, there may be other officers drawn to 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 via 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 friction between sending officers to higher risk crime locations (high E_{bdh}) and emergency calls in surrounding areas that provides an opportunity to identify $f3_{l}$ despite the bias previously discussed.

Table ( ) presents regression estimates for the first stage of our analysis: the impact of the response ratio (RR) on police presence.[13] On average, a beat receives police coverage for 67 percent of each hour. In specification (i) we find that increasing the response ratio from 0 to 1 (moving from allocated beat patrol officers answering 0 outside calls to spending all of their time answering outside calls) decreases police coverage by 0.280. This would imply that the allocation of officers to calls outside of their beat results in a 42 percent decrease in police coverage. However, we may be concerned that beats or hours with lower crime risks and less allocated officers are more likely to have high response ratios. In specification (ii) we control for characteristics at the beat level as well as month and hour fixed effects and still find a significant impact of response ratio on police presence (-0.253 (0.028)). In our final specification which includes location fixed effects and controls for time varying day characteristics, we find that a one unit change in the response ratio decreases police presence by 26 percent. This can be compared to

[13] The response ratio for each location and time is calculated using equation (1).

a 15 percent drop in police presence on holidays and weekends.

We find very similar results when examining the impact of the expected response ratio (ERR) in Table (4). Here the expected allocation of officers to calls outside their beat results in a decrease in police presence of 0.132 (s.e. 0.011), implying a 20 percent change. It seems reasonable that this instrument has less of an effect on police presence at a given beat than the actual response ratio (RR) as it only serves as a proxy for the fraction of officers answering calls outside the beat. The result for both instruments is significant at the one percent level and illustrates the strong impact of 911 calls on police coverage.

Both of our instruments use incidents occurring in surrounding areas as an exogenous factor impacting presence in the given area. Neither instrument would fall under the weak instrument category, as the F-statistic on the excluded instruments is above 20 for both specifications. The reduced form specification finds a similar relative difference in the direct impact of the instrument on crime, an estimate of 0.005 (0.001) for the response ratio and 0.008 (0.001) for the expected response ratio. Our main concern in implementing the response ratio instrument is that it may be lower in hours where incidents occurred if less officers are available to be allocated elsewhere. This would bias our estimated deterrence effect towards zero. We therefore provide estimates of the deterrence effect for both the response ratio and the expected response ratio.

Equation ( ) is estimated for total crimes in Table (5) using OLS, fixed effects, and 2SLS models. In specification (i) we find a significant and positive effect of police presence on crime when controlling for observed location characteristics as well as time fixed effects. This effect only grows in size when controlling for location fixed effects as well as weather and day characteristics in specification (ii). We find 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).

Columns (iii)-(iv) of Table (5) provides estimates of the deterrence effect when actual police presence (P_{bdh}) is instrumented with the response ratio (RR_{bdh}). In specification (iii) we control for observed location characteristics and time fixed effects and estimate a deterrence impact of -0.034 (0.008). Adding in location fixed effects, as well as weather, and time of day characteristics in specification (iv) shrinks the deterrence estimate to -0.030 (0.006). This implies that adding 60 minutes of presence to a given beat at a given hour results in a 20 percent decrease in crime $\left(100 \quad \frac{-0.03}{0.148}\right)$. If we focus on average police presence per hour (6 minutes), a 10 percent increase in police presence implies a 1.2 percent decrease in crime.

The last columns of Table (5) measure the deterrence effect when actual police presence (P_{bdh}) is instrumented with the expected response ratio (ERR_{bdh}). Consistent with our concern that the response ratio (RR_{bdh}) may underestimate the deterrence effect, we estimate larger deterrence effects when applying the expected response ratio (see columns (v)-(vi)). Our estimated deterrence impact of -0.062 (0.013) suggests that a 10 percent increase in police presence results in a 2.5 percent decrease in crime.

Our estimates in Table (5) also provide information on how different weather and time characteristics impact crime outcomes. We find that crime is 22 percent more likely to occur on weekends. Higher temperatures increase the occurrence of crime, and bad weather lowers the probability of crime.

In Tables (6)-(8) we separately examine the impact of police on different types of crimes (violent crimes, burglaries, general disturbances, and theft) following the same format as in Table (5). All crime types exhibit a positive correlation between police presence and crime that disappears when instrumenting for police presence with the response ratio. The estimated deterrence effect is significantly larger when instrumenting with the expected response ratio for all specifications. We find that police have the largest effect on violent crimes (see Table (6)), where a 10 percent increase in police presence, decreases violent crime by 1.8-2.8 percent.[14] In Table (7), we find that this same change

[14] We classify violent crimes as stabbings, shootings, robberies, assaults, kidnappings, and armed

in police presence results in a 1-2.7 percent decrease in general disturbances.[15]

We also find that crime types are impacted differently by changes in visibility and weather. Violent crimes, and public disturbances are more likely to occur in warmer weather and during twilight. Burglaries 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.

We do not find a significant impact of police presence on either burglaries or theft when instrumenting with the response ratio and including location and time fixed effects (see Tables (9) & (8)).[16] Draca et al. also reported a zero deterrence effect for burglary (Draca et al., 2011). They explained that this type of crime may be difficult to prevent through general police presence as the incident occurs inside private dwellings.[17] The lack of effect on theft is more difficult to explain and has not been reported in the previous crime literature. It is important to note that the theft rate is relatively low at one percent which may make it difficult to identify a robust impact. Additionally, when instrumenting for police presence using the expected response ratio we continue to find zero effect on burglaries, but report a significant deterrence effect on theft.

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encounters. The deterrence impact was calculated by taking the estimate impact of an additional police vehicle on violent crime (0.019 & 0.028) relative to the average violent crime rate (0.063) which is equal to 30 & 44 percent. Since the average amount of police presence is 0.6, a 10 percent increase in police presence requires dividing the full hour impact (a 165% increase in police presence) by 16.5.

[15] We characterize public intoxication, illegal parking, suspicious behavior, prostitution, loud music, gun fire, speeding, road rage, and panhandlers as public disturbances.

[16] We also estimate the impact of police presence on each type of crime when controlling location time fixed effects. This allows us to address the concern that unobserved crime risks may not only vary between hours and locations, but that specific areas may face different risks at different hours. Thus, we compare the impact of changes in policing that were driven by changes in the response ratio at the same location and time of day. With these additional controls, our estimates are slightly larger in size for all crimes except public disturbances. We do not find a significant impact of policing on theft and burglary.

[17] An additional explanation could be that burglaries may often be reported with a time lag as they generally occur when individuals are not home. If this is the case then it would be difficult to estimate the deterrence effect on burglaries at hour long intervals.

