THE PINHAS SAPIR CENTER FOR DEVELOPMENT
TEL AVIV UNIVERSITY

“Does Police Presence Reduce Car Accidents?”

Sarit Weisburd[i]

Discussion Paper No. 12-16

August 2016

I appreciate financial support received from the The Pinhas Sapir Center for Development at Tel Aviv University.
I would like to thank The Police Foundation for providing me with the data for this study. This work would not have been possible without the help of Elizabeth Groff and Greg Jones. Additionally, I would like to thank Lieutenant Rupert Emison and Lieutenant Scott Bratcher for providing insight and information on the Dallas Police Department. I am very grateful for the GIS assistance provided by Adi Ben-Nun, Nir Horvitz, Elka Gotfyrd, and Ruthie Harari-Kremer at The Hebrew University Center for Computational Geography.

[i] Sarit Weisburd – The Eitan Berglas School of Economics, Tel Aviv University. Email: saritw@post.tau.ac.il

Abstract

This paper estimates the impact of police presence on car accidents using a unique data- base that tracks the exact location of Dallas Police Department patrol cars throughout 2009. To address the concern that officer location can be a result of car accidents that have already occurred, 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 2.1 to 3.5 percent increase in car accidents. I show that this effect is likely driven by a decrease in traffic citations, highlighting the potential drawbacks of the rapid response policing strategy.

1 Introduction

Motor vehicle accidents are the leading cause of death for people under age 34 in most developed countries, with an estimated annual cost of over 160 billion dollars in the US alone.[1] One common solution proposed for the accident problem is increasing police visibility based on the assumption that this will promote safer driving behavior. Becker's model (1968) provides a theoretical basis for this assumption where a person commits a crime only if the expected benefit of the crime exceeds the benefit of using his/her time and resources for another activity. This model may be relevant for driving behavior since faster and riskier driving techniques are likely to minimize commuting time. It predicts that more police presence increases the probability of punishment and will therefore result in more cautious driving and fewer accidents.

Studies conducted in different countries and locations provide evidence that drivers respond to focused deterrence efforts by police officers.[2] These papers often measure how an increase in the intensity of enforcement (ticketing, speed monitoring, etc.) targeted at a high-risk area changes driving behavior. A causal interpretation of these results is dependent upon the assumption that speeding trends between the treatment and control roads are identical absent police intervention.[3] An additional concern is that these focused deterrence efforts cannot be maintained for long periods and thus, their application to general policing strategy remains unclear. Indeed, the accident literature has reported mixed results regarding deterrence effects created by increases in police

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[1] The annual cost of car accidents in the US was calculated by the motorist advocacy group AAA after considering costs of medical care, emergency and police services, property damage, lost productivity, and quality of life (Clifford, 2008).

[2] See works by Cooper (1975), Hauer et. al. (1982), Sisiopiku and Patel (1999), Vaa (1997), and Waard et. al. (1994).

[3] Finding a relevant control road is complex as it must be similar enough to the treatment road to facilitate comparison yet different enough to minimize the number of drivers who can shift their route to the control road to avoid the increase in police presence at the treatment road.

enforcement that occur over a large geographic area for an extensive period of time.[4]

In contrast to previous research, I estimate the effect of police presence on driving behavior even when the intensity of enforcement may remain unchanged. I measure how different utilization of the same police force can change the distribution of car accidents within a city. In other words, will a police vehicle that is present on route A and then called to address an incident on route B alter accident outcomes along these different paths? While the crime literature often subscribes to a "hot spots" approach where police are most effective when allocated to specific problem areas it is not clear whether or not this is the case for car accidents.[5] By focusing on the usage of an entire police force throughout the year, I hope to reach a broader understanding of the general effect of police presence on behavior.

Analyzing the immediate impact of police presence on car accidents requires access to information on the location of police officers and car accidents 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 car accidents, 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 both crime and car accident incidents, the use of AVL systems to analyze where police patrol is rare and seldom integrated with incident data. In Dallas, Texas, over the course of 12 months (throughout 2009), AVL systems were active in all 873 police patrol vehicles and data on their location was saved and stored.[6] I focus on the beat (a geographic patrol area averaging one square mile in size) each car was allocated to patrol as well as where

[4] A study conducted on the Random Road Watch police intervention program in Queensland (Australia) found that this program decreased the annual number of car accidents by 12 percent (Newstead et. al., 2001). However, a similar program conducted between April 1997 and 1998 in Israel referred to as the 700-project found little evidence of a deterrence effect (Hakkert et. al., 2001).

[5] See works by Braga et. al. (1999), Sherman & Weisburd (1995), and Weisburd & Green (1995).

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

these officers were actually present throughout the day. Information on incidents of car accidents was acquired from a separate database that tracks calls for service (911 calls) placed by local citizens to the police department.[7] Thus, the current project is not motivated by a specific policing experiment, or large change in routine police activity, but rather, takes advantage of a large amount of data (roughly 100 million pings of information) to provide an estimate of the social returns of an additional hour of police patrol in the current policing system.

A deterrence mechanism that is based on police interactions would imply that areas or times of day with higher levels of police presence will report fewer car accidents. Similarly, one might expect a decrease in car accidents during periods where officers are present and writing up traffic citations. However, this ignores the allocation of officers to riskier locations during riskier periods. An additional concern is simultaneity bias, as the occurrence of a car accident is likely to increase police presence and traffic citations as officers are called to respond to the incident. These factors are illustrated in Figure (1), where the write-up of a traffic citation is positively correlated with an increase in police presence and an increase in the probability of a car accident.[8] Thus, while this dataset provides a unique picture of police presence across a city, the location of officers may be determined by driving behavior, which complicates the estimate of a deterrence effect.

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

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

[8] While there are 873 Dallas patrol vehicles tracked in this study, on average there are 132 cars on active patrol per hour. These cars are allocated among 232 beats. Thus, the most common allocation points are either 0 or 1 car allocated per hour.

under 8 minutes.[9] I use incidents where patrol officers are assigned to calls outside of their area of patrol to capture an element of randomness regarding whether or not police are present at a given location and time. Thus, I introduce the *Response Ratio* instrument (RR), equal to the fraction of time officers assigned to a given beat spend answering calls outside of that beat to identify a causal effect of police presence on car accidents. I show that beats and intervals of time with a higher RR have significantly lower levels of both police presence and traffic citations (see Figure 2).[10] I argue that the RR measurement is an exogenous factor impacting police presence and thus, provides an opportunity to estimate a causal deterrence effect of policing on driving behavior.

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 car accidents at the given beat. For the first assumption to hold, car accidents occurring at the same hour in different areas of Dallas must be uncorrelated. My results are robust to controlling for both hour fixed effects and location fixed effects. It therefore seems unlikely that my estimates could be explained by high response ratios across Dallas at specific hours when car accidents peak throughout the city.

