

# Does Police Presence Reduce Car Accidents?<sup>1</sup>

Sarit Weisburd  
The Hebrew University

June 13, 2013

<sup>1</sup>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. I would like to thank my advisor Saul Lach for his guidance and support. 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. Finally, I want to express my appreciation to Yona Rubinstein, Philip Cook, Eric Gould, and Naomi Hausman for their helpful comments and suggestions on an earlier draft. I gratefully acknowledge financial support from the Israel National Road Safety Authority Doctoral Fellowship. E-mail: < sarit.weisburd@mail.huji.ac.il >.

## **Abstract**

Using data collected from geographic locators attached to police vehicles in Dallas, Texas over a one year period, we estimate the effect of policing on accident outcomes. We model the occurrence of an accident as a non-homogeneous Poisson process and differentiate between the immediate effect of police presence and the long-term effect of policing on expectations of future police presence. In order to address concerns of simultaneity bias, we both control for location specific fixed effects and measure the effect of "random patrol" created when police vehicles pass through an area en route to or returning from a call at another location. Our estimates suggest that at least two days of high intensity stationary police presence at a given time interval and location can reduce that area's accident rate by almost 40 percent during the following week. We also find that the presence of a stationary police vehicle can immediately reduce the accident rate by at least 9 percent, while the presence of moving police vehicles can produce the opposite effect.

# 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.<sup>1</sup> 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.<sup>2</sup> 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.<sup>3</sup> 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

---

<sup>1</sup>This estimate 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).

<sup>2</sup>See works by Cooper (1975), Hauer et. al. (1982), Sisiopiku and Patel (1999), Vaa (1997), and Waard et. al. (1994).

<sup>3</sup>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.<sup>4</sup>

In contrast to previous research, we estimate the effect of police presence even when the intensity of enforcement may remain unchanged. We measure how different utilizations of the same police force can change the distribution of car accidents within a city. In other words, will a police vehicle that chooses to take route *A* as opposed to 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.<sup>5</sup> By focusing on the usage of an entire police force throughout the year we hope to reach a broader understanding of the general effect of police presence on behavior.

Measuring how the allocation of officers affects accident outcomes requires detailed information on police location as opposed to an aggregate measure of police force size.<sup>6</sup> Even when such data are available, allocation of police officers is driven by community needs and therefore police may be located in more accident prone areas at more accident prone times. Thus, there may exist unobserved location characteristics which result in more dangerous intersections receiving increased police attention and exhibiting higher accident rates. These unobserved location characteristics can also change over time due to activity in the area (e.g. a street festival or construction) and raise concerns regarding simultaneity bias when measuring the effect of police presence on car accidents.

An effective solution to the simultaneous relationship between police presence and crime has been to focus on exogenous causes that resulted in direct changes in police presence or activity. In two separate papers, Di Tella and Schargrodsky (2004) and

---

<sup>4</sup> 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).

<sup>5</sup> See works by Braga et. al. (1999), Sherman & Weisbord (1995), and Weisbord & Green (1995).

<sup>6</sup> This is the common measure applied in the deterrence literature. See papers by Marvell and Moody (1996), Corman and Mocan (2000), Evans & Owens (2007).

Gould and Stecklov (2009) measure the effect of an increase in police presence following acts of terrorism. Shi examines the effect of a decrease in police activity after an April 2001 incident in Cincinnati where a white officer shot and killed an unarmed African-American adolescent (Shi, 2009). These papers all reach the conclusion that police affect crime.

This paper utilizes detailed micro data collected by The Police Foundation mapping both police presence and car accidents over time in Dallas, Texas. Police presence was measured using geographic locators placed in most police vehicles (873 in total) between January and December of 2009. These locators provide information on the location and speed of each vehicle at 30 second intervals. Data on car accidents was acquired from a separate database that tracks calls for service placed by local citizens to the police department.

In order to address the issue of simultaneity bias created by unobserved differences between locations, we compare accident outcomes at the same location and time of day that face different levels of police presence. We also estimate the effect of "random patrol," i.e. police vehicles that are in a given area only because they are en route to, or returning from, answering a call. Random patrol cars will still cover the full range of police activity from stationary to high-speed movement. They may originally be moving quickly to handle an emergency, and afterwards be conducting their general patrol at a slightly different location. While the number of police vehicles in a given location will be directly affected by the policing needs at that location and point in time, this is not the case for random patrol vehicles. By definition, these police officers are not actively participating in a deterrence effort, but rather en route to or from a service call. Their location was determined by a call for assistance that caused them to gravitate towards a new location. Thus, examining random patrol removes the simultaneity bias that is present when accident risks determine police placement.

We differentiate between an immediate effect, where people alter their driving

behavior the moment a police vehicle becomes visible, and a long-term effect. A long term effect, referred to in the literature as a "halo effect," implies that seeing a police vehicle changes future expectations of police presence, and thus, future driving behavior. Previous research has focused primarily on the immediate effect of police presence, while sometimes reporting a smaller expectations effect. We find that the expectations effect is in fact stronger than the immediate effect.

Our measured deterrence effect is specific to stationary police vehicles whose average speed remains below 15 m.p.h. over a 15 minute interval.<sup>7</sup> Treating the arrival time of car accidents as a nonhomogenous poisson process, we find evidence of an expectations effect where increasing the number of days with above median police presence can result in lower accident rates.<sup>8</sup> Thus, an area that moves from zero to two days of increased presence in the last week is expected to decrease its accident rate today by almost 40 percent.<sup>9</sup> Each additional day of above median police presence reduces the accident rate by an additional 5 percent. While these outcomes can be explained by the effect of policing on expectations, we also estimate a smaller immediate effect of policing on accident outcomes. We find that the presence of a stationary vehicle in a given location and time decreases the probability of an accident by at least 9 percent. This immediate deterrence effect does not hold for moving police vehicles that may actually increase the accident rate in high traffic density areas of Dallas.

Our findings suggest that increased deterrence could be achieved without increasing the amount of police patrol, but rather, by optimizing the timing and location of police

---

<sup>7</sup>An alternative definition would have been to count only police vehicles that do not move over a 15 minute interval. However, this definition would have ignored vehicles who have just arrived at an area or are surveying a neighborhood with stop and go movement. As the lowest speed limit in Dallas is 25 mph, we believe 15 mph is sufficiently low to characterize stationary presence.

<sup>8</sup>The Poisson process is unique in that it allows outcomes to be "memoryless," i.e. the occurrence of an accident in a given area does not affect the probability of a future accident at that place.

<sup>9</sup>While this estimate is large it is important to consider the context. We are measuring the effect of an additional day of presence on a small geographic area (roughly 217 acres). The average probability of an accident in one of these areas is 0.13 percent, thus a 40 percent increase translates into a 0.05 percentage point change.

vehicles. When expectations are formed based on increases in police presence, variation in police presence over time and across locations is a key ingredient for deterring car accidents. To the best of our knowledge, this is the first paper that attempts to identify how police officers following their daily routine affect accident outcomes. It introduces a new way of looking at the intensity of traffic enforcement, not by what police are doing, but rather, by where they are going.

This paper proceeds as follows. In the next section we introduce the data used for this project as well as our technique for measuring police presence. Section 3 discusses our empirical strategy and Section 4 presents estimates of both the immediate effect of police presence and the effect of police expectations on accidents. Section 5 concludes.

## **2 Using Available Data to Construct Measures of Police Presence & Accident Risks**

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 exact geographic location and speed of each of these police vehicles. The ping also includes a report indicator for vehicles that are responding to a call for service. This report indicator provides important information regarding whether this vehicle is on general patrol or responding to a call. In contrast to an aggregated count of the number of active police officers per city, this data allows us to map the activity of each individual squad car throughout the day.

The original database for 2009 consists of almost a half billion pings of information. These pings represent latitudinal and longitudinal coordinates collected at different points of time on the map of Dallas, Texas. To analyze the effect of police presence on car accidents it is necessary to define both a geographic unit of analysis and a uniform measure of time. We therefore divide the city of Dallas into 1,152 geographic areas of analysis and use the vehicle pings to measure the number of different types of police

vehicles present in each area over each 15 minute interval of 2009. Thus, 30 pings of information from a given vehicle that remained in the same speed category and geographic area for a full 15 minute interval will result in 1 vehicle count for that unit of analysis. A different police vehicle that moved between two reporting areas in this 15 minute interval will result in an additional vehicle count in both of those reporting areas.

The 1,152 geographic areas of analysis (referred to as reporting areas) are the smallest geographic unit defined by the Dallas Police Department (see Figure 1) and range in size from 3-30,000 acres (with a mean of 217 acres, and median of 120 acres). The reason these reporting areas range in size is that they were defined in an attempt to divide the city into areas with equal levels of policing needs. Thus, smaller reporting areas are more heavily populated and larger reporting areas include parks and industrial zones.

We define our unit of time measurement  $t$  as a 15 minute interval where  $t = 1$  on 1/1/2009 between 12AM and 12:15 AM and  $t = 35,040$  on 12/31/2009 between 11:45PM and 12AM the following day. Thus, an increase in one  $t$  equals a 15 minute change in time. The final dataset is a panel of 40,366,080 observations. Each observation corresponds to the observed characteristics of a given reporting area over a 15 minute interval in 2009 (such as population, number of schools, number of police vehicles, visibility, weather conditions, etc.).