In this paper we have argued that our instruments provide a causal deterrence estimate by focusing on exogenous shifts in police presence. However, our analysis cannot rule out the possibility that crimes occurring in other beats may be correlated with the occurrence of crime at the given beat. This would occur if crime groups decide to target a few areas at the same time, or when community events occur simultaneously in multiple beats.

In order to ensure that across beat crime correlations are not driving our results we run our analysis using a response ratio and expected response ratio that are defined specifically by car accident incidents. While we would expect an officer in beat A that is called to an accident incident in beat B to decrease police presence at beat A, it seems unlikely that a car accident should have any direct impact on crime. Tables (10 & 11) provide our estimates using the accident focused response ratio and expected response ratio. We continue to find a significant deterrence effect of police presence on crime when using both instruments.

5 A Closer Look at the Mechanisms of Deterrence

Our estimates suggest that police allocation and presence at the beat level has a significant deterrence effect on crime. The next step is to understand the mechanism by which police presence changes behavior. What are police 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?

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 our deterrence results it is relevant to understand the extent to which the response ratio and expected response ratio instruments impact active police patrol. We do this by focusing on how changes in police presence that are driven by out of beat calls impact arrests (a proxy for active police presence).

In Table 12, we find a significant impact of police presence on arrests when instrumenting with both the response ratio and expected response ratio. Thus, an additional police vehicle increases the probability of arrest by 3.5 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.[18]

Both active and passive police patrol would suggest that smaller beats where officers are more likely to be seen are more affected by losing a police vehicle than larger beats. In Table (13) we run our 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). We find that police vehicles have a larger impact on crime in smaller areas when using the response ratio and expected response ratio instruments. When instrumenting for police presence with the expected response ratio (ERR) we find that each additional car reduces crime by 0.124 (0.035) in the smaller beats versus 0.061 (0.022) in midsize beats and 0.041 (0.015) in the larger beats. This implies that adding 60 minutes of presence to a small beat at a given hour results in an 85 percent decrease in crime $\left(100 \quad \frac{-0.124}{0.145}\right)$, versus a 29 percent decrease in large beats $\left(100 \quad \frac{-0.041}{0.141}\right)$.

It is interesting to note that at the margin both small and large beats are similarly impacted by a 10 percent increase in police presence. This is driven by the reality where large beats average 57 minutes of police presence per hour, versus small beats that average 20 minutes of presence per hour. Thus, while large beats have a measured deterrence impact that is 3 times lower than small beats they also average roughly 3 times the amount of police presence as small beats. We find that a 10 percent increase in police presence results in a 2.8 percent decrease in crime for the smallest and largest beats. It is the midsize beats averaging 30 minutes of presence per hour, where a 10

[18]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.

percent increase in police presence results in a lower, 1.9 percent decrease in crime. This baseline rate of police presence per beat may also contribute to the size of the deterrence effect. Thus, taking an officer away from a beat that averages little to no police presence may be more detrimental than the impact at a beat that has consistently high levels of police presence.

Throughout this paper we have focused on estimating the immediate impact of police presence on crime. In Table (14) we consider how police presence in previous hours impacts crime in hour t. 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 (i)-(iii) we consider the impact of police presence in the previous hour, previous 2 hours, and previous 3 hours on crime, instrumenting for actual police presence with the expected response ratio. We do not find a significant impact of past presence on current crime in any of these specifications. The only crime type that shows some sensitivity to previous presence is violent crime when examining police presence in the last 2 hours (specification (v)). However, the impact is only significant at the 10 percent level and disappears when focusing on police presence in the previous 1 hour or previous 3 hours.

6 Conclusion

Despite 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 extreme budget cuts resulting from the economic downturn.[19] With lower budgets, police departments are being forced to make tough choices regarding police activities

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

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). Thus, a police department that is very involved in neighborhood based crime reduction activities may get little reward for its effort. 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.[20] Indeed, The Dallas 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).

Our results raise concerns that focusing police efforts on 911 calls may have significant costs in terms of crime deterrence. We estimate that each 10 percent decrease in police presence at a given beat and hour increases crime at that location by 1.2 to 2.5 percent. Our estimates are especially relevant to 911 calls as our instruments focus on shifts in police presence that are created when officers are allocated to respond to incidents outside of their beat. Our analysis asks the question, what happens when a police car leaves its allocated area to fulfill other departmental duties? Our answer is 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.

In addition to raising concerns regarding the trend of decreasing police force size throughout the US, this paper provides some insight into the mechanism through which police reduce crime. Our outcomes are particularly interesting given recent studies that

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

imply that policing is only effective when focused at specific high crime locations.[21] One interpretation of our 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. Thus, within the beat, allocated police may be focused on specific hot spot areas that they are forced to abandon when answering a call.

It is often argued that when police presence is increased so are arrests, thus resulting in fewer criminals and less crime. Indeed, we find a significant impact of police presence on arrests when using both the response ratio and expected response ratio instruments. Importantly, the focus of our analysis is the immediate impact of police at a given hour on crime. Thus, we interpret our results as identifying a change in behavior where less people commit crimes as opposed to a long term incapacitation effect where more criminals are being taken off the streets.[22]

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

[22] 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: Dealing With Zero's

Estimating the values of the response ratio and expected response ratio when zero cars are allocated at that time and location is a nontrivial question, as $APatrol_{bdh} = 0$ for 37 percent of our sample. Setting ERR_{bdh} or RR_{bdh} to 0 or 1 could delegitimize the instrument as allocation is likely to be directly correlated with crime risks. Simply dropping these areas and times from the analysis could severely impact the representativeness of our sample.

We focus on the minimum nonzero level of allocated police coverage at each location b and hour h. We define Y_{bh} as all days in 2009 when beat b had a nonzero amount of allocated coverage at hour h. When $APatrol_{bdh} = 0$ we set RR_{bdh} and ERR_{bdh} to be equal to,

$$\widetilde{ERR}_{bdh} = \max\left(0, \frac{\sum_{x \notin b \in D} incidents_{xdh}}{\sum_{x \notin b \in D} APatrol_{xdh}} \frac{1}{\min_{d' \in Y_{bh}}(APatrol_{bd'h})}, 1\right) \tag{4}$$

Equation (4) serves as a proxy for ERR_{bdh} where days and hours with more outside incidents and lower allocated patrol at the division level are likely to result in lower levels of actual police presence. The minimum level of allocated patrol that is above zero provides a baseline for patrol at that location and time.[23] Thus, $\widetilde{ERR}_{bdh}$ remains a decreasing function of allocation, as areas with generally higher levels of allocated patrol are likely to have more police presence.