The second assumption requires that the assignment of an officer to an out of beat call is uncorrelated with the car accident risk at his/her allocated beat. This assumption is more complex as a car accident in a given beat could directly lower RR at that beat (as the allocated officers may have less time to spend answering outside calls). In order to address this concern, I also consider an alternative instrument (the *Expected Response Ratio)* based on the intention to assign cars to outside beats.

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

[10] Officers are often being shifted between beats and therefore even in hours when allocated officers spend all of their time answering out of beat calls (response ratio = 1) other police officers may enter the beat. Thus, when the response ratio is equal to 1 police presence in the beat does not necessarily equal 0.

My results suggest that the number of officers patrolling a beat has a significant impact on the probability of a car accident. I first demonstrate that there is a positive correlation in the data between police presence and car accidents. This positive correlation remains significant even when controlling for location and time fixed effects. This result is not surprising, given that the occurrence of a car accident will likely draw officers to that location. 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 *Response Ratio* (*RR*) instrument, I estimate that a 10 percent decrease in police presence results in a 2.1 percent increase in car accidents. The *Expected Response Ratio* (*ERR*) yields a higher deterrence estimate of 3.5 percent for the same change in police presence.[11]

This paper proceeds as follows. In the next section I present a general framework for analyzing the impact of police on car accidents 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

Becker (1968) introduced a model where a person commits a crime if the expected benefit of the crime exceeds the benefit of using his/her time and resources for another activity. This model can be applied to driving behavior since faster and riskier driving techniques are likely to minimize commuting time. It predicts that more police presence increases the probability of punishment and will therefore result in more cautious driving and fewer accidents.

[11] The lower estimate from the *Response Ratio* instrument can be explained by the possible correlation between car accidents occurring internally at the beat and the probability of being allocated to an outside call.

I model car accidents as the direct result of unsafe driving. This is a simplifying assumption as it is clear that not all unsafe driving results in a car accident, and similarly, not all car accidents are caused by unsafe driving. However, it seems reasonable to assume that unsafe driving should increase the probability of a car accident, and a car accident can be considered an indication that unsafe driving occurred at this location. Thus, a car accident occurs whenever an individual finds the benefits of unsafe driving (e.g. decreased travel time) to be above the cost (e.g. sanctions and car accident risks). Thus, the number of car accidents (C) will be a function of the the rewards (r) and expected sanctions (s) from driving dangerously,

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

We would expect that rational drivers would be more likely to engage in a dangerous driving with a higher reward (r) and lower probability of sanction (s). However, it is unclear how drivers calculate the expected sanction from driving dangerously. 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 car accidents (C).

2.2 Previous Research

Previous research has shown that drivers respond to focused increases in the intensity of police enforcement.[12] One of the earlier studies conducted at urban junctions in the US found that police presence can significantly reduce traffic violations (Cooper, 1975). However, this effect disappeared as soon as the officer was no longer present at the intersection. Vaa (1997) also found a significant policing effect, where 9 hours per day of police activity on treatment roads decreased driving speed by 0.9-4.8 kms/hour relative

[12] See works by Cooper (1975), Hauer et. al. (1982), Sisiopiku and Patel (1999), Vaa (1997), and Waard et. al. (1994).

to control roads. This later paper did find evidence of a halo effect, as the speed decrease persisted for an additional 2-8 weeks after termination of the treatment period. These types of experiments tend to include both extensive media coverage and a large increase in enforcement (generally at least 3 times the pre-intervention level) and it is unclear if a smaller scale effort across a larger geographic area will provide similar results.

The literature has reported mixed results from increases in police enforcement that occur over a large geographic area for an extensive period of time. A study conducted on the Random Road Watch police intervention program in Queensland, Australia found that this program decreased the annual number of car accidents by 12 percent (Newstead et. al., 2001). Much of the success of the program (evaluated between December 1991 and July 1996) was attributed to the random allocation of officers over different time intervals and locations. However, a similar program conducted between April 1997 and 1998 in Israel referred to as the 700-project (due to the 700 kms of road that received increased enforcement) found little evidence of a deterrence effect (Hakkert et. al., 2001). The authors conclude, "focused activity that is shorter in time, more concentrated in area/enforcement subject and more flexible in performance of police operations, will gain advantage over the 700-project results."

These papers provide an estimate of how focused increases in police deterrence can affect accident rates. The programs are applied specifically at problematic road segments where a significant portion of accidents occur. A causal interpretation of these results is dependent upon the assumption that speeding trends between the treatment and control roads are identical absent police intervention.[13]

An alternative method is to estimate how legislation related to police presence affects accident outcomes. Thus, an entire country (or state) receives a treatment effect and behavior can be compared to that observed prior to the legislation. In a study looking

[13] An additional concern is that drivers may shift their route to the control roads in order to avoid the increase in police presence at treatment areas.

at the impact of deterrence policies on reckless driving in Portugal, the authors conclude that the government could be more effective in reducing traffic accidents by increasing the "certainty of punishment" via increased police enforcement (Tavares et. al., 2008). They reach this conclusion after regressing the rate of accidents in Portugal between 1995-2004 on indicators regarding new legislation of increased traffic fines, on-the-spot payment, and lower legal blood-alcohol limits. In essence, changes in allowed blood alcohol concentration levels are used as a proxy for enforcement since their data does not allow a direct estimate of police enforcement. While this approach was suggested by Legge and Park (1994), it relies on a strong assumption that stricter legislation results in higher levels of enforcement. An alternative explanation of the significant positive effect of the decrease in allowed blood alcohol concentration levels on accidents is simply that people drank less as a direct result of the legislation change (severity of punishment) regardless of police presence (probability of punishment). Due to these identification issues in previous research, it is important to find a direct measure of general police presence in order to analyze the effect of enforcement on accidents.

Much of the research regarding police presence has focused on the impact of police on criminal activity, not car accidents.[14] While car accidents are not always outcomes of devious or criminal behavior, both the general findings regarding the effects of police presence on behavior and the research techniques applied to analyze criminal activity are relevant for this analysis.

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.[15] 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

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[14] See works by Corman and Mocan (2002), Evins and Owens (2007), Klick and Tabarrok (2005), Marvell and Moody (1996), Sherman and Weisburd (1995), and Shi (2009).

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

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 effect of police presence on crime, as well as instrumenting techniques.[16] 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.

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, this is the first paper to examine the impact of everyday policing on car accidents. I consider the 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 car accident 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 car accidents.

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

[16] 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)).

exists to support that claim (Sherman, 2013).[17] 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 incentivising safe behavior today and responding to incidents that occurred in the past.