We introduce the concept of total police presence ( $num\_police_{r,t}$ ) as the number of police cars out of the 873 tracked vehicles that pass through a given area  $r$  over interval  $t$ ,

$$num\_police_{r,t} = \sum_{i=1}^{873} I[\text{police vehicle } i \text{ is located in } r \text{ at time } t] \quad (1)$$

Counting actual vehicle presence as opposed to allocated police presence is made possible by the AVL locators. It provides the econometrician with a more accurate measure

of the observed deterrence encountered by drivers.<sup>10</sup> We include a police vehicle in  $num\_police_{r,t}$  as long as it entered location  $r$  for some part of interval  $t$ . It is unclear if police presence at time  $t$  will result in an immediate decrease in accidents. On the one hand, we would expect people to drive more carefully after viewing a police vehicle. Police officers can also have an incapacitation effect by taking dangerous drivers off the road (via arrest, or confiscating their driver's license). On the other hand, police officers driving through an area at high speeds or with flashing lights can surprise drivers and increase the accident rate.

Our data also allow us to separate total police presence into stationary and moving police presence. Stationary vehicles, whose average speed remains below 15 m.p.h. over a 15 minute interval, are both more likely to be focused on traffic patrol and less likely to create confusion via sirens and flashing-lights. Thus, stationary vehicles may have a more significant deterrence effect on driving behavior.

We define two additional variables in order to measure the long term effect (expectations effect) of police presence on driving behavior. These variables will provide an opportunity to examine whether or not individuals choose their driving behavior based on perceived expectations for police presence in a given location and time of day. While some studies have attempted to measure the length of time a deterrence effect remains once the intervention ended, little is known about the type of police presence necessary to change individual expectations and future driving behavior.

The first expectations measure ( $days\_of\_presence_{r,t}$ ) counts the number of times in the past 7 days when at least one vehicle was patrolling at that location over the 2 hour interval surrounding  $t$  [ $t - 4, t + 4$ ]. The second expectations measure ( $days\_above\_median_{r,t}$ ) counts only those days when police presence was above the median level of presence at given location ( $r$ ) and time interval [ $t - 4, t + 4$ ]. Thus,

---

<sup>10</sup>Observing actual police presence can also create additional complications due to simultaneity bias. We account for this issue by focusing on within location comparisons and random patrol vehicles.

$$days\_of\_presence_{r,t} = \sum_{i=1}^7 I \left[ \sum_{j=-4}^4 (num\_police_{r,t-(24 \times 4 \times i)+j}) > 0 \right] \quad (2)$$

$$\begin{aligned} & days\_above\_median_{r,t} \\ &= \sum_{i=1}^7 I \left[ \sum_{j=-4}^4 (num\_police_{r,t-(24 \times 4 \times i)+j}) > median_{2009} \left( \sum_{j=-4}^4 (num\_police_{r,t-(24 \times 4 \times i)+j}) \right) \right] \end{aligned} \quad (3)$$

where  $I(\cdot)$  is the indicator function. Both measures take on the values 0,...,7 as a count of the number of times within the past 7 days when a deterrence effect may have been created.<sup>11</sup> Instead of measuring police presence only at the specific point of time  $t$ , we count presence in the larger 2 hour interval surrounding  $t$   $[t - 4, t + 4]$  in the previous seven days. While commuters are likely to follow similar driving patterns throughout the week it seems reasonable that they may deviate by an hour in either direction.

One possibility is that drivers form expectations of police presence based on the frequency in which they encounter police officers at specific locations during their daily commute (equation (2)). Thus, when  $num\_police_{r,t} > 0$  this will affect people's driving behavior around the time interval  $t$  for the next 7 days. However, equation (3) will be more relevant if individuals update their expectations of police presence only when they encounter deviations from the norms of police vehicle presence (defined as the median level of police presence in 2009 at that location  $r$  and interval  $[t - 4, t + 4]$ ). Specifically commuters, who expect a given number of police officers per location to be focused on crime patrol (not traffic patrol), are likely to be affected by changes in police presence, as opposed to a count of police vehicles.<sup>12</sup>

---

<sup>11</sup>We also allowed for a longer deterrence memory of 2 weeks or 1 month, but found the effect to be concentrated in the last 7 days. This finding is consistent with discussions with traffic enforcement agents who claimed that multiple encounters within a week drive deterrence.

<sup>12</sup>Importantly, police officers on traffic patrol use exactly the same vehicles as those on crime patrol in Dallas, Texas.

The measure of expectations provided by equations (2 and 3) will be most accurate for Dallas drivers who follow the same driving path at the same time throughout the week (due to a work commute, school drop-off/pick-up, etc.). Different individual belief systems can alter how these measures affect driving behavior. If drivers believe that police presence follows a "random walk" then the location of a police officer at a given time  $t$  cannot predict future police presence. This belief system would predict a zero effect of past police presence on accident outcomes. Alternatively, higher measures of previous police presence would result in safer driving if people believe that police presence is "persistent." But if people believe in "mean reversion," then increased police presence could result in more dangerous driving, since an increase in police presence in previous days decreases the perceived probability of presence today (as a finite number of officers need to patrol the entire city).

Figure 2 illustrates how stationary police presence measured using equation (1) varies within the same location (reporting area #2057) and time of day over the course of a month. While equation (1) refers to the number of vehicles in a given 15 minute interval, we sum the number of vehicles in the two hour interval surrounding each point in time  $[t - 4, t + 4]$ . Thus, each point on the graph refers to the number of stationary police cars during morning (7-9 AM) and evening rush-hour (4-6 PM) between Monday, January 5<sup>th</sup> and Saturday, January 31<sup>st</sup>. Figure 2 provides a visual representation of how police presence during morning and evening rush-hour can be used to calculate expectations at 8 AM and 5 PM in equations 2 and 3.

Our first measure of expectations (equation 2) counts the number of days out of the past week in which there was a police car present within the given two hour window. For certain areas and time intervals where the level of police presence remains relatively high this measure will remain constant in the data. For example in reporting area #2057 there is no date in January where the number of stationary vehicles present during rush hour was zero (see Figure 2). Thus, at 8 AM and 5 PM, stationary  $days\_of\_presence_{r,t}$

is equal to 7 for reporting area #2057 during the entire month of January.

Our second measure of expectations in equation (3) attempts to capture the effect of relative high patrol. We measure expectations by counting the days out of the last week in which police presence was above the median level of presence at that location and time of day. Thus, on January 12<sup>th</sup>, stationary  $days\_above\_median_{r,t}$  equals 4 for 8 AM (police presence exceeded the median level of police presence (9 vehicles) on January 7th-10th). One week later, on January 19<sup>th</sup>, stationary  $days\_above\_median_{r,t}$  equals 3 at 8 AM (see Figure 2). Thus, using equation (3), we find expectations of police presence to be higher at 8 AM on January 12th than 8 AM January 19th.

These measures provide an estimate of changes in police presence that occur over time  $t$ . They provide a framework for differentiating between the immediate and long term effect of police on individual behavior. In the following subsection we discuss additional data that was collected in order to capture variability in accident risks over different reporting areas and time periods.

## 2.1 Reporting Area Characteristics

The Dallas Police Department records information on every call reporting incidents of crime or car accidents to the police department via a "calls for service" database. All car accidents with injuries or that require towing must be reported to the police department.<sup>13</sup> Thus, for each reporting area  $r$  and 15 minute interval  $t$  we measure the number of crime and car accidents reported.

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 6 provides a map of the city divided into divisions and beats (each beat includes roughly 5 reporting areas). Figure 5 illustrates how the

---

<sup>13</sup>This dataset may be missing smaller accidents that were not reported to the police department. This would bias our results towards zero if people are more likely to report a small accident when police are visible in their area.

number of accidents vary throughout the year within the 7 divisions of Dallas. While accidents in all areas peak in the winter months, most divisions also show fluctuations in the accident rate throughout the year.

We collect additional information on temperature, visibility, precipitation, sunrise, and sunset in Dallas in order to control for variability in the probability of an accident over time. Using geographic mapping software we characterize reporting areas by the types of roads, as well as number of schools, parks and type of development (residential, business, etc.).

Table 1 presents the mean monthly values for each of these variables by reporting area, summarized at the division level. It highlights the importance of geographic data which allows us to differentiate between different areas in the city. The majority of traffic accidents occur in reporting areas that are located in the Northern side of the city. This statistic holds for minor, major, and major accidents occurring on freeways. These reporting areas tend to be more densely populated and are known to have higher levels of traffic congestion.

The distribution of accidents differs from that of crime that is more evenly distributed between reporting areas. This statistic is not surprising given that the primary determinant of beat borders and size was in order to allow an even distribution of policing needs throughout the city - focusing primarily on crime. The highest level of police presence is in the Central Division. Not only does this area have higher policing needs as the city center it also connects the other divisions of the city.

Table 1 also provides mean estimates of police presence as defined in equations (1). Thus, the average reporting area encounters between 2 and 4 police vehicles per hour. Less than 1 of these vehicles is characterized as stationary (traveling at a speed below 15 m.p.h.). It is interesting to note that very few of these vehicles are focused on traffic patrol (about 10 percent of the Dallas police force), yet the remaining 90% of Dallas police vehicles may still create a significant deterrence effect because there is no

visible distinction between traffic and crime patrol vehicles. In the next section we lay out our empirical strategy for estimating the deterrence effect of police presence on car accidents.