[23] As previously discussed, while the radio name matches each patrol car to one beat this is only a proxy for allocated patrol as cars are often assigned to more than 1 beat. Thus, the minimum level of patrol at that beat and hour on other allocated days can provide information on the general level of presence at that location.

Figure 1: The Endogenous Relationship Between Policing and Crime

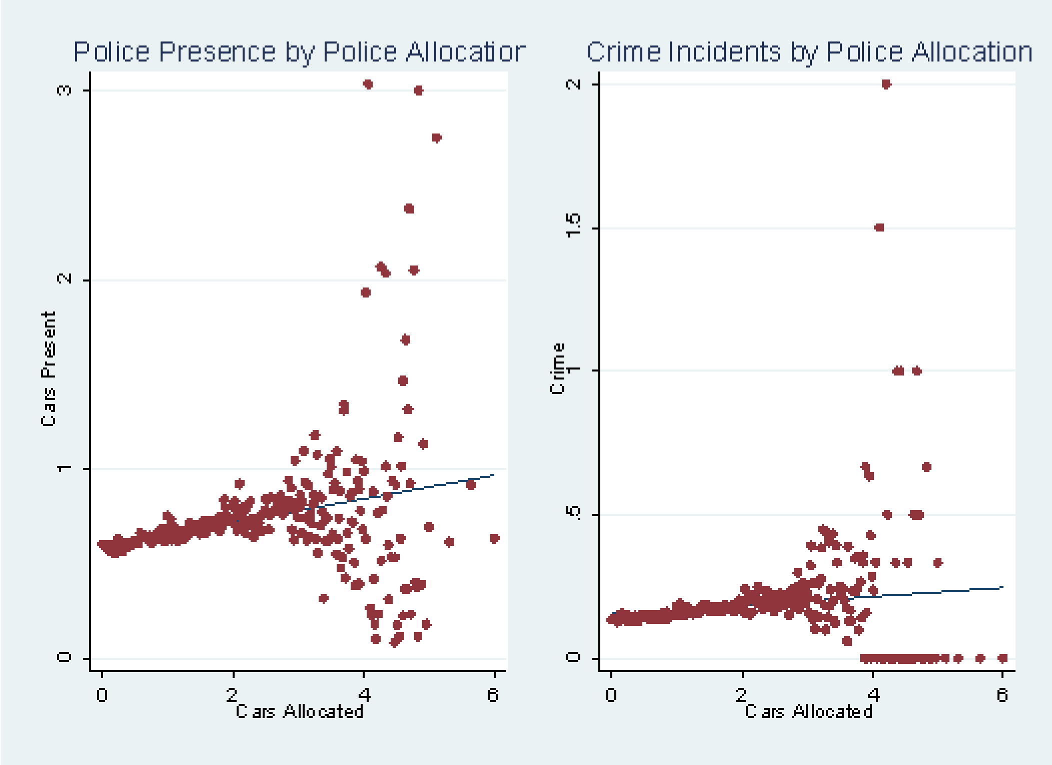

Figure 2: Instrumenting for Police Presence Using the Response Ratio

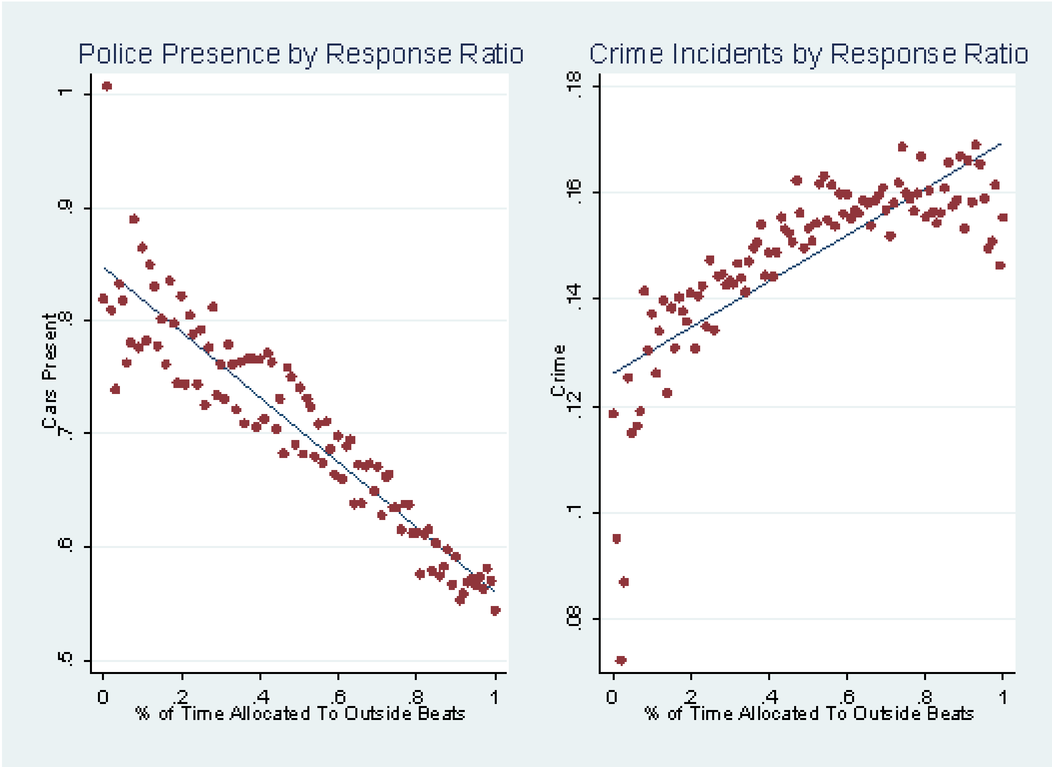

Figure 3: Dallas Beats

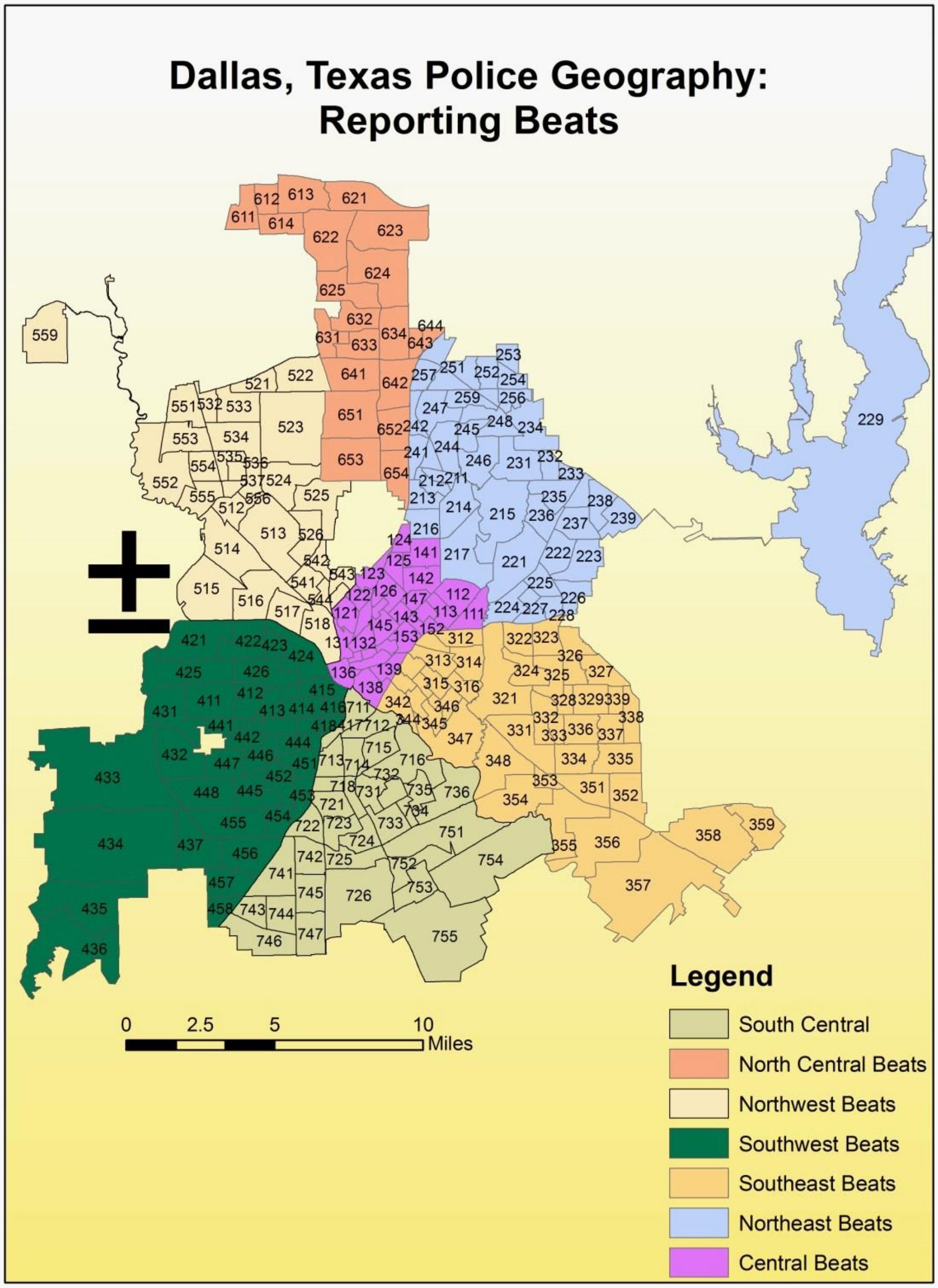

Table 1: Beat Characteristics Summarized by Division

	CENTRAL	NORTH CENTRAL	NORTH EAST	NORTH WEST	SOUTH CENTRAL	SOUTH EAST	SOUTH WEST
Schools	1.103	1.955	1.452	1.355	1.297	1.154	1.909
	(1.345)	(1.704)	(1.580)	(1.854)	(1.244)	(0.933)	(1.627)
Acres	390.1	1074.2	1418.3	974.0	954.5	1041.2	1454.3