3 The Data

In equation (1), I model car accidents as an outcome of rewards (r) and expected sanctions (s) . My empirical analysis will 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 car accidents and police in 2009. The DPD call database records the time and location of each reported car accident 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 car accidents.[18]

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

[17] 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, Kirchmaier & Vidal (2015) find that faster response times increase the likelihood of detecting crimes when using an instrumenting strategy.

[18] 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.

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 accident risks.

The analysis is conducted on geographic beats at hour long time intervals. I use the call database to count the number of car accidents reported for each beat b and hour h. The main analysis focuses on 45,307 calls reporting car accidents in Dallas, Texas in 2009. Figure 5 illustrates how the number of car accidents vary over time in different areas of Dallas. While beats in the Northern divisions have a higher accident rate than those in the Southern divisions, they follow similar trends where car accidents peak around April-May and then again in October. Beats in the Central division have the highest accident rate for the first 6 months of the year, after which they converge to the accident rate of beats in the Northern divisions.

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).[19]

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 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.[20] 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.[21]

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

[19] 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.

[20] 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.

[21] 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.

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 car accidents, police allocation and police presence by beat at the division level. The majority of car accidents occur in beats that are located in the Northwest 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 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 unclear relationship between police presence and car accidents is already made apparent in Table 2. Beats in the Northwest division average fifty percent more police presence than beats in the Northeast division and they exhibit a significantly higher accident rate. The Northwest has significantly higher road density and traffic which could be contributing both to the higher level of police presence and the prevalence of car accidents. In order to identify a causal effect of policing on car accidents, I focus on an instrument that impacts the level of police presence in a given beat, but should not directly impact car accidents at that beat.

The *Response Ratio* (RR_{bh}) is calculated for each beat (b) and hour (h) as the fraction of time police cars allocated to the given beat (A_{bh}) 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 time of day t can be constructed for each hour h as $t = h \bmod 24$. Let $mcalls_{ibh}$ be the number of minutes patrol car i spends answering calls outside of allocated beat b during hour h. I define $mpatrol_{ibh}$ to be the number of minutes patrol car i was allocated to spend in beat b during hour h. Let $APatrol_{bh} = \sum_{i \in A_{bh}} mpatrol_{ibh}$ be the total amount of allocated patrol. I calculate the *Response Ratio* (RR_{bh}) as,

$$RR_{bh} = \frac{\sum_{i \in A_{bh}} mcalls_{ibh}}{APatrol_{bh}} \tag{2}$$

It makes sense that higher *Response Ratios* (hours in which beat officers spend a larger fraction of their time assigned to out of beat calls) result in lower police presence. However, one could be concerned that whether or not an officer is assigned to an out of beat call may be directly correlated with car accidents at his/her beat. For example, if police are unavailable because they are responding to a within beat car accident this could result in low RR_{bh} and high car accidents, without any change in police presence. I address this concern by introducing an alternative instrument, the *Expected Response Ratio,* which is unrelated to the assignments of the allocated beat officers.

In Figure (8) , I map out the average amount of police coverage on weekdays for the highest crime beat within each division. Not surprisingly, hours with low *Response Ratios* ($RR_{bh} < 0.1$) where less than 10 percent of the allocated officer's time is spent answering outside calls have higher police presence than hours with high *Response Ratios* ($RR_{bh} > 0.9$) where over 90 percent of their allocated time is spent answering outside calls. Generally, police presence during hours with high *Response Ratio*'s is about 24 minutes lower (a difference of 0.4 in Figure (8)) than police presence in those same beats during low *Response Ratio* hours.

Figure (8) also maps the *Expected Response Ratio* (ERR_{bh}) which is the expected time officers allocated to beat (b) at hour (h) spend responding to outside calls, divided by the allocated minutes of presence at given location and time. In other words, I assume the allocated officer will have to answer the average number of incidents being handled by out of beat officers in his/her division. I therefore set the numerator as 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).[22] The denominator remains the number of minutes of allocated patrol at that beat (see equation (2)),

$$ERR_{bh} = \max\left(\frac{30 \times \sum_{x \neq b \in D} incidents_{xh}}{\sum_{x \neq b \in D} APatrol_{xh}} \times \frac{1}{APatrol_{bh}}, 1\right) \quad (3)$$

By construction the *Expected Response Ratio* (ERR_{bh}) 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 an 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. The added strength of the ERR_{bh} instrument is that it is determined only by activity outside of the beat, whereas a lower *Response Ratio* (RR_{bh}) may result from internal incidents.[23]

In the next section I lay out my empirical strategy for estimating the deterrence effect of police presence on car accidents. 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 car accidents remain positively correlated.

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

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

4 Empirical Strategy and Results

In Section 2, I discussed a general framework for deterrence where police presence (P) is likely to impact car accidents (C) by increasing the expected sanctions (s) from driving dangerously. In equation (4) I apply this framework to the Dallas data, modelling the occurrence of a car accident (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 driving dangerously (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 car accidents across different times and beats. If policing is uncorrelated with the remaining unobserved factors impacting car accidents (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 incidents of both crime and car accidents. Using detailed geographic data can further complicate the relationship as one would expect that when a car accident occurs in a given hour more police will immediately enter the beat in response to the incident. 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 car accident to offer additional assistance. An added concern is that there may be seasonal differences in car accident 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 accident locations and the plausibly random timing of emergency calls in surrounding areas that provide a first stage for police presence P_{bh},

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

While the allocated level of presence can be determined by the perceived incident risk in that area (δ_{bh}), actual presence is impacted by an exogenous factor RR_{bh} as defined in equation (2), or alternatively, ERR_{bh} as defined in equation (3). The estimated coefficient on the instrument ($\widehat{\alpha}_1$) is expected to be negative, since an increase in the fraction of time allocated officers spend on out of beat calls (higher RR_{bh} or ERR_{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 *Response Ratio* (RR) on police presence as defined in equation (5).[24] On average, a beat receives police coverage for 60 percent of each hour. In specification (1), I find that increasing the *Response Ratio* from 0 to 1 (moving from allocated beat patrol officers answering 0 outside calls during that hour to spending all of their time answering outside calls) decreases police coverage by 0.280 ($60 \times 0.28 = 17$ minutes).[25]

[24] The response ratio for each location and time is calculated using equation (2).

[25] There are two reasons why allocated police officers spending all of their time on out of beat calls does not decrease police presence at that hour by 60 minutes. First, when an allocated officer leaves the beat he/she can be replaced by outside officers. Second, on average each beat only receives police presence for 36 minutes out of every hour.