### 3 Empirical Strategy

Let  $T_1 < T_2 < \dots < T_N$  denote the car accident times at a given location  $r$ , where  $T_k$  records the number of 15 minute intervals that elapsed between  $t = 0$  (midnight December 31st 2008) and the  $k^{th}$  accident. Thus, if the first accident occurred on January 1<sup>st</sup> 2009 at 2:05 AM then  $T_1 = \frac{120}{15} = 8$ . These accident occurrences can be described as a counting process  $\{N(t), t \geq 0\}$  by examining the cumulative number of accidents generated over 15 minute intervals  $t$ ,

$$N(t) = \sum_{k=1}^N I(T_k \leq t)$$

where  $I(\cdot)$  is the indicator function.

$N(t)$  is often the only statistic available, e.g., how many accidents occurred over the past month. However, as factors affecting car accidents are likely to vary over the course of a month (weather conditions, visibility, police presence, etc.) we are more interested in the probability of an accident at each small interval of time  $[t, t + \Delta t]$ . Let  $\Delta N(t) = N(t + \Delta t) - N(t)$  denote the number of car accidents in the interval  $[t, t + \Delta t]$  where  $\Delta t$  denotes a time infinitesimally smaller than  $t$ . Treating car accidents as a recurrent event, we define the instantaneous probability of an accident occurring at time  $t$  conditional on the history of car accidents before time  $t$  ( $H(t) = \{N(s) : 0 \leq s < t\}$ ) as

$$\lambda(t|H(t)) = \lim_{\Delta t \rightarrow 0} \frac{\Pr \{\Delta N(t) = 1 | H(t)\}}{\Delta t} \quad (4)$$

When examining car accidents in a given location we can assume that  $\lambda(t|H(t))$

is not affected by the history of events up to that point  $H(t)$  nor the duration of time that has elapsed without an accident. The reason for this is that car accidents occurring over time involve different people and do not change the characteristics of the reporting area  $r$ . This assumption would not be appropriate if we were examining drivers and not locations, since as  $t$  (in this case representing driving time and not calendar time) increases and the given driver become less alert, the instantaneous probability of an accident may increase.<sup>14</sup> It is this memoryless property of road segments that allows us to determine the distribution of car accidents. Thus, we model the instantaneous probability of an accident  $\lambda$  as a function of location and time characteristics ( $x$ ) as well as police presence ( $p$ ), and assume an exponential specification to assure positive values,

$$\lambda(t|H(t)) = e^{x_t\beta_0 + \beta_1 p_t} \quad (5)$$

This equation stems from the understanding that numerous factors such as driving behavior, vehicle capabilities, road characteristics, and driving conditions will affect accident outcomes (see Appendix A for a simple accident model). We are interested in estimating how the amount of police presence ( $p$ ) at a given location affects the probability of an accident ( $\lambda$ ). If police have a deterrent effect on accidents we would expect a statistically significant negative effect of police presence ( $\beta_1 < 0$ ).

If  $x$  and  $p$  were to remain constant over time this would result in the classic Poisson distribution (with the unique characteristic of independent and stationary increments). Since these characteristics vary over time - the result is a non-homogenous Poisson process. We define  $z(t) = (x_t, p_t)$  such that equation (5) simplifies into,

$$\lambda(t|H(t)) = e^{z'(t)\beta} \quad (6)$$

---

<sup>14</sup>It is also possible that the instantaneous probability of an accident for a given driver changes after involvement in an accident (increased insurance costs or psychological effects could result in more careful driving).

We model accident outcomes as a Poisson process over time  $t$ . This means that we do not allow two events to occur simultaneously at the same location. If the police received multiple calls regarding accidents at the same location and 15 minute interval we treat them as one accident. Then the probability of  $N$  accidents occurring over the interval  $[0, \tau]$  at times  $T_1 < T_2 < \dots < T_N$  is,<sup>15</sup>

$$\Pr\{T_1, T_2, \dots, T_N\} = \prod_{i=1}^N \lambda(T_i | H(T_i)) \times \exp\left(-\int_0^\tau \lambda(v | H(v)) dv\right) \quad (7)$$

Thus, we obtain the following log likelihood function,

$$l(\beta) = \left[ \sum_{i=1}^N \ln \lambda(T_i | H(T_i)) \right] - \int_0^\tau \lambda(v | H(v)) dv \quad (8)$$

While the first term in equation (8) after applying definition (6) is simply a summation of  $z'(t)\beta$  at points of time  $t$  where an accident occurred, the second term is more complex. Estimating  $\int_0^\tau e^{z'(t)\beta} dt$  requires dividing the interval  $[0, \tau]$  into  $k$  subintervals of length  $\Delta_j = t_j - t_{j-1}$ ,  $[t_0 = 0, t_1], [t_1, t_2], \dots, [t_{k-1}, t_k = \tau]$  over which  $z(t)$  remains constant ( $k \geq N$  because after an accident occurs a new subinterval must begin).<sup>16</sup> Thus, we compute  $\int_{t_{j-1}}^{t_j} \lambda(v | H(v)) dv = (t_j - t_{j-1})e^{z'(t_j)\beta}$  for each interval  $\Delta_j$  allowing us to write equation (8) as,

<sup>15</sup>We arrive at equation (7) from:  $\Pr\{T_1, T_2, \dots, T_N\} = \prod_{i=1}^N \lambda(T_i | H(T_i)) \times \int_0^\tau \{1 - \lambda(v | H(v))\} dv$ . since  $\log \{1 - \lambda(v | H(v))\} = -\lambda(v | H(v))$  then taking the exponential of both sides results in:  $\{1 - \lambda(v | H(v))\} = \exp\left(-\int_0^\tau \lambda(v | H(v)) dv\right)$ .

<sup>16</sup>Importantly, this estimation technique allows us to significantly decrease the number of observations (without loss of information) for our analysis. Our original dataset consists of 1,152 reporting areas  $\times$  35,040 time periods. We are able to aggregate these individual time periods into subintervals  $\Delta_j$  over "times of day" (0-6 AM, 6-9 AM, 9-4 PM, 4-7 PM, 7 PM-midnight) where stationary police presence remained constant, and the area remained accident free. This technique both decreases computational difficulties, and allows a comparison between accident-free intervals and the 15 minute moments when accidents occur.

$$l(\beta) = \left[ \sum_{i=1}^N z'(T_i)\beta \right] - \sum_{j=1}^k \Delta_j e^{z'(t_j)\beta} \quad (9)$$

This estimation technique can be broadened to include the  $r = 1, \dots, R$  reporting areas. Thus, we estimate coefficients included in  $\beta$  using information on  $z_r(t)$  as covariates will vary across time and location,

$$l(\beta) = \left[ \sum_{r=1}^R \sum_{i=1}^{N_r} z'_r(T_i)\beta \right] - \sum_{r=1}^R \sum_{j=1}^{k_r} \Delta_j e^{z'_r(t_j)\beta} \quad (10)$$

We apply maximum likelihood estimation to estimate the effect of policing on the accidents rate (see Appendix B for details).

### 3.1 Dealing with Endogeneity

Equation (10) estimates how changes in police presence affect the probability of an accident under the assumption that police presence is exogenously determined. However, if more police vehicles are sent to more accident prone areas we may not be measuring the true deterrence effect. Even when examining police presence at the same area over 15 minute intervals, the occurrence of an accident could increase police presence as vehicles arrive at the scene to provide assistance.

Figure 3 illustrates that there are specific locations where the majority of accidents occur, more specifically, 10 percent of reporting areas account for 50 percent of all accidents occurring in Dallas. Even after controlling for observed differences between locations there are likely to remain unobserved characteristics that could result in both high levels of police presence and accidents. For example, the Dallas police department annually allocates 42 sites holding high rates of accidents with injuries as high surveillance areas. Figure 4 demonstrates the resulting higher level of police presence in these problem areas. If police are sent to more accident prone areas then reverse causality would plague our results.

In order to account for unobserved differences between reporting areas, we stratify

equation (6) so that each location has its own baseline accident rate function ( $\alpha_r$ ),

$$\lambda_r(t|H(t)) = \alpha_r e^{z'_r(t)\beta}$$

This allows the instantaneous probability of an accident to differ between reporting areas  $r, r^*$  even if the observed covariates are equal ( $z_r(t) = z_{r^*}(t)$ ).<sup>17</sup> We exclude police vehicles that arrived at location  $r$  at time  $t$  in response to an accident that occurred at that specific date and time using the report indicator attached to each police vehicle ping. These police vehicles are present in the area as a direct result of a car accident and therefore would create a positive bias in our estimate of the policing effect. We also control for unobserved time characteristics that remain constant across location by including a time of day dummy as well as a weekend or holiday indicator in the vector  $z_r(t)$  in equation (10). Thus, we conduct fixed effect analysis comparing accident outcomes at the same time of day and location with different levels of police presence.