	(206.9)	(754.6)	(4565.3)	(700.5)	(1022.1)	(1143.4)	(2127.9)
Population	3258	8613.9	6243.6	4913.4	3081.4	3997.7	5842.9
	(2695.9)	(4148.7)	(2950.7)	(3381.1)	(1446.0)	(1832.9)	(3087.2)
Miles of Roads	6.217	9.531	5.991	8.967	6.365	6.323	8.971
	(3.770)	(6.299)	(3.836)	(5.453)	(5.369)	(3.628)	(7.304)
Household Size	1.922	2.230	2.486	2.445	2.906	3.240	3.212
	(0.544)	(0.376)	(0.368)	(0.579)	(0.250)	(0.579)	(0.522)
Percent Black	0.153	0.121	0.233	0.152	0.715	0.435	0.259
	(0.116)	(0.0844)	(0.147)	(0.160)	(0.168)	(0.271)	(0.233)
Percent Hispanic	0.290	0.249	0.328	0.454	0.246	0.474	0.620
	(0.202)	(0.213)	(0.155)	(0.263)	(0.157)	(0.240)	(0.241)
Percent Young Adults (20•34)	0.419	0.264	0.267	0.315	0.203	0.219	0.243
	(0.117)	(0.117)	(0.0860)	(0.102)	(0.0235)	(0.0243)	(0.0362)
Household Income	163,602	236,403	152,705	179,257	137,303	100,377	183,627
	(111862)	(353509)	(262355)	(223402)	(92673)	(55421)	(125406)
Number of Beats	29	22	42	31	37	39	33