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 a 47 percent decrease in police coverage. Specification (1) cannot rule out the concern that beats or hours with lower accident risks and less allocated officers are more likely to have high *Response Ratios.* However, when I control for characteristics at the beat level as well as month and hour of the day fixed effects in specification (2), I continue to find a similar significant impact of *Response Ratio* on police presence (-0.266 (0.032)). In the final specification which includes location fixed effects, along with hour fixed effects, and controls for time varying day characteristics, I find that a one unit change in the *Response Ratio* decreases police presence by 29 percent $\left(\frac{\widehat{\alpha}_1=0.176}{P_{bh}=0.6} \times 100\right)$. This can be compared to a 17 percent drop in police presence on holidays and weekends.

I find very similar results when examining the impact of the *Expected Response Ratio* (ERR) in Part B of Table (3). This outcome is importance because a concern with the *Expected Response Ratio* is that it may have lower predictive power than the *Response Ratio* as it increases whenever incidents occur in the division outside of the beat (b) even if the allocated officers were not assigned to the incident (see equation (3)). I find that increasing the expected allocation of officers to calls outside their beat from zero to 1 (see Column (3) of Part B) results in a decrease in police presence of 0.126 (s.e. 0.010), implying a 21 percent change $\left(\frac{\widehat{\alpha}_1=0.126}{P_{bh}=0.6} \times 100\right)$. 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 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 changes in the *Response Ratio* have a very straightforward interpretation regarding changes in police presence, it is difficult to rule out concerns regarding whether or not the exclusion restriction holds for this instrument.[26] I therefore provide estimates of the deterrence effect using both the *Response Ratio* and the *Expected Response Ratio* instrument in the subsequent tables.

I estimate the impact of police presence on car accidents 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 car accidents (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 car accidents 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 0.002 increase in car accidents (at an average car accident rate of 0.022).

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 *Response Ratio* (RR_{bh}). 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 accident 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 accident 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 -0.005 (0.002). Adding in location fixed effects, as well as weather,

[26] If the *Response Ratio* is lower in hours when incidents occurred (because fewer officers are available) this would bias the estimated deterrence effect towards zero. I elaborate on this point after discussing my deterrence estimates from equation (4) when instrumenting for police presence with the *Response Ratio*.

and time of day characteristics in specification (4) increases the deterrence estimate to -0.008 (0.002). While β_1 in equation (4) represents the effect of an additional police vehicle (P_{bh}) on car accidents, 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 36 percent increase in car accidents $\left(100 \times \frac{0.008}{0.022}\right)$. If I focus on average police presence per hour (36 minutes), a 10 percent decrease in police presence implies a 2.1 percent increase in car accidents (elasticity of -0.21).

In Section 3, I discussed the concern that the *Response Ratio* instrument may underestimate the deterrence effect if increases in beat level car accidents (C_{bh}) directly reduce RR_{bh}.[27] In the last columns of Table (4), I estimate a deterrence effect by instrumenting for actual police presence (P_{bh}) with the *Expected Response Ratio* (ERR_{bh}). Consistent with my concern that the response ratio (RR_{bh}) may underestimate the deterrence effect, I find larger deterrence effects when applying the *Expected Response Ratio* (see column (6) versus column (4)). The estimated deterrence impact of -0.013 (0.004) 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 3.5 percent increase in car accidents.

Table (4) also provides information on how different location, weather, and time characteristics impact car accident outcomes. Each additional mile of roads, results in a 10 percent increase in car accidents. I find that car accidents are generally more likely to occur on weekends and during bad weather. The highest probability of an accident is at 6 PM in the evening, and April is the most dangerous month for car accidents.

[27] It is simplest to think about this in terms of reduced form estimates which are proportional to the effects estimated using two stage least squares (although positive in sign since an increase in the response ratio decreases police presence and increases crime). If crime in beat b directly lowers the *Response Ratio* in beat b (as less officers are available to be assigned to outside incidents) the unobserved factors that impact crime will be negatively correlated with the *Response Ratio.* Since $\frac{\partial Crime}{\partial Response\ Ratio} > 0$ this will bias the deterrence estimate towards zero.

5 A Closer Look at the Mechanisms of Deterrence

My estimates suggest that police presence at the beat level can significantly impact driving behavior. The next step is to understand the mechanism by which police presence changes behavior. What are patrol officers doing to prevent car accidents? Are police officers more effective when allocated to smaller areas?

Police officers engage in both active patrol (e.g. writing citations) and passive patrol (e.g. car patrol, paperwork) when working a beat. Even when engaging in active patrol, for the majority of officers, their main focus is likely to be crime and not car accidents. In order to correctly interpret my deterrence results, it is relevant to understand the extent to which the *Response Ratio* and *Expected Response Ratio* instruments impact police patrol that is directed specifically towards controlling driving behavior. This differentiation is important for gaining insight into whether or not officers patrolling the streets are primarily effective in impacting driving behavior only when that is their direct focus. I therefore examine how the assignment of officers to out of beat calls impacts the distribution of citations. I then analyze whether or not this change in citations may be driving the deterrence estimates from the previous section.

Figure (9) maps the distribution of traffic citations in Dallas Texas throughout the year. Beats average roughly 2 citations per day, with the Central division beats receiving the highest level of citations in the first 6 months of the year. Due to the relatively low prevalence of citations when examining beat by hour intervals, I drop 39 beats that average less than one traffic citation per day from this analysis and focus on the 193 remaining beats. In Table (5), I find a significant impact of both the *Response Ratio* and the *Expected Response Ratio* on the probability of receiving a traffic citation. In specification (1), I find that increasing the *Response Ratio* from 0 to 1 (moving from allocated beat patrol officers answering 0 outside calls during that hour to spending all of their time answering outside calls) decreases citations by 0.03. On average, at any given beat in any given hour there is a 7 percent chance of receiving a traffic citation, therefore the allocation of officers to calls outside of their beat results in a 43 percent decrease in traffic citations. This estimate is robust to adding in additional controls as well as location and time fixed effects. I find a similar effect when using the *Expected Response Ratio* as an instrument for traffic citations, a shift in the ERR from 0 to 1 decreases traffic citations by 40 percent. This significant change in traffic citations that is driven by the instruments uses in this paper imply that much of the estimated impact of police presence, may be a direct result of a change in active patrol (police ticketing).

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 driving behavior. Furthermore, 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.[28] With lower budgets, police departments are being forced to make tough decisions regarding police activities and deployment. Understanding how these deployment techniques impact crime and car accidents is key for optimizing outcomes given the current budgets.

This is the first study that looks at how the location of police affects individual behavior across an entire city. In contrast to previous research, I am not studying how an increase or decrease in the size of a police force affects behavior, nor how concentrated police presence at a given location for a set period changes driving behavior. My main contribution is to provide an analysis of how the day-to-day interaction between an active police force and the population they protect can change accident outcomes.