However, a cultural event or construction could still cause  $num\_police_{r,t}$  (equation (1)) to be correlated with the risk of a car accident at a given point of time. Thus, even after controlling for unobserved location specific road characteristics there may still exist unobserved factors affecting accident outcomes that vary over time within location and would bias our estimate of the effect of police presence on accidents. This may be less of a problem when examining the effect of  $days\_of\_presence_{r,t}$  (equation (2)) on accident outcomes since after controlling for location fixed effects, the allocation of officers on previous days is unlikely to be driven by the risk of an accident today. Thus, while we may expect police presence in a given reporting area  $r$  to increase during construction (when accident risks have increased) it seems unlikely that the police department would choose to increase police presence in the days leading up to construction.<sup>18</sup> However,

---

<sup>17</sup>This amounts to including  $R - 1$  dummy variables for locations in equation (10) which could raise a concern regarding the "incidental parameters" problem. However, Cameron and Trivedi (1988) show that in the Poisson framework, maximum likelihood estimation will still provide consistent estimators.

<sup>18</sup>It is interesting to note that our results suggest that increasing police presence in the days leading

this still remains an issue of concern if previous police presence ( $days\_of\_presence_{r,t}$ ) is in any way correlated with current police presence ( $num\_police_{r,t}$ ).

We overcome this identification problem by focusing on how call-ins to the police department reporting crime, car accidents, or general disturbances affect the presence of police vehicles.<sup>19</sup> Each squad car in the police car location data (AVL dataset) that is answering a call for assistance carries a unique incident indicator that can be mapped into the Dallas Police Department's call data. Linking the two datasets allows us to identify vehicles that are answering a call, as well as the location of the incident they are responding to. We refer to these vehicles as random patrol ( $RPatrol$ ),

$$RPatrol_{r,t} = \sum_{i=1}^{873} I[\text{police vehicle } i \text{ located in } r,t \text{ is assigned to a traffic call that occurred outside of } r] \quad (11)$$

A car is counted in random patrol if it is present at that specific location  $r$  and time interval  $t$  and is en route to or returning from a traffic call at another location. If the call reported a crime and not a car accident then the vehicle is counted as an RPatrol vehicle even at the reporting area where the incident took place. While RPatrol vehicles may be more likely to be moving than other police vehicles, they still cover the full range of speeds. Not all reports to the police are emergencies where police vehicles must rush to the incident with sirens and flashing lights. Additionally, police cars dealing with a crime report may park and remain stationary for a significant period of time. Thus, RPatrol vehicles are a subset of total police presence and include both stationary and moving police vehicles.

The measure of random patrol ( $RPatrol$ ) takes advantage of a gravitation effect created by the occurrence of a crime or accident in a different location. Once a crime

---

up to construction could create an expectations effect by which people would drive more carefully on the days when the construction takes place. However, due to constraints on the number of vehicles available across locations this technique may not be feasible.

<sup>19</sup>While it seems unlikely that a call for service will move vehicles to the opposite side of Dallas, we do find evidence in the data that cars are often sent to neighboring patrol areas.

is reported to the police it changes the route of surrounding police cars that are called to the area to manage the problem. Thus, police presence will exogenously increase in surrounding areas. In contrast to  $num\_police_{r,t}$  in equation (1),  $RPatrol_{r,t}$  in equation (11) captures an exogenous measure of police presence driven by activity outside of area  $r$ . If the effect of RPatrol vehicles is equal to that of non RPatrol vehicles and the presence of RPatrol vehicles is uncorrelated with the presence of non RPatrol vehicles, we can estimate the effect of general police presence using only RPatrol vehicle presence.<sup>20</sup> However, it is unclear if the effect of RPatrol vehicles is indeed equal to that of non RPatrol vehicles. While drivers cannot differentiate between them based on their appearance, RPatrol vehicles are less likely to be focused on deterrence. We discuss this further in the results section.

These characteristics outline the complexity of estimating a causal effect of police presence on car accidents. In general, the Central and Northern regions have more police vehicles present per hour and more accidents per month. One interpretation could be that more police results in more accidents. Alternatively, different locations at different time of days may face different policing needs and accident risks. We summarize the effects of different types of police presence on car accidents in the following section.

## 4 Empirical Results

Our empirical results test the impact of different types of police presence on accident outcomes by estimating equation (10). We begin by considering the long term effect of police presence, i.e. how expectations of police presence based on prior activity affect driving behavior today. We then test the immediate effect of police presence on accident

---

<sup>20</sup>While RPatrol by construction is uncorrelated with unobserved policing needs of a given location it may still be correlated with general police presence. This correlation would be negative if general police become RPatrol vehicles once an incident occurs. A positive correlation could exist if general officers who are not allocated to the call also gravitate towards the location of the incident. These vehicles will not be categorized as RPatrol (as they do not carry the incident indicator) but are likely to be found in reporting areas with RPatrol vehicles. While we estimate a statistically significant positive correlation, its size of 0.055 is small enough to be safely ignored.

outcomes, first using an aggregate measure of total police presence, and then separating this measure into moving and stationary presence. In order to ensure that simultaneity bias is not affecting our results, we also measure an immediate effect specifically for random patrol vehicles and compare Rpatrol outcomes to those of general police presence. While our analysis is conducted over the seven divisions of Dallas we focus our discussion on the Northwest division. Accident analysis is especially relevant in the Northern divisions that are known for having higher traffic congestion and car accident rates. The Northwest division is the most representative of Dallas reporting area characteristics in terms of population and size. We show that some of our estimates vary between the Northern and Southern divisions of Dallas and provide some intuition for these results.

In Table 2 we report estimates for the effects of expectations resulting from total police presence, stationary police presence, as well as relative high patrol (equation (3)) on driving behavior. We allow each additional day of presence in the past week to have a different effect on the probability of an accident. This is important as a transition from zero to one day of presence may not be equivalent to a movement from six to seven days of presence.

Column 1 provides an estimate of how expectations formed from total police presence (equation 2) affect accident outcomes. We control for observed covariates over time and across locations that may affect accident outcomes such as time of day, weather, size, population, and land use. While the measured effect is not statistically significant, its positive sign is the opposite of what we would have expected from a deterrence effect.<sup>21</sup> In column 2, we control for location fixed effects which results in a change in sign that is consistent with an omitted variable bias story. Thus, once we compare accident outcomes within the same location, increased police expectations no longer have a positive effect on accidents. For the remaining specifications of Table 2 we refine our

---

<sup>21</sup>Had this outcome been statistically significant it would have been consistent with a belief system where expectations are formed based on a "mean reversion" of police presence. Thus, an increase in past presence will decrease the expectation of presence today.

definition of police presence to stationary vehicles that are more likely to be involved in accident deterrence (i.e. tracking vehicle speeds etc.) and are more easily associated with a given area (as opposed to a moving police vehicle).

We measure a strong, statistically significant negative effect of police expectations on accident outcomes when focusing specifically on the location of stationary police vehicles (columns 3-4). Interestingly, this effect does not consistently increase with days of police presence and disappears when a given location has more than five days of police presence (column 3).<sup>22</sup> The last column of Table 2 examines the effect of increases in police surveillance on individual expectations (equation 3). It is only in this specification where we find that more days of high-intensity police presence (where the number of stationary vehicles exceeds the median level for that reporting area and time of day) result in lower accident rates. Thus, two days of high-intensity presence reduces the instantaneous probability of an accident by almost 40 percent ( $[e^{-0.472} - 1] \times 100$ ).<sup>23</sup> Each additional day of high-intensity presence results in a reduction of about five percent in the probability of an accident.

It is relevant to both clarify the interpretation of this measured 40 percent decrease and compute the percentage point change it induces. We measure the effect of police presence at a given location in Dallas at that location and specific time of day. This 40 percent decrease in accidents is specific to that location and time and in no way

---

<sup>22</sup>In Section 3 we noted that different beliefs regarding the distribution of police presence will result in different outcomes of police expectations on accidents. Individuals may believe in persistence up to a certain point, where a very high level of police presence signals a random walk. In other words, one or two days of police presence (in the past week) will cause individuals to view the possible presence of an officer today as very likely, but viewing officer presence every day for the last 6-7 days will not change individual expectations for police presence today. It is possible that individuals understand that police have a wide range of focus beyond driving behavior and thus, are unlikely to visit the same location at the same time interval day after day with the goal of penalizing dangerous drivers.

<sup>23</sup>It is interesting to note that the measured expectations effect is strongest during rush-hour. Thus, even one day of elevated police presence during rush-hour significantly decreases the probability of an accident in the next 7 days. We would expect the majority of drivers during rush-hour to be commuters who both notice and update expectations for police presence during their daily commute. Non-commuters may be less likely to follow the same driving pattern day after day and thus, may not be aware of police presence on previous days.

represents a 40 percent decrease in accidents throughout all of Dallas (unless police increased presence in all areas of Dallas). An average reporting in the northwest region of Dallas has 48 accidents per year. Thus, the instantaneous probability of an accident in any 15 minute interval is 0.13 percent, and a 40 percent decrease changes the probability to 0.08 percent. Thus, we estimate that two days of high-intensity police presence results in a 0.05 percentage point decrease in the instantaneous probability of an accident for each 15 minute interval.

While the focus of this paper is analyzing the effect of police presence on driving behavior, our data also provides an opportunity to measure how other location and time characteristics affect accident outcomes. In all specifications we find that precipitation and driving during evening rush hour (4-7 PM) significantly increase the probability of an accident. We also find that accidents are less likely to occur on holidays and weekends. In specification (1), which does not include location specific fixed effects, we are able to estimate the effect of location characteristics on the accident rate (e.g. number of schools, parks, percent residential, etc.). We find that accidents are less likely to occur in residential areas. These results are in line with previous findings that suggest that vehicle congestion is a key predictor of accident outcomes.