Figure 4: The Distribution of Crime in 2009

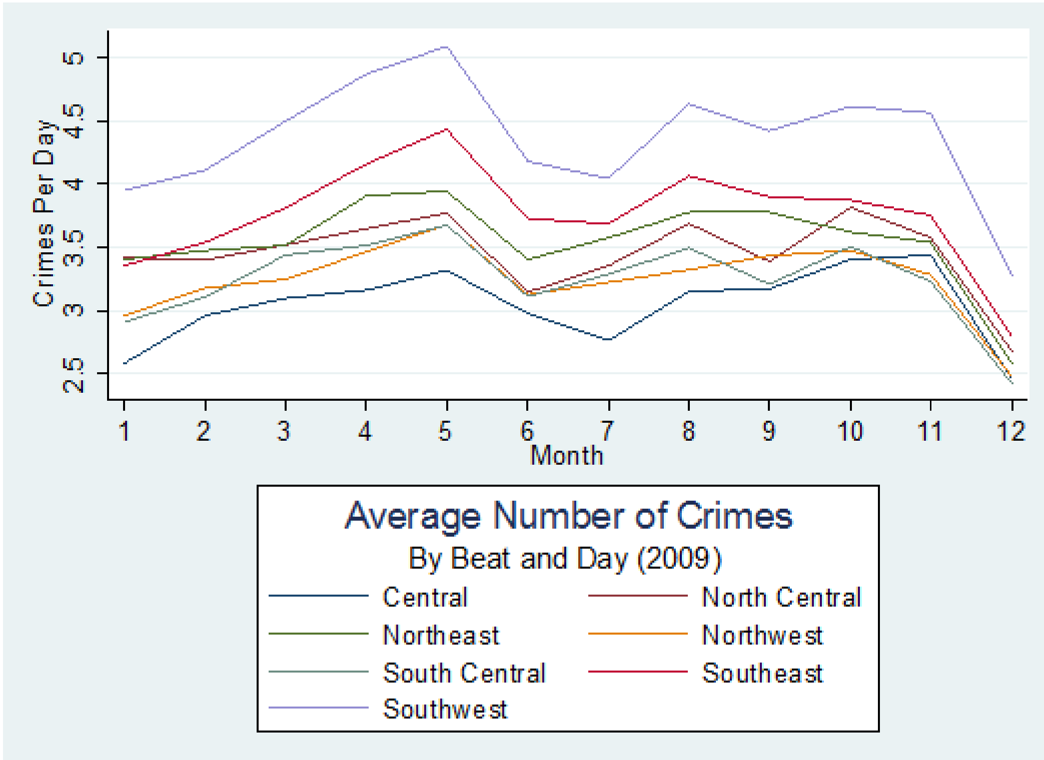

Figure 5: The Allocation of Police in 2009

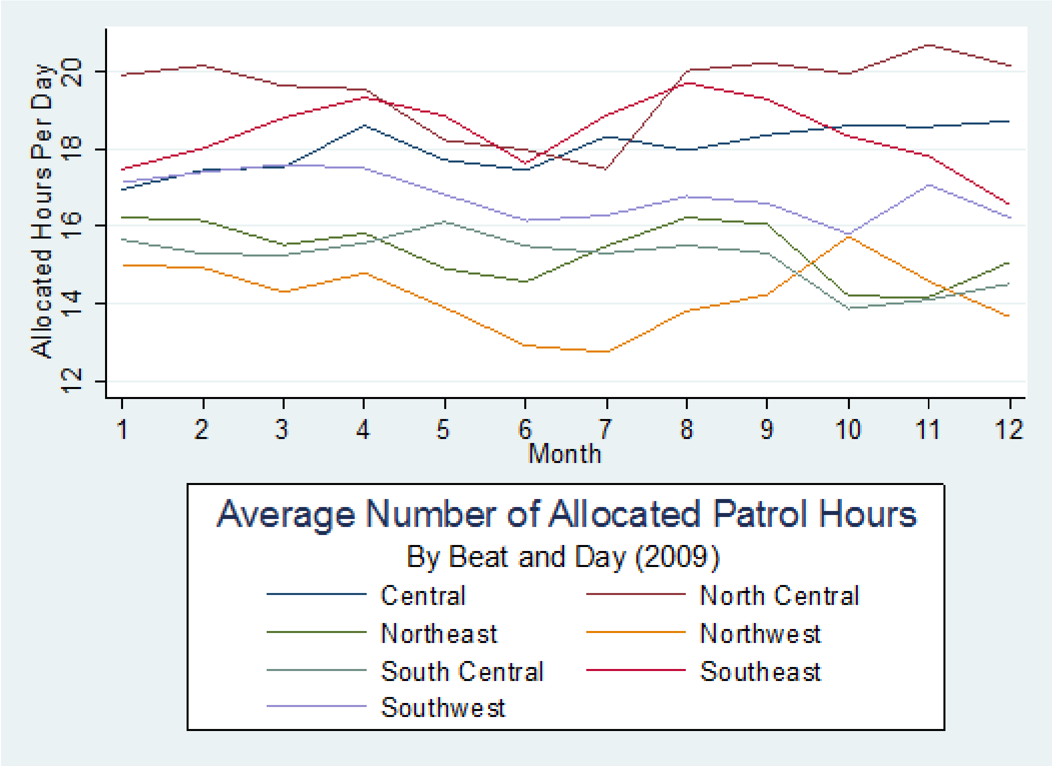

Figure 6: Police Presence in 2009

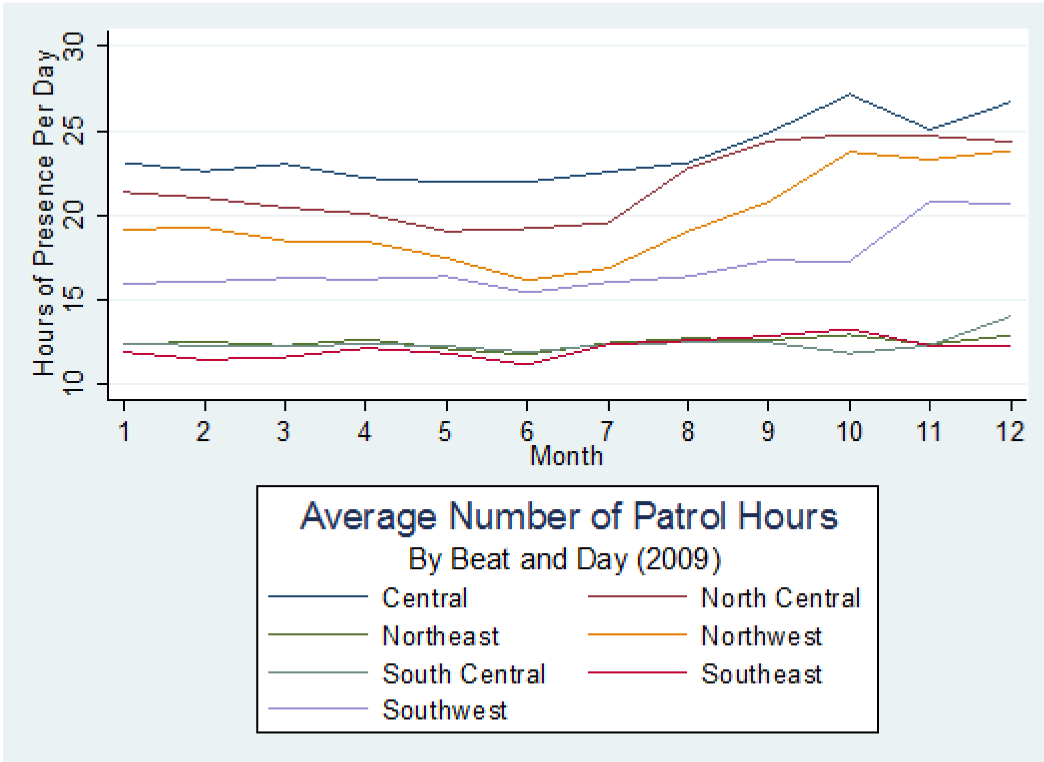

Table 2: Hourly Means for Beats Summarized by Division

	CENTRAL	NORTH CENTRAL	NORTH EAST	NORTH WEST	SOUTH CENTRAL	SOUTH EAST	SOUTH WEST
Criminal Disturbances	0.0489	0.0577	0.0522	0.0506	0.0396	0.0529	0.0707
	(0.0226)	(0.0220)	(0.0245)	(0.0207)	(0.0171)	(0.0215)	(0.0300)
Burglaries	0.0157	0.0238	0.0216	0.0196	0.0183	0.0202	0.0239
	(0.00717)	(0.0110)	(0.0101)	(0.00543)	(0.00829)	(0.00822)	(0.00815)
Violent Crimes	0.0521	0.0505	0.0631	0.0511	0.0683	0.0736	0.0742
	(0.0200)	(0.0253)	(0.0289)	(0.0195)	(0.0191)	(0.0199)	(0.0159)
Theft	0.0107	0.0126	0.0118	0.0143	0.00990	0.0108	0.0137
	(0.00292)	(0.00455)	(0.00551)	(0.00507)	(0.00290)	(0.00377)	(0.00372)
Total Crimes	0.127	0.144	0.149	0.136	0.136	0.157	0.182
	(0.0442)	(0.0583)	(0.0628)	(0.0351)	(0.0367)	(0.0355)	(0.0475)
Allocated Police Coverage	0.754	0.815	0.644	0.595	0.636	0.770	0.702
	(0.247)	(0.152)	(0.178)	(0.127)	(0.133)	(0.193)	(0.205)
Police Coverage	0.992	0.912	0.522	0.825	0.519	0.508	0.713
	(1.387)	(0.673)	(0.465)	(0.927)	(0.496)	(0.491)	(0.558)
Police Coverage (Not on Call)	0.932	0.822	0.455	0.745	0.441	0.430	0.615
	(1.382)	(0.663)	(0.460)	(0.916)	(0.490)	(0.480)	(0.550)