The results presented in this paper raise concerns that frequently assigning officers

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

to out of beat 911 calls may have significant costs in terms of deterring unsafe driving behavior. I estimate that each 10 percent decrease in police presence at a given beat and hour increases car accidents at that location by 2.1 to 3.5 percent. These estimates are especially relevant to 911 calls as my instruments focus on shifts in police presence that are created when 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. I find evidence that when patrol officers are assigned to out of beat calls, traffic citations decrease, a clear indicator of a decrease in active patrol. 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) impacts the way people drive. 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 car accidents, 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 saves lives. 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 Vidal & Kirchmaier (2015)), it can also disrupt preemptive police activity. My results suggest that optimizing the impact of policing on our neighborhoods requires weighing the costs and benefits of assigning officers to out of beat calls.

This paper expands the scope of deterrence research beyond criminal behavior to the general population. The significant effect of police patrol vehicles on accident outcomes carries an important policy implication. The location of police matters even when their primary focus may not be accident prevention. Routes chosen by police officers during routine patrol can have a direct effect on the accident rate. In this age of reduced police funding, I find that the high toll of accident costs on our society can be reduced by increasing the visibility of police on our streets.

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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.

6.2 Appendix B: 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 $APatrol_{bh} = 0$ for 37 percent of my sample. Setting ERR_{bh} or RR_{bh} 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 my sample.

I focus on the minimum nonzero level of allocated police coverage at each location b and time of day $t = h \bmod 24$ (t ranges from 0 to 23). For each time of day t, I define H_b^t as all hours in 2009 when beat b had a nonzero amount of allocated coverage at given time of day t. When $APatrol_{bh} = 0$ I set RR_{bh} and ERR_{bh} to be equal to,

$$\widehat{ERR}_{bh} = \max\left(\frac{30 \times \sum_{x \neq b \in D} incidents_{xh}}{\sum_{x \neq b \in D} APatrol_{xh}} \times \frac{1}{\min_{h' \in H_b^t}\left(APatrol_{bh'}\right)}, 1\right) \tag{6}$$

Equation (6) serves as a proxy for ERR_{bh} 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.[29] Thus, $\widehat{ERR}_{bh}$ remains a decreasing function of allocation, as areas with generally higher levels of allocated patrol are likely to have more police presence.

[29] 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.

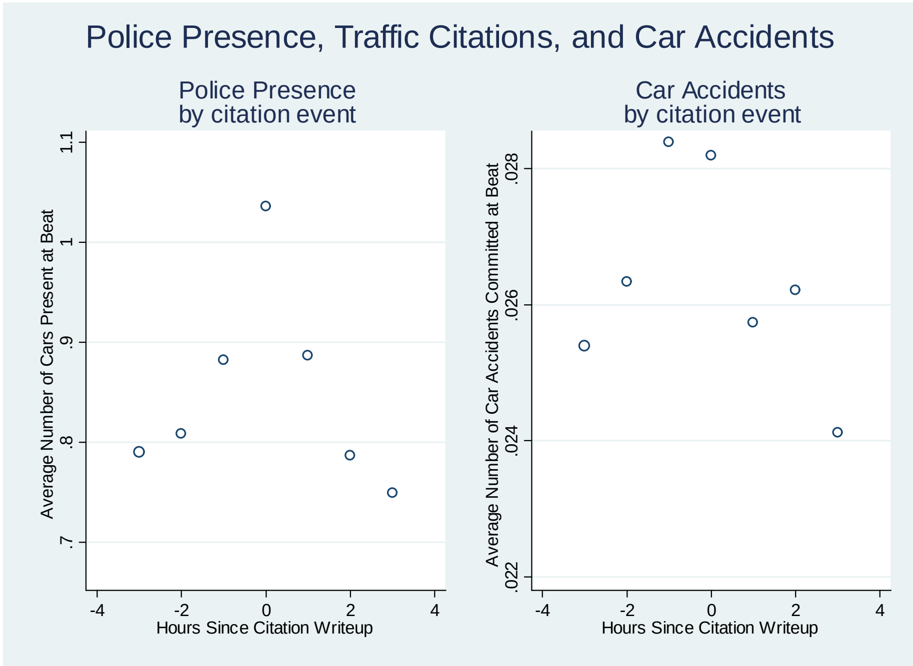

Figure 1: The data was collapsed at number of hours elapsed since nearest traffic citation.

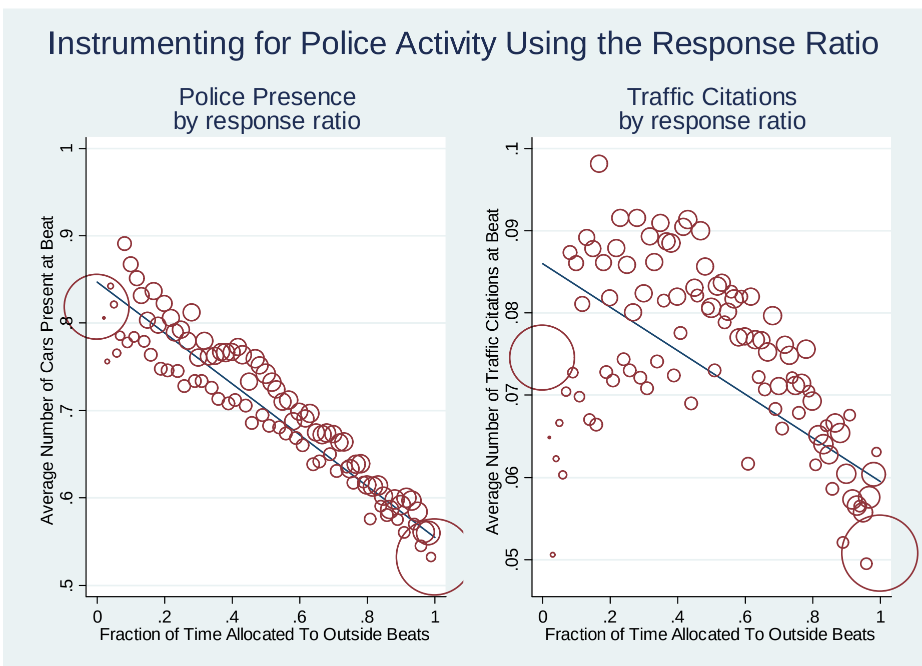

Figure 2: The data was collapsed at each fraction of hour allocated to out of beat calls. The size of the circle relates to the density of observations at that fraction of time allocated to out of beat calls.