Our estimates from Table 2 suggest that when police presence in a given area exceeds the median level of presence for that time period for at least 2 out of 7 days it can have a long term effect on driving behavior. Thus, expectations seem to be updated specifically when police presence is above its median level for that time of day in that area. We next examine whether or not police presence at time  $t$  will also result in an immediate decrease in accidents.

Table 3 summarizes the immediate effect of different types of police presence in location  $r$  and time  $t$  on accident outcomes while controlling for current expectations for police presence (equation 3).<sup>24</sup> We find a statistically significant positive immediate

---

<sup>24</sup>We do not count police officers that were called to the area as a result of a traffic accident (reverse

effect of total police vehicles (equation 1) on the accident rate, even when controlling for location specific fixed effects (column 1). After separating total police presence into moving and stationary vehicles, we find that this result is driven by moving police vehicles that consistently have a positive effect on accident outcomes, while stationary vehicles exhibit a deterrence effect (columns 2-4). Assuming a constant marginal effect of stationary police vehicles, we find that each additional vehicle decreases the accident rate by 4.4 percent (column 2). We measure a larger effect of 15.1 percent when comparing accident outcomes at the same location and time with and without stationary police presence (column 3).<sup>25</sup> These results stand in contrast to the effect of moving police vehicles, where each additional vehicle increases the accident rate by 8.6 percent.

Although we include location and time fixed effects in all specifications of Table 3, there still exists a concern regarding temporary unobserved shocks within a given location which can increase both police presence and the accident rate. We therefore consider the effect of stationary random patrol on the accident rate in column 4. These are cars that are located in a given reporting area only because they were answering a call in a neighboring area or a crime call in this area (equation 11). Interestingly, we do not find a significantly different effect when focusing our analysis on random patrol. Thus, despite the importance of controlling for differences between locations we do not find evidence of bias created by unobserved shocks in a given location. However, an alternative interpretation is that the deterrence effect of Rpatrol vehicles may in fact be smaller than that of general police patrol. RPatrol vehicles may be less focused on their surroundings and may be spending less time in each reporting area (i.e., more likely to move between a few reporting areas in a given 15 minute interval). While focusing on the speed of vehicles allows us some control over vehicle movement, we cannot rule out causality).

---

<sup>25</sup>Less than 5 percent of observations recorded more than 1 stationary police vehicle in a given reporting area and 15 minute interval. Thus, for many reporting areas, the relevant measure is not the number of vehicles, but the presence of at least one vehicle.

the possibility that using Rpatrol provides a lower bound of the deterrence effect created by general police presence.

In Table 4 we summarize the results of this analysis for the remaining six divisions of Dallas. All of the divisions of Dallas show a significant negative effect of police expectations on accident outcomes. However, divisions differ in the number of days necessary to create an expectation for police presence. In the southern divisions, even one day of stationary police presence (in the past week) that is above the median level for that time of day will significantly decrease the accident rate by 20 to 32 percent at that location. This effect appears in the Northeast division only after two days of elevated stationary police presence, the Central division after 3 days, and the North Central region after 4 days of presence.

Five out of these six divisions show a statistically significant negative effect of immediate stationary random patrol on accident outcomes. The immediate presence of a stationary RPATROL vehicle reduces the accident rate by between 9 and 15 percent for the North Central and Northeast divisions. The measured effect is larger (16-20 percent) in the Southern regions of Dallas. We do not find a significant effect of stationary random patrol in the Central region. One explanation for this could be that since this area sees a consistently heavy stream of police officers, individuals are less likely to attribute their presence to traffic patrol. In other words, we will only measure an effect of random patrol if drivers themselves are unaware that this is a police vehicle that is simply en route to another location.

While the southern divisions exhibit a strong immediate effect of stationary police presence on accident outcomes, we find no evidence that moving police presence increases accident rates in these locations (columns 4-6). This outcome differs from the Central and Northern reporting areas where we find that moving police vehicles increase the accident rate by 6 to 9 percent (columns 1-3). As the Northern reporting areas experience higher traffic density, this could imply that moving police vehicles are dangerous, specifically in

high-traffic areas where cars have less reaction time and space to avoid accidents.

The results in Table 4 show that the effect of policing may not be equal in different types of areas. We return our focus to the Northwest division in order to measure the differential effects of policing in areas facing different accident risks. Table 5 explores whether or not the effect at high accident risk areas (those that include road sections determined as "accident hot spots" by the Dallas Police Department) is different than that estimated in less accident prone areas.<sup>26</sup> Importantly, we find that police play an important role in both low and high risk areas. Interestingly, only the more at risk areas show a significant immediate decrease in the probability of an accident when a police car is present (an estimated 22 percent decrease). This contrasts with moving police presence that increases the accident rate in the low and high risk areas, with a stronger effect at low risk locations (that are perhaps less accustomed to police activity or whose road infrastructure may be less appropriate for fast travel). Both types of locations show a significant effect of police expectations on accident rates, but less accident prone areas require a less concentrated level of weekly police presence to reduce the accident rate (one day versus four days). Thus, to reach the optimal deterrence level it may be necessary to employ different types of police presence in different locations.<sup>27</sup>

## 5 Conclusion

Despite an abundance of research and views regarding the deterrent effects of policing on crime and car accidents, 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

---

<sup>26</sup>The "hot spot" accident locations are determined annually by the Dallas police department as areas that include the 100 intersections with the highest numbers of accidents with injuries.

<sup>27</sup>We note that this analysis is not focused on the specific dangerous intersection, but rather on larger geographic areas that do or do not include an "accident hot-spot." Thus, we may find an even larger effect of policing at the specific dangerous intersection.

order to deal with the extreme budget cuts resulting from the economic downturn.<sup>28</sup> It is important that we understand not only the consequences of these budget cuts but also find ways in which to maximize the return of policing with fewer officers available for patrol.

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, we are 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. Our 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.

Using information collected from GPS locators attached to most Dallas Police Vehicles we were able to consistently track the location of police officers throughout the day. This data allowed us to differentiate between moving and stationary vehicles and thus, distinguish between their separate effects. We were also given access to information linking vehicles to crime and accident call-ins which allowed us to focus on random patrol. These police vehicles are in a given location not because of assignment, but because they are responding to a call in a different area.

Our results imply that much of police deterrence is created by updating individual expectations rather than an immediate change in behavior. In our analysis, driving behavior responds to changes in stationary and not total police presence. Our estimates suggest that expectations are consistently updated not by whether or not a police vehicle is present, but rather, by days of high surveillance (above the median level of police presence for that location and time of day). Thus, two days of high surveillance presence over the last week are expected to decreases the accident rate by almost 40 percent. We also find evidence that when controlling for police expectations, the presence of a

---

<sup>28</sup>Information released in "The Impact of The Economic Downturn on American Police Agencies" by the US Department of Justice, October 2011

stationary police vehicle can reduce the accident rate by at least 9 percent.

Despite the deterrence effect created by stationary police presence, we also find that police vehicles that are moving at high speeds can increase the accident rate in specific areas of Dallas. An additional moving vehicle in the northern divisions that face higher levels of traffic density is expected to increase the accident rate by 6 to 9 percent. This finding suggests that we must focus not only on the routes police choose in order to create a deterrence effect but also routes that will minimize the effect of high-speed moving police vehicles on accident outcomes.

We find a significant effect of police expectation on accident outcomes throughout the entire city of Dallas, in stark contrast to the crime literature which has often reported significant policing effects only when applied to "hot spot" areas. This, begs the question, is the deterrence effect of policing on car-accidents, substantially different than that of policing on crime? Future research is needed in order to continue to model the separate mechanisms by which police affect behavior and test these models for crime as well as car accidents.

This paper expands the scope of deterrence research beyond criminal behavior to the general population. The significant effect of random patrol, police vehicles who are en route to another location, 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, when responding to calls, completing paperwork, or taking a lunch break, can have a direct effect on the accident rate. In this age of reduced police funding, we find that the high toll of accident costs on our society can be reduced by increasing the visibility of police on our streets.

## References

- [1] Ashenfelter, Orly and Michael Greenstone. "Using Mandated Speed Limits to Measure the Value of a Statistical Life", *Journal of Political Economy*, Vol. 112, No. S1 (Feb., 2004).
- [2] Becker, Gary S., "Crime and Punishment: An Economic Approach", *Journal of Political Economy*, Vol. 76 (1968).
- [3] Braga, A. A., D.L. Weisburd, E.J. Waring, L.G. Mazerolle, W. Spelman, and F. Gajewski. "Problem-Oriented Policing in Violent Crime Places: A Randomized Controlled Experiment. *Criminology*, Vol. 37 (1999), pp. 541-580.
- [4] Cameron, A. Colin and Pravin K. Trivedi. *Regression Analysis of Count Data*. Cambridge, UK: Cambridge University Press, 1998. Print.
- [5] Ceccarini, Olivia. "Does Experience Rating Matter in Reducing Accident Probabilities? A Test for Moral Hazard." *University of Pennsylvania Job Paper* (Nov., 2007).
- [6] Chiappori, Pierre-Andre, Bruno Jullien, Bernard Salanie, and Francois Salanie. "Assymmetric Information in Insurance: General Testable Implications." *The RAND Journal of Economics*, Vol. 37, No. 4 (Winter, 2006), pp. 783-798.
- [7] Clifford, Catherine. "U.S. Car Accident Cost: \$164.2 Billion." *CNNMoney.com* (2008, March 5th).
- [8] Cook, Richard J, and Jerald F. Lawless. *The Statistical Analysis of Recurrent Events*. New York: Springer, 2007. Print.
- [9] Cooper, P J. "Effects of Increased Enforcement at Urban Intersections on Driver Behavior and Safety." *Transportation Research Record*, Vol. 540 (1975), pp. 13-21.