On Call Outside of Allocated Beat	0.375	0.368	0.377	0.378	0.392	0.450	0.401
	(0.118)	(0.0728)	(0.123)	(0.0813)	(0.0868)	(0.115)	(0.127)
Response Ratio	0.492	0.439	0.584	0.600	0.588	0.585	0.579
	(0.0294)	(0.0222)	(0.0537)	(0.0312)	(0.0350)	(0.0301)	(0.0437)
Expected Response Ratio	0.228	0.164	0.314	0.299	0.294	0.280	0.297
	(0.0534)	(0.0245)	(0.0530)	(0.0421)	(0.0352)	(0.0507)	(0.0548)
Number of Beats	29	22	42	31	37	39	33

Figure 7: Police Presence at 8 PM (High Versus Low Response Ratios)

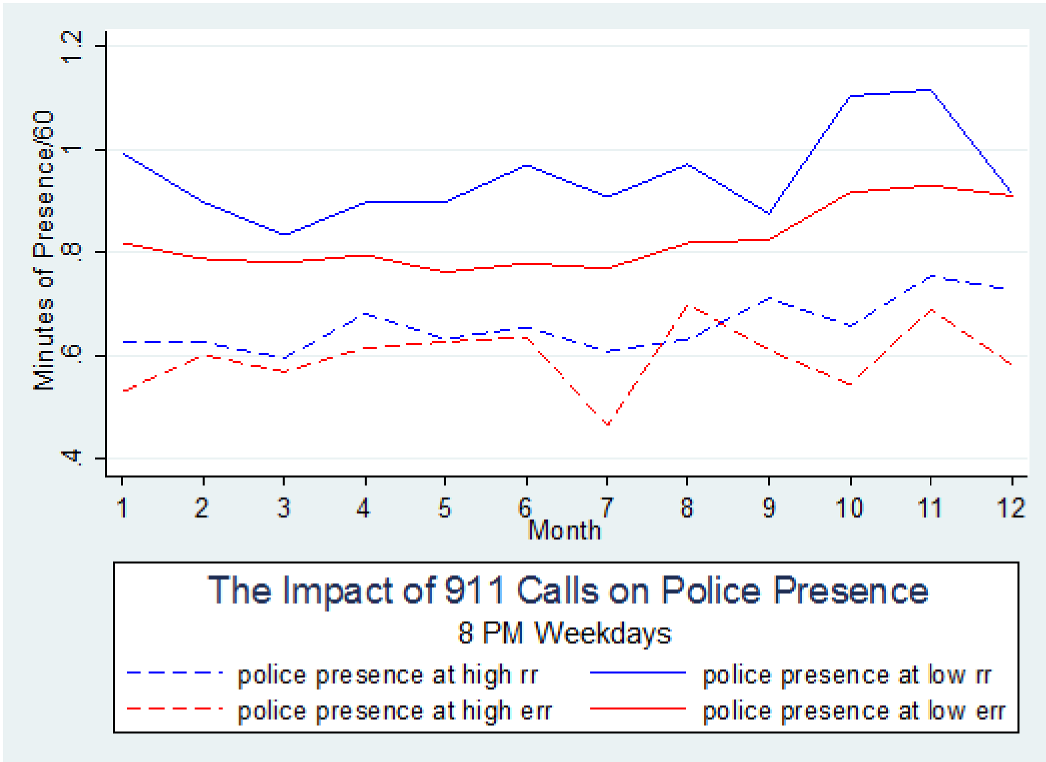

Table 3: Response Ratio as a Predictor of Police Presence

	(i)	(ii)[2]	(iii)
Response Ratio[1]	•0.280***	•0.253***	•0.176***
	(0.032)	(0.028)	(0.012)
Individuals in HH		•0.236	
		(0.185)	
Percent Hispanic		0.281	
		(0.446)	
Percent Asian		•0.132	
		(1.377)	
Percent Teens		8.024	
		(7.066)	
Temperature			0.000
			(0.000)
Precipitation			•0.000
			(0.001)
Twilight			0.000
			(0.003)
Dark			0.005
			(0.006)
Holiday			•0.094***
			(0.011)
Weekend			•0.100***
			(0.013)
Time Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	2026298	2026298	2026298

Standard errors account for clustering at the beat level

[1] Fraction of time cars allocated to beat spent answering outside calls

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, percent children, and percent vacant homes.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Expected Response Ratio as a Predictor of Police Presence