Figure 3: Dallas Beats

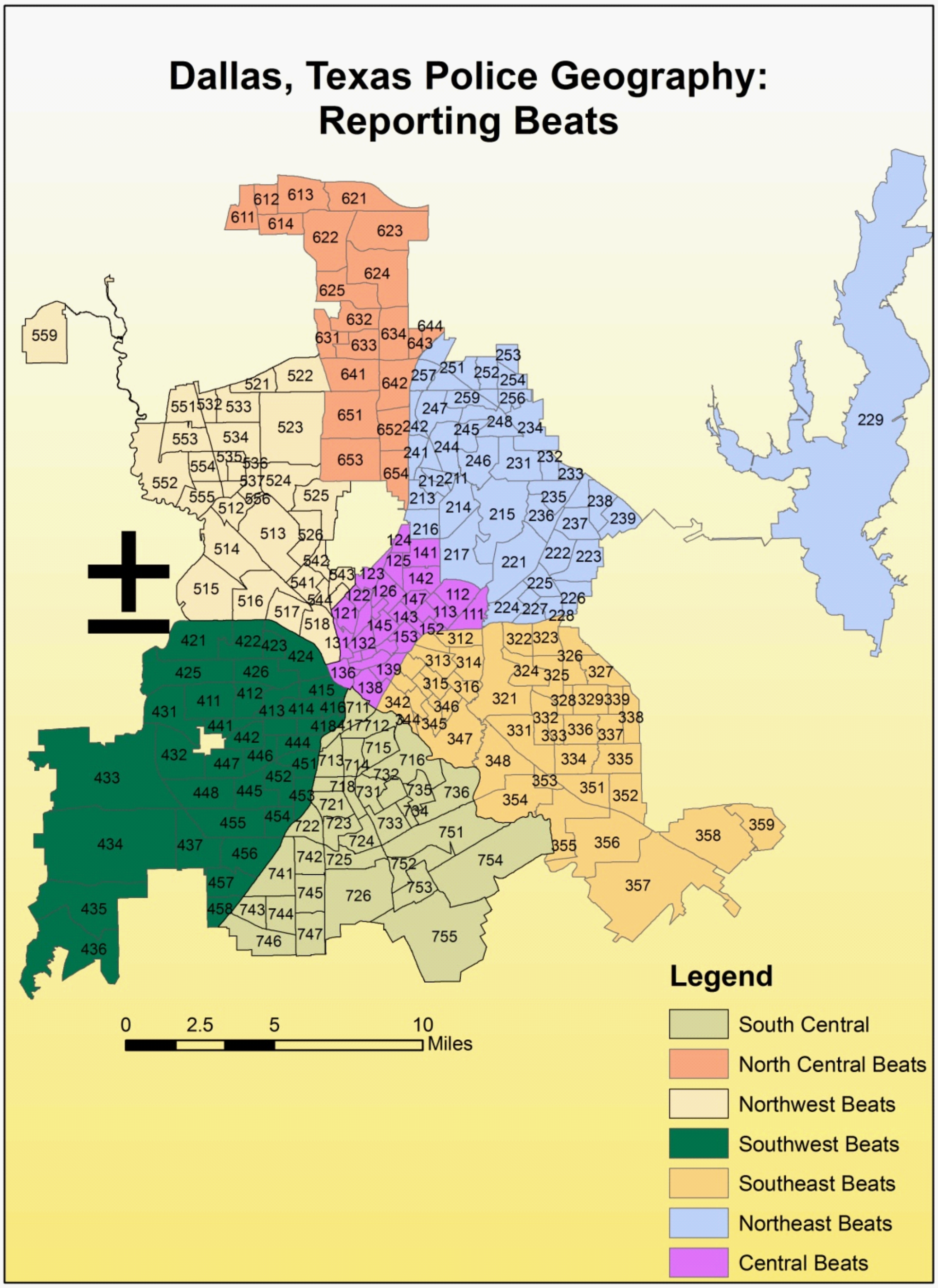

Figure 4: The Distribution of Car Accidents in 2009

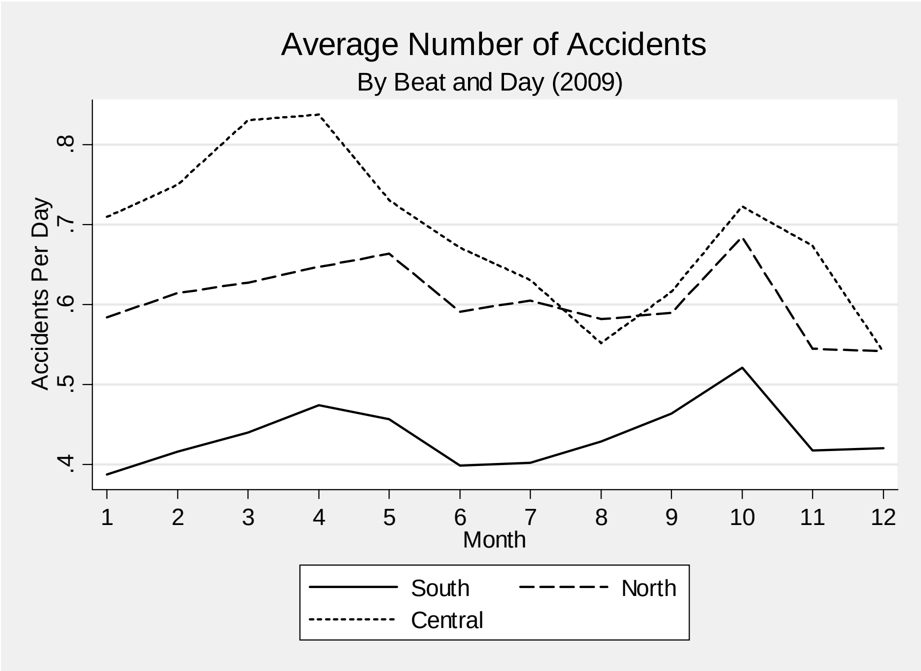

Figure 5: The data was collapsed at each beat and day of year. The South line is the average number of crimes commited per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of crimes commited per beat and day in the Northeast, Northwest, and North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

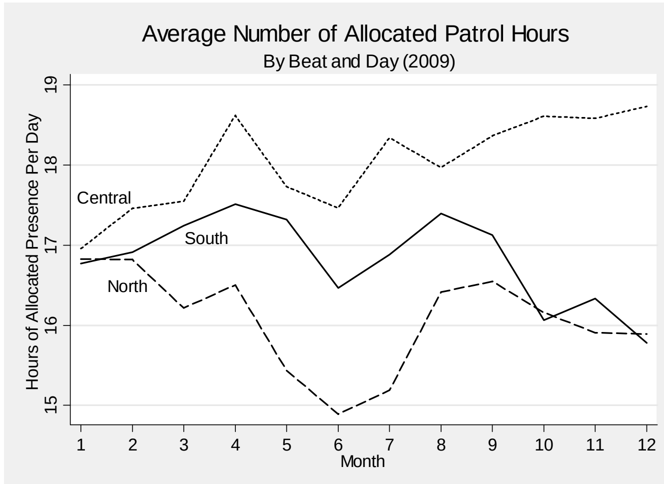

Figure 6: The data was collapsed at each beat and day of year. The South line is the average number of allocated patrol hours per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of allocated patrol hours per beat and day in the Northeast, Northwest,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