- [10] Corman, Hope and H. Naci Mocan. "A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City." *American Economic Review*. Vol. 90, No. 3 (Jun.,2002), pp.584-604.
- [11] Di Tella, Rafael and Ernesto Schargrodsky. "Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack." *American Economic Review*. Vol. 94, No. 1 (Mar.,2004), pp.115-133.
- [12] Durlauf, Steven N. and Daniel S. Nagin, "Imprisonment and crime." *Criminology & Public Policy*, Vol. 10 (2011), pp. 13–54.
- [13] Evans, William N. and Emily G. Owens. "COPS and Crime." *Journal of Public Economics*. Vol. 91 (2007), pp. 181-201.
- [14] Gould, Eric D. and Guy Stecklov. "Terror and the Costs of Crime." *Journal of Public Economics*. Vol. 93 (2009), pp. 1175-1188.
- [15] Hakkert, A.S., V. Gitelman, A. Cohen, E. Doveh, and T. Umansky. "The Evaluation of Effects on Driver Behavior and Accidents of Concentrated General Enforcement on Interurban Roads in Israel." *Accident Analysis & Prevention*, Vol. 33 (2001), pp. 43-63.
- [16] Klick, Jonathon and Alexander Tabarrok. "Using Terror Alert Levels to Estimate the Effect of Police on Crime." *Journal of Law and Economics*, Vol. 48, No. 1 (Feb., 2005), pp. 267-279.
- [17] Legge, J. S. Junior, and J. Park. "Policies to Reduce Alcohol-Impaired Driving: Evaluation Elements of Deterrence." *Social Science Quarterly*, Vol. 75, No. 3 (1994), pp. 594-606.
- [18] Marvell, Thomas B and Carlisle E. Moody, "Specification Problems, Police Levels, and Crime Rates, *Crimonology*, Vol. 34, No. 4 (1996), pp. 609-646.

- [19] Peden, Margie, Richard Scurfield, David Sleet, Dinesh Mohan, Adnan A. Hyder, Eva Jarawan, and Colin Mathers. *World Report on Road Traffic Injury Prevention*. World Health Organization, Geneva, 2004.
- [20] Sherman, Lawrence W. and David Weisburd. "General Deterrent Effects of Police Patrol in Crime "Hot Spots": A Randomized, Controlled Trial." *Justice Quarterly*, Vol. 12, No. 4 (Dec., 1995).
- [21] Shi, Lan. "The limits of oversight in policing: Evidence from the 2001 Cincinnati riot." *Journal of Public Economics*, No. 93 (2009), pp. 99–113.
- [22] Sisiopiku V and Patel H. "Study of the Impact of Police Enforcement on Motorists' Speeds." *Transportation Research Record*, Vol. 1693 (1999), pp. 31-36.
- [23] Tavares, Antonio, F., Silvia M. Mendes, and Claudia S. Costa. "The Impact of Deterrence Policies on Reckless Driving: The Case of Portugal." *European Journal on Criminal Policy and Research*, Vol. 14, No. 4 (Dec., 2008), pp. 417-429.
- [24] Vaa T. "Increased Police Enforcement: Effects on Speed." *Accident Analysis and Prevention*, Vol. 29 (1997), pp. 373-385.
- [25] Waard, Dick De and Ton Rooijers. "An Experimental Study to Evaluate the Effectiveness of Different Methods and Intensities of Law Enforcement on Driving Speed on Motorways" *Accident Analysis and Prevention*, Vol. 26 No. 6 (1994), pp. 751-765.
- [26] Weisburd, D. and L. Green. "Policing Drug Hot Spots: The Jersey City Drug Market Analysis Experiment. *Justice Quarterly*, Vol. 12 (1995), pp. 711-736.

## 6 Appendix A: What Determines the Occurrence of a Car Accident?

Individuals live in a society where time is scarce and they must split their active time  $T$  between commuting time ( $\frac{h_c}{T}$ ) and work/family/leisure time ( $\frac{h_o}{T}$ ). Where hours of commuting time,  $h_c = \frac{M}{s}$  is determined by miles of commuting distance  $M$  and driving speed  $s$ .

We model the probability of an accident ( $p_A$ ) as a function of individual, vehicle, and road characteristics ( $z_i$ ) as well as speed ( $s_i = \frac{M_i}{h}$ ).<sup>29</sup> The probability of receiving a fine ( $p_F$ ) is a function of driving speed ( $s_i$ ) as well as the level of police deterrence ( $d$ ). While  $z_i$  is exogenously determined, the individual chooses  $s_i$  to maximize his/her utility ( $U(s)$ ),

$$U(s) = \max_s B(s) - C(s)$$

The benefit  $B(s)$  of driving speed is equal to  $w(1 - \frac{h_c}{T}) = w(1 - \frac{M}{sT})$ .<sup>30</sup>

The cost of driving speed  $C(s)$  is either a ticket or an accident and thus, with a given speed limit  $\bar{s}$ , accident cost  $A$ , and fine  $F$ ,

$$C(s) = \begin{cases} Ap_A(z_i, s_i) & \text{for } s_i \leq \bar{s} \\ Ap_A(z_i, s_i) + Fp_F(s_i, d) & \text{for } s_i > \bar{s} \end{cases} \rightarrow$$

$$U(s) = \begin{cases} w(1 - \frac{M}{sT}) - Ap_A(z_i, s_i) & \text{for } s_i \leq \bar{s} \\ w(1 - \frac{M}{sT}) - Ap_A(z_i, s_i) - Fp_F(s_i, d) & \text{for } s_i > \bar{s} \end{cases}$$

Thus, we can solve for the optimal  $s^*$  by calculating the first order condition:

<sup>29</sup>While we focus on speed as driving behavior this model can be easily modified to covers a broad range of behavior such as changing lanes, lack of driving-focus, etc.

<sup>30</sup>In essence all characteristics of  $z_i$  can play a role in determining the benefit of minimizing commuting time - since different individuals with different vehicles hold different values for commuting time (for example someone with a more comfortable car may be open to higher  $h_c$ ). We focus on wage ( $w$ ) as it is an accepted indicator for the value of time.

$$\text{For } s_i \leq \bar{s}, \frac{wM}{Ts^2} = A \frac{dp_A}{ds} \rightarrow s^* = \min \left( \sqrt{\frac{wM}{TAp'_A}}, \bar{s} \right)$$

$$\text{For } s_i > \bar{s}, \frac{wM}{Ts^2} = A \frac{dp_A}{ds} + F \frac{dp_F}{ds} \rightarrow s^* = \max \left( \sqrt{\frac{wM}{T(Ap'_A + Fp'_F)}}, \bar{s} \right)$$

Thus, an individual will choose to speed if  $\sqrt{\frac{wM}{T(Ap'_A + Fp'_F)}} > \bar{s}$  and  $U \left( \sqrt{\frac{wM}{T(Ap'_A + Fp'_F)}} \right) > U(\bar{s})$ . Importantly, police presence ( $d$ ) decreases the optimal speed from  $\sqrt{\frac{wM}{TAp'_A}}$  to either  $\sqrt{\frac{wM}{T(Ap'_A + Fp'_F)}}$  or the speed limit  $\bar{s}$ .

The effect of driving speed on accidents is documented in a paper by Ashenfelter and Greenstone who found that increasing speed limits by 10 mph increased driving speed by 2.5 mph and resulted in a 35 percent increase in fatalities (Ashenfelter & Greenstone, 2004).

## 7 Appendix B: Maximum Likelihood Estimation

For simplicity, we focus our discussion on equation (9) but this technique also applies to equation (10). Thus, we consider the following log likelihood function,

$$l(\beta) = \left[ \sum_{i=1}^N z'(T_i)\beta \right] - \sum_{j=1}^k \Delta_j e^{z'(t_j)\beta}$$

We can then compute:

$$1. \text{ gradient}(\beta) = \frac{dl(\beta)}{d\beta} = \sum_{i=1}^N z'(T_i) - \sum_{j=1}^k z'(t_j) \Delta_j e^{z'(t_j)\beta}$$

$$2. H(\beta) = \text{Hessian}(\beta) = \frac{dl(\beta)}{d\beta d\beta} = - \sum_{j=1}^k z(t_j) z'(t_j) \Delta_j e^{z'(t_j)\beta}$$

$$3. \text{ Variance}(\beta) = H(\beta)^{-1} \left[ \sum_{i=1}^N \left( z'(T_i) - \sum_{j=1}^{k < T_i} z'(T_j) \Delta_j e^{z'(t_j)\beta} \right)' \left( z'(T_i) - \sum_{j=1}^{k < T_i} z'(T_j) \Delta_j e^{z'(t_j)\beta} \right) \right] H(\beta)$$

Cook & Lawless note that this maximum likelihood estimation is equivalent to standard estimation techniques used in survival analysis (Cook & Lawless, Ch. 3 pg. 64). In essence, equation (7) can also be written as:

$$\Pr\{T_1, T_2, \dots, T_N\} = \prod_{j=1}^N \left[ \lambda(T_j | H(T_j)) \exp \left( - \int_{T_{j-1}}^{T_j} \lambda(u | H(u)) du \right) \right] \times \exp \left( - \int_{T_N}^{\tau} \lambda(u | H(u)) du \right) \quad (12)$$

Where  $T_0 = 0$ .<sup>31</sup> Expression (12) describes the likelihood arising from a sample of  $N + 1$  independent survival times over the intervals  $[T_0, T_1], \dots, [T_n, \tau]$  with each interval except the last ending in an event. We can then use survival software techniques to include time-dependent covariates and estimate  $\hat{\beta}$ .