	(i)	(ii)[2]	(iii)
Expected Response Ratio[1]	•0.236***	•0.180***	•0.132***
	(0.022)	(0.019)	(0.011)
Individuals in HH		•0.243	
		(0.185)	
Percent Hispanic		0.271	
		(0.447)	
Percent Asian		•0.171	
		(1.380)	
Percent Teens		8.190	
		(7.069)	
Percent Vacant Homes		•1.251	
		(0.885)	
Temperature			•0.000
			(0.000)
Precipitation			•0.001
			(0.001)
Twilight			•0.001
			(0.003)
Dark			0.004
			(0.006)
Holiday			•0.095***
			(0.011)
Weekend			•0.104***
			(0.013)
Time Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	2026298	2026298	2026298

Standard errors account for clustering at the beat level

[1] Expected fraction of time cars allocated to beat spent answering outside calls

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, percent children, and percent vacant homes.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The Effect of Police Presence on Crime

	OLS		IV =RR		IV =ERR	
	(i)[2]	(ii)	(iii)[2]	(iv)	(v)[2]	(vi)
Police Vehicles[1]	0.009***	0.013***	•0.034***	•0.030***	•0.068***	•0.062***
	(0.003)	(0.002)	(0.008)	(0.006)	(0.017)	(0.013)
Individuals in HH	•0.025*		•0.036**		•0.044**	
	(0.013)		(0.015)		(0.019)	
Percent Hispanic	0.048*		0.059*		0.068	
	(0.026)		(0.032)		(0.043)	
Percent Asian	•0.220***		•0.229**		•0.236*	
	(0.077)		(0.101)		(0.137)	
Percent Teens	0.395**		0.741**		1.024*	
	(0.200)		(0.336)		(0.547)	
Percent Vacant Houses	0.027		•0.027		•0.070	
	(0.076)		(0.085)		(0.105)	
Temperature		0.001***		0.001***		0.001***
		(0.000)		(0.000)		(0.000)
Precipitation		•0.001***		•0.001***		•0.001***
		(0.000)		(0.000)		(0.000)
Twilight		0.008***		0.008***		0.008***
		(0.002)		(0.002)		(0.002)
Dark		0.002		0.002		0.002
		(0.002)		(0.002)		(0.002)
Holiday		0.009***		0.005***		0.002
		(0.002)		(0.002)		(0.002)
Weekend		0.037***		0.032***		0.028***
		(0.002)		(0.002)		(0.002)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2026298	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, and percent children.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The Effect of Police Presence on Violent Crimes

	OLS		IV =RR		IV =ERR	
	(i)[2]	(ii)	(iii)[2]	(iv)	(v)[2]	(vi)
Police Vehicles[1]	0.004***	0.006***	•0.020***	•0.019***	•0.032***	•0.028***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.008)	(0.006)
Individuals in HH	•0.011*		•0.017**		•0.019**	
	(0.006)		(0.007)		(0.008)	
Percent Hispanic	0.027***		0.034**		0.037*	
	(0.010)		(0.015)		(0.019)	
Percent Asian	•0.070**		•0.075		•0.078	
	(0.035)		(0.050)		(0.063)	
Percent Teens	0.174*		0.370**		0.466*	
	(0.090)		(0.174)		(0.246)	
Percent Vacant Houses	0.111***		0.081**		0.066	
	(0.033)		(0.039)		(0.047)	
Temperature		0.001***		0.001***		0.001***
		(0.000)		(0.000)		(0.000)
Precipitation		•0.000		•0.000		•0.000
		(0.000)		(0.000)		(0.000)
Twilight		0.004***		0.003***		0.003***
		(0.001)		(0.001)		(0.001)
Dark		0.000		0.000		0.000
		(0.001)		(0.001)		(0.001)
Holiday		0.008***		0.006***		0.005***
		(0.001)		(0.001)		(0.001)
Weekend		0.016***		0.013***		0.012***
		(0.001)		(0.001)		(0.001)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2026298	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, and percent children.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: The Effect of Police Presence on Public Disturbances

	OLS		IV =RR		IV =ERR	
	(i)[2]	(ii)	(iii)[2]	(iv)	(v)[2]	(vi)
Police Vehicles[1]	0.002***	0.005***	•0.017***	•0.008***	•0.038***	•0.023***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.009)	(0.007)
Individuals in HH	•0.006		•0.010		•0.016*	
	(0.006)		(0.007)		(0.009)	
Percent Hispanic	0.013		0.018		0.024	
	(0.012)		(0.015)		(0.022)	
Percent Asian	•0.135***		•0.139***		•0.143**	
	(0.035)		(0.043)		(0.066)	
Percent Teens	0.159*		0.315*		0.490	
	(0.088)		(0.162)		(0.300)	
Percent Vacant Houses	•0.048		•0.072**		•0.099**	
	(0.032)		(0.036)		(0.048)	
Temperature		0.001***		0.001***		0.001***
		(0.000)		(0.000)		(0.000)
Precipitation		•0.001***		•0.001***		•0.001***
		(0.000)		(0.000)		(0.000)
Twilight		0.003***		0.003***		0.003***
		(0.001)		(0.001)		(0.001)
Dark		•0.000		•0.000		0.000
		(0.001)		(0.001)		(0.001)
Holiday		0.007***		0.006***		0.004***
		(0.001)		(0.001)		(0.001)
Weekend		0.024***		0.023***		0.021***
		(0.002)		(0.002)		(0.002)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2026298	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, and percent children.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: The Effect of Police Presence on Thefts

	OLS		IV =RR		IV =ERR	
	(i)[2]	(ii)	(iii)[2]	(iv)	(v)[2]	(vi)
Police Vehicles[1]	0.001**	0.001***	•0.000	•0.001	•0.003*	•0.006***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Individuals in HH	•0.003**		•0.003**		•0.004***	
	(0.001)		(0.001)		(0.002)	
Percent Hispanic	0.009***		0.009***		0.010***	
	(0.003)		(0.003)		(0.003)	
Percent Asian	0.000		0.000		•0.001	
	(0.011)		(0.012)		(0.014)	
Percent Teens	0.008		0.016		0.040	
	(0.026)		(0.025)		(0.030)	
Percent Vacant Houses	•0.007		•0.009		•0.012	
	(0.009)		(0.009)		(0.010)	
Temperature		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Precipitation		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Twilight		0.001**		0.001**		0.001**
		(0.000)		(0.000)		(0.000)
Dark		0.001		0.001*		0.001*
		(0.000)		(0.000)		(0.000)
Holiday		•0.002***		•0.002***		•0.003***
		(0.000)		(0.001)		(0.001)
Weekend		•0.000		•0.000*		•0.001***
		(0.000)		(0.000)		(0.000)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2026298	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, and percent children.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: The Effect of Police Presence on Burglaries