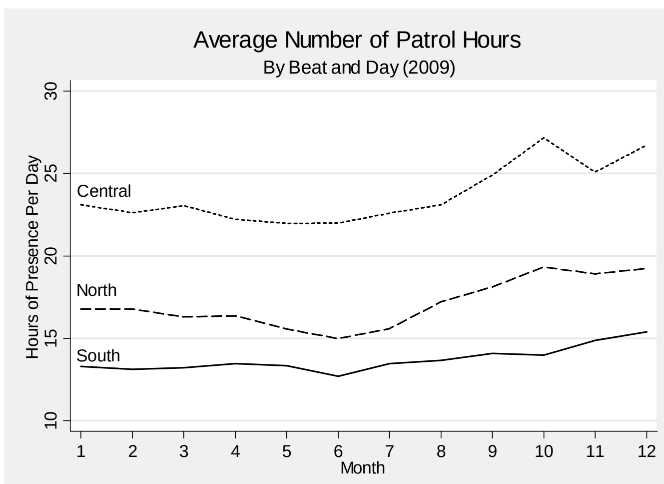

Figure 7: The data was collapsed at each beat and day of year. The South line is the average hours of actual police presence per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average hours of actual police presence per beat and day in the Northeast, Northwest,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

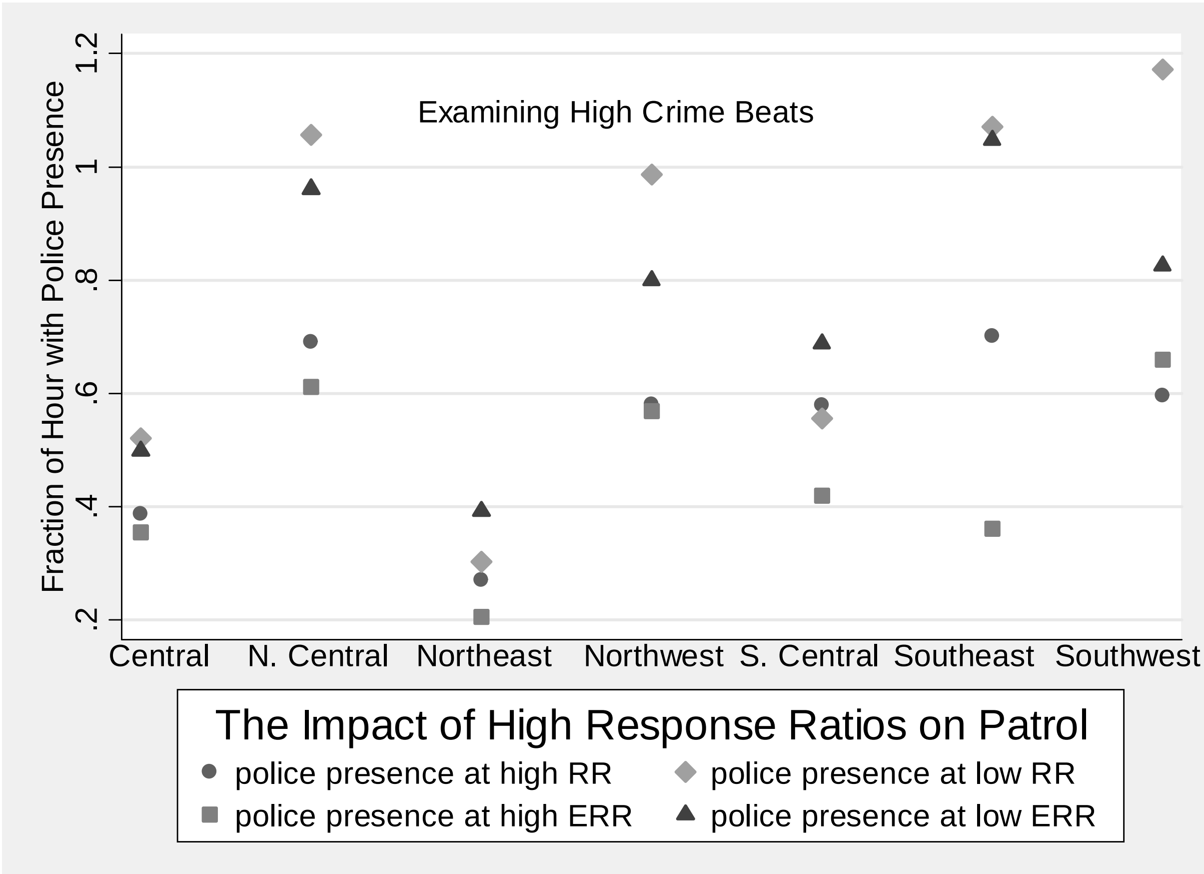

Figure 8: This figure illustrates levels of police presence during weekdays at the highest crime beat in each division. Police presence at high RR is the average amount of actual police patrol at each of the 7 beats during hours when the Response Ratio was greater than 0.9 (allocated officers spent over 90 percent of their time responding to out of beat calls). Police presence at low RR is the average amount of actual police patrol at each of the 7 beats during hours when the Response Ratio was less than 0.1 (allocated officers spent less than 10 percent of their time responding to out of beat calls). Police presence at high ERR is the average amount of actual police patrol at each of the 7 beats during hours when the Expected Response Ratio was greater than 0.9 (the amount of calls occurring in the division outside the beat would predict that allocated officers will spend at least 90 percent of their time assigned to out of beat calls). Police presence at low ERR is the average amount of actual police patrol at each of the 7 beats during hours when the Expected Response Ratio was less than 0.1 (the amount of calls occurring in the division outside the beat would predict that allocated officers will spend less than 10 percent of their time assigned to out of beat calls).