We note that there exists an alternative likelihood function to equation (8) since the number of car accidents per unit of time in a given location can be modelled as

---

<sup>31</sup>This simply uses the mathematical rule, that for any interval with points  $t_1 < t_2 < t_3$  then  $\int_{t_1}^{t_3} f(t) dt = \int_{t_1}^{t_2} f(t) dt + \int_{t_2}^{t_3} f(t) dt$ . Therefore:  $\exp \left( \int_{t_1}^{t_3} f(t) dt \right) = \exp \left( \int_{t_1}^{t_2} f(t) dt + \int_{t_2}^{t_3} f(t) dt \right) = \exp \left( \int_{t_1}^{t_2} f(t) dt \right) \times \exp \left( \int_{t_2}^{t_3} f(t) dt \right).$

having a non-homogeneous Poisson distribution. The key assumption that guarantees a Poisson distribution is that the event of a car accident in non overlapping time intervals are independent because the occurrence of an accident in a given location should not affect the occurrence of a future accident (once the debris from this accident has been removed). This of course would not hold if we were examining the accident rate of individual drivers who have been shown to be less likely to be involved in a second accident once the first has occurred (see Cessarini (2007), Chiappori(2006)). In essence the assumption of independent increment simply means that the road segment itself cannot "learn" from past accidents.. It can then be shown that  $N(\tau)$ , the number of car accidents occurring between time 0 and  $\tau$ , has distribution

$$P(N(\tau) = y) = \frac{e^{-\int_0^\tau e^{z'(t)\beta} dt} (\int_0^\tau e^{z'(t)\beta} dt)^y}{y!} \quad \text{for } y = 0, 1, 2, \dots \quad (13)$$

Equation (13) has two key shortcomings to equation (7). The first is that, equation (13) could be missing important information about the distribution of accidents as it focuses attention on an interval of time with changing accident probabilities, while equation (7) considers the probability distribution as a whole. A second issue arises if  $z(t)$  includes internal covariates that are influenced by  $H(t)$ , in this case the accident process is no longer Poisson and equation (13) does not hold. For these reasons we focus our analysis on equation (7) .

Figure 1: Dallas Reporting Areas

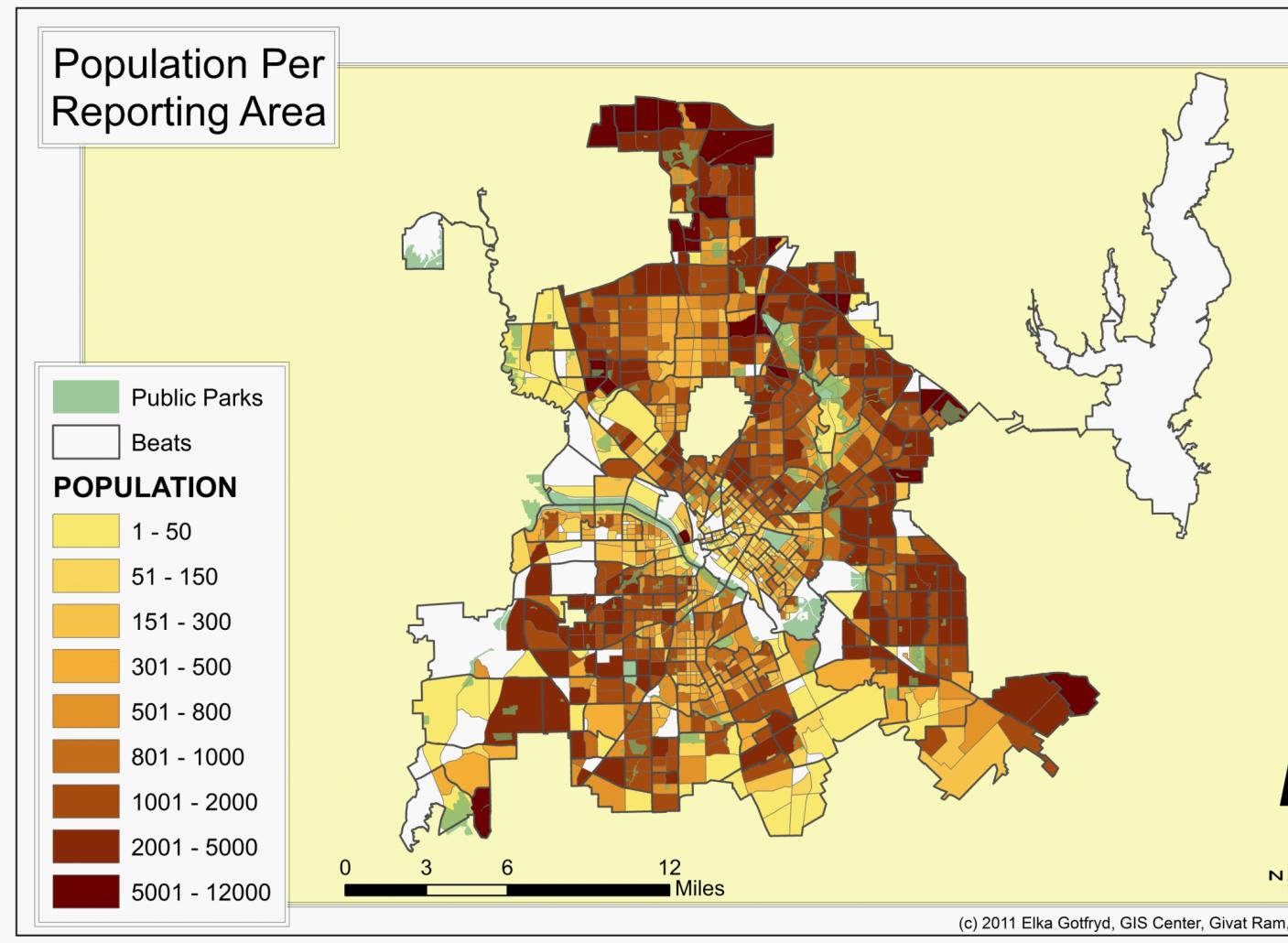


Figure 2: Police Presence During Rush Hour

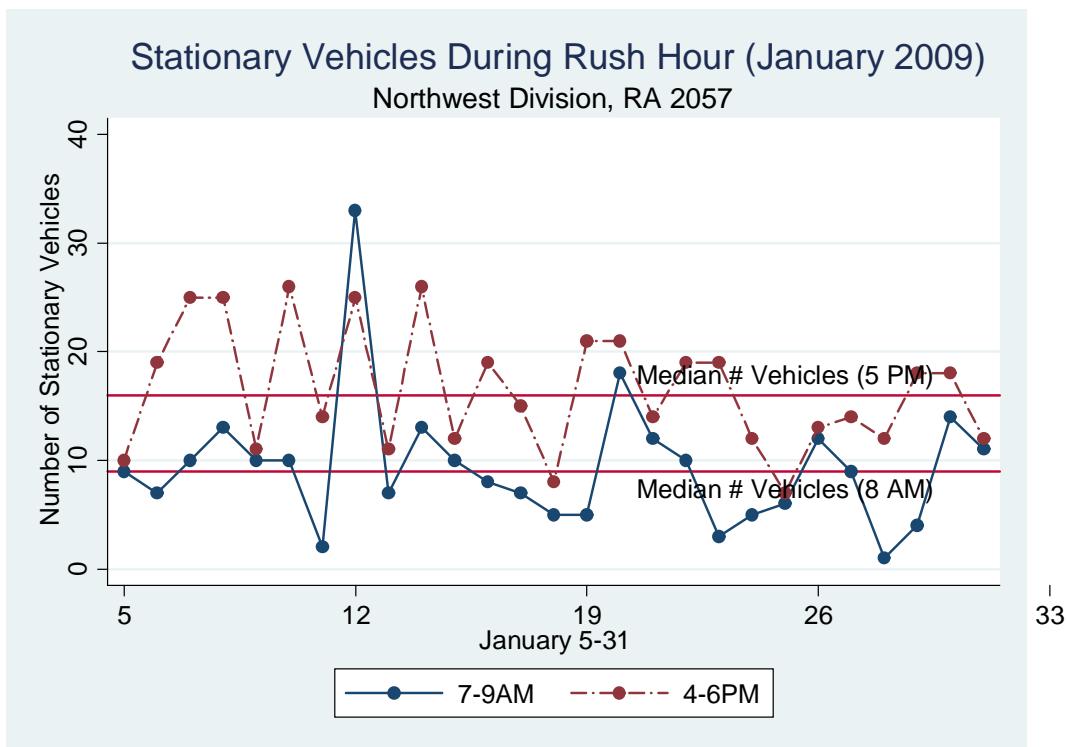


Figure 3: Concentration of Total Monthly Accidents Across Reporting Areas

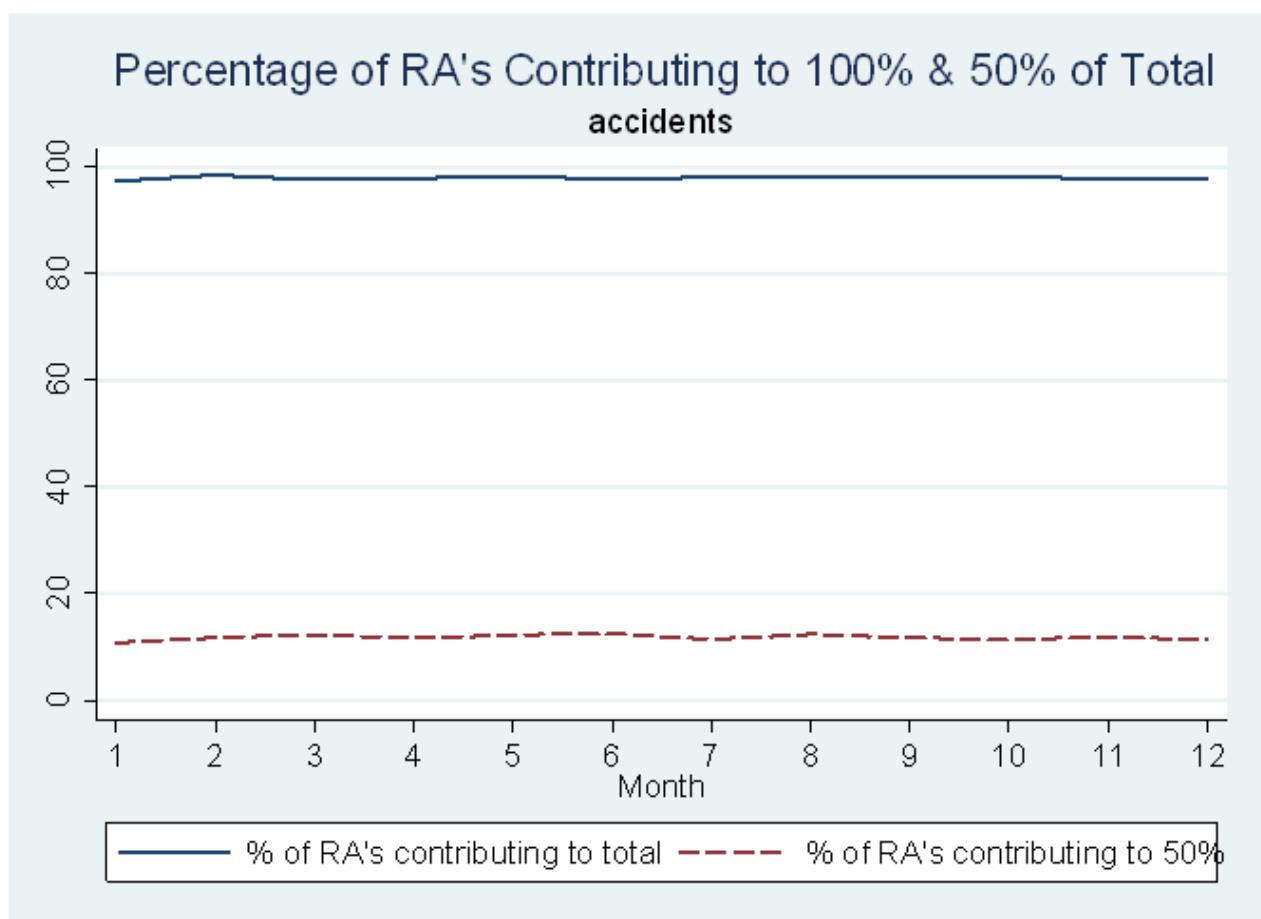


Figure 4: Police Presence

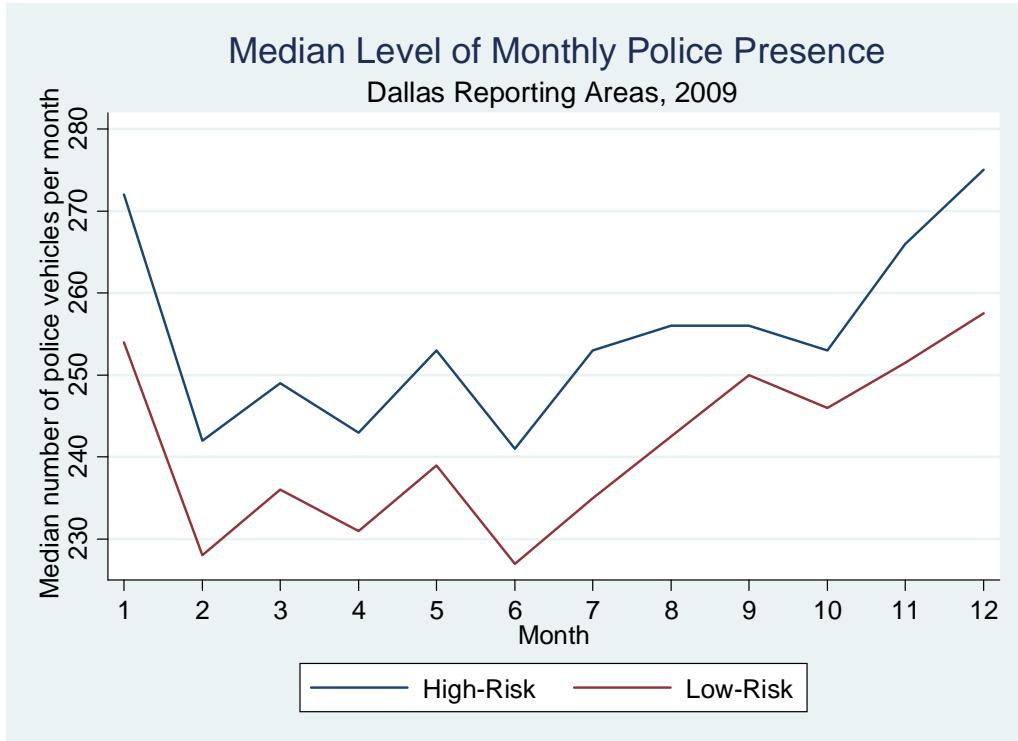


Figure 5: Calls for Police Assistance

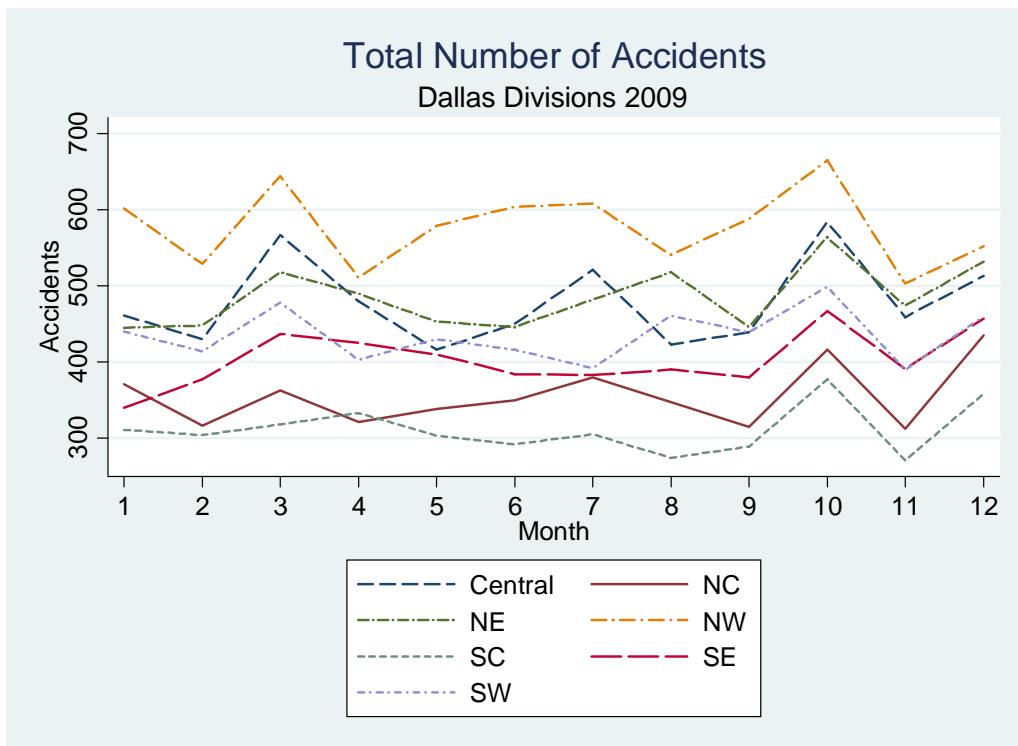


Figure 6: Dallas Beats