	OLS		IV =RR		IV =ERR	
	(i)[2]	(ii)	(iii)[2]	(iv)	(v)[2]	(vi)
Police Vehicles[1]	0.002***	0.002***	0.003*	•0.001	0.005*	•0.005
	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
Individuals in HH	•0.006**		•0.006**		•0.005*	
	(0.003)		(0.003)		(0.003)	
Percent Hispanic	•0.001		•0.002		•0.002	
	(0.005)		(0.005)		(0.005)	
Percent Asian	•0.015		•0.014		•0.014	
	(0.015)		(0.015)		(0.015)	
Percent Teens	0.053		0.040		0.027	
	(0.034)		(0.039)		(0.047)	
Percent Vacant Houses	•0.029**		•0.027*		•0.025	
	(0.015)		(0.014)		(0.016)	
Temperature		0.000**		0.000**		0.000**
		(0.000)		(0.000)		(0.000)
Precipitation		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Twilight		0.001**		0.001**		0.001**
		(0.001)		(0.001)		(0.001)
Dark		0.001		0.001		0.001
		(0.001)		(0.001)		(0.001)
Holiday		•0.004***		•0.004***		•0.004***
		(0.001)		(0.001)		(0.001)
Weekend		•0.003***		•0.004***		•0.004***
		(0.000)		(0.000)		(0.000)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2026298	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

[2] Additional controls: percent black, average individual income, average household income, size of beat, miles of road within beat, and percent children.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: The Deterrence Effect of Police by Crime Category (IV=Car Accident Response Ratio)

	All Crimes (i)	Violent crimes (ii)	Public Disturbances (iii)	Theft (iv)	Burglary (v)
Police Vehicles[1]	•0.030***	•0.019***	•0.008***	•0.001	•0.001
	(0.006)	(0.003)	(0.003)	(0.001)	(0.002)
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	0.005***	0.006***	0.006***	•0.002***	•0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Weekend	0.032***	0.013***	0.023***	•0.000*	•0.004***
	(0.002)	(0.001)	(0.002)	(0.000)	(0.000)
Location & Time FE's	Yes	Yes	Yes	Yes	Yes
N	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: The Deterrence Effect of Police by Crime Category (IV=Car Accident Expected Response Ratio)

	All Crimes (i)	Violent crimes (ii)	Public Disturbances (iii)	Theft (iv)	Burglary (v)
Police Vehicles[1]	•0.101***	•0.052***	•0.038***	•0.007**	•0.004
	(0.017)	(0.009)	(0.009)	(0.003)	(0.004)
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	•0.002	0.003**	0.003*	•0.003***	•0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Weekend	0.023***	0.010***	0.019***	•0.001***	•0.004***
	(0.003)	(0.001)	(0.002)	(0.000)	(0.001)
Location & Time FE's	Yes	Yes	Yes	Yes	Yes
N	2026298	2026298	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: The Impact of Police Presence on Arrests

	IV=RR		IV=ERR
	(i)[2]	(ii)	(iii)
Police Vehicles[1]	0.018***	0.035***	0.033***
	(0.006)	(0.007)	(0.006)
Individuals in HH	•0.013**		
	(0.006)		
Percent Hispanic	0.055***		
	(0.015)		
Percent Asian	•0.024		
	(0.061)		
Percent Teens	•0.184		
	(0.146)		
Percent Vacant Houses	0.145***		
	(0.042)		
Temperature		0.000***	0.000***
		(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	0.002
		(0.001)	(0.001)
Weekend		0.012***	0.011***
		(0.002)	(0.002)
Time Fixed Effects	Yes	Yes	Yes
Location Fixed Effects	No	Yes	Yes
Observations	2026298	2026298	2026298

Standard errors account for clustering at the beat level

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

[2] Additional controls: percent Black, average individual income, average household income, size of beat, miles of road within beat, percent children, and percent vacant homes.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: The Deterrence Effect of Police on Crime by Beat Size

	Instrument=RR			Instrument=ERR		
	Small[2]	Midsize[3]	Large[4]	Small[2]	Midsize[3]	Large[4]
Police Vehicles[1]	•0.051***	•0.018*	•0.030***	•0.124***	•0.061***	•0.041***
	(0.016)	(0.010)	(0.008)	(0.035)	(0.022)	(0.015)
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	•0.001***	•0.002***	•0.000	•0.002***	•0.002***	•0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Twilight	0.013***	0.006***	0.007***	0.013***	0.006**	0.007***
	(0.003)	(0.002)	(0.003)	(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	0.013***	0.010***	•0.007**	0.009***	0.006*	•0.008**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Weekend	0.033***	0.040***	0.021***	0.030***	0.035***	0.019***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	Yes	Yes	Yes	Yes	Yes	Yes
Observations	556599	799844	669855	556599	799844	669855

Standard errors account for clustering at the beat level

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

[2] Small is defined as a beat that covers less than 4 miles of roads

[3] Midsize is defined as a beat that covers 4 to 8 miles of roads

[4] Large is defined as a beat that covers more than 8 miles of roads

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: The Impact of Previous Police Presence on Crime (Instrument=ERR)

	All Crimes			Violent Crimes		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Police Vehicles[1]	•0.056**	•0.062***	•0.055***	•0.025*	•0.032***	•0.029***
	(0.024)	(0.018)	(0.016)	(0.013)	(0.010)	(0.009)
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***	•0.000*	•0.000*	•0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Twilight	0.009***	0.009***	0.009***	0.004***	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	•0.005**	•0.005**	•0.006***	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Weekend	0.030***	0.030***	0.030***	0.013***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Police Vehicles In	0.009			0.004		
Previous Hour[2]	(0.025)			(0.014)		
Police Vehicles In		0.021			0.016*	
Previous 2 Hours[3]		(0.018)			(0.009)	
Police Vehicles In			0.010			0.014
Previous 3 Hours[4]			(0.017)			(0.008)
Location & Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2026065	2025832	2025599	2026065	2025832	2025599

Standard errors account for clustering at the beat level

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

[2] Police vehicles per beat within previous hour (60 minutes = 1 vehicle)

[3] Police vehicles per beat hour within previous 2 hours (120 minutes = 1 vehicle per hour)

[4] Police vehicles per beat hour within previous 3 hours (180 minutes = 1 vehicle per hour)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$