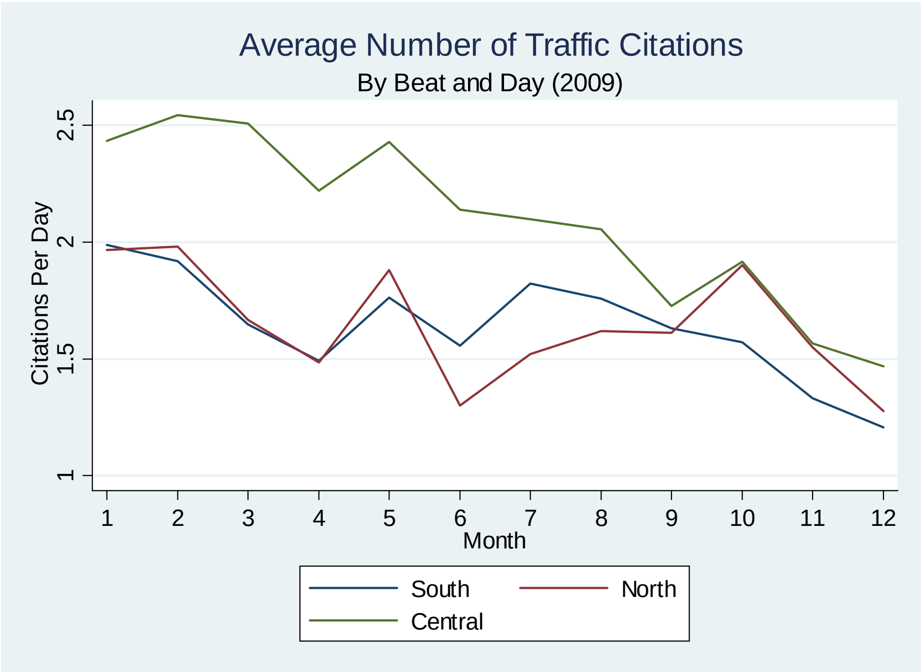

Figure 9: The data was collapsed at each beat and day of year. The South line is the average number of traffic citations per beat and day in the Southeast, Southwest, and South Central Divisions. The North line is the average number of traffic citations per beat and day in the Northeast, Northwest, and 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)
Car Accidents	0.029	0.028	0.019	0.032	0.016	0.015	0.024
	(0.172)	(0.169)	(0.140)	(0.182)	(0.131)	(0.125)	(0.157)
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[1]	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[2]	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)
Response Ratio (RR)[3]	0.492	0.439	0.580	0.600	0.588	0.585	0.579
	(0.348)	(0.346)	(0.343)	(0.346)	(0.347)	(0.339)	(0.344)
Expected RR[4]	0.222	0.158	0.296	0.288	0.283	0.273	0.288
	(0.293)	(0.234)	(0.330)	(0.327)	(0.323)	(0.321)	(0.324)
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] Police vehicles allocated to beat per hour (60 minutes = 1 vehicle)

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

[3] Fraction of time cars allocated to beat spent answering outside calls (RR=1 implies allocated cars spent all of their time on out of beat assignments)

[4] Expected fraction of time cars allocated to beat spent answering outside calls (ERR=1 implies that the number of outside incidents that occurred in the division were expected to utilize all of the officers allocated to beat).

Table 3: Response Ratio and Expected Response Ratio as Predictors of Police Presence

	(1)	(2)	(3)
A. Instrumenting for Police Presence with the Response Ratio (mean police presence=0.6)			
Response Ratio[1]	-0.279***	-0.266***	-0.176***
	(0.032)	(0.032)	(0.012)
Percent Hispanic		-0.481	
		(0.438)	
Percent Asian		-0.376	
		(1.259)	
Holiday			-0.095***
			(0.011)
Weekend			-0.101***
			(0.013)
B. Instrumenting for Police Presence with the Expected Response Ratio (mean police presence=0.6]			
Expected Response Ratio[2]	-0.225***	-0.192***	-0.126***
	(0.021)	(0.020)	(0.010)
Percent Hispanic		-0.482	
		(0.441)	
Percent Asian		-0.427	
		(1.260)	
Holiday			-0.095***
			(0.011)
Weekend			-0.105***
			(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. Specification (2) includes additional controls: percent black, 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]Fraction of time cars allocated to beat spend answering outside calls.
[2]Expected fraction of time cars allocated to beat spend answering outside calls.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 4: The Effect of Police Presence on Car Accidents

	OLS		IV=RR[2]		IV=Expected RR[3]	
	(1)	(2)	(3)	(4)	(5)	(6)
Police Vehicles[1]	0.001**	0.002***	-0.005***	-0.008***	-0.009**	-0.013***
	(0.0003)	(0.0003)	(0.002)	(0.002)	(0.004)	(0.004)
Miles of Road	0.002***		0.002***		0.002***	
	(0.0003)		(0.0003)		(0.0004)	
Percent Children	-0.060***		-0.073***		-0.081***	
	(0.024)		(0.024)		(0.027)	
April	0.003***	0.003***	0.003***	0.003***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
October	0.004***	0.003**	0.005***	0.003**	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
6 PM	0.006***	0.006***	0.007***	0.007***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation		0.003***		0.003***		0.003***
		(0.0003)		(0.0003)		(0.0003)
Twilight		0.001**		0.001**		0.001**
		(0.001)		(0.001)		(0.001)
Holiday		-0.003***		-0.004***		-0.004***
		(0.001)		(0.001)		(0.001)
Weekend		0.002***		0.001**		0.001
		(0.0005)		(0.0005)		(0.001)
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 car accident rate is 0.022 (s.d. 0.152), average police presence is 0.605 (s.d. 1.079). Standard errors in parenthesis account for clustering at the beat level. Specifications (1),(3), and (5) include additional controls for: percent Black, Asian and Hispanic, as well as average individual income, average household income, size of beat, percent teens, and percent vacant homes. Specifications (2), (4) and (6) also control for temperature and darkness.

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

[2]The fraction of time assigned officers spent answering out of beat calls.

[3]The expected fraction of time assigned officers spent answering out of beat calls.

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

Table 5: Response Ratio and Expected Response Ratio as Predictors of Traffic Citations

	(1)	(2)	(3)
A. Instrumenting for Traffic Citations with the Response Ratio (mean traffic citations=0.079)			
Response Ratio[1]	-0.031***	-0.034***	-0.033***
	(0.003)	(0.002)	(0.002)
April		-0.019***	-0.019***
		(0.003)	(0.004)
Precipitation			-0.004***
			(0.0004)
Twilight			-0.009***
			(0.002)
Holiday			-0.011***
			(0.003)
B. Instrumenting for Traffic Citations with the Expected Response Ratio (mean traffic citations=0.07			
Expected Response Ratio[2]	-0.041***	-0.032***	-0.028***
	(0.003)	(0.003)	(0.002)
April		-0.020***	-0.020***
		(0.003)	(0.004)
Precipitation			-0.004***
			(0.0004)
Twilight			-0.009***
			(0.002)
Holiday			-0.011***
			(0.003)
Time Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	1,678,751	1,678,751	1,678,751

Notes: Each observation is a beat and hour in 2009. Standard errors account for clustering at the beat level. Specification (2) includes additional controls: percent black, 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, and dark.

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

[2]Expected fraction of time cars allocated to beat spend answering outside calls.

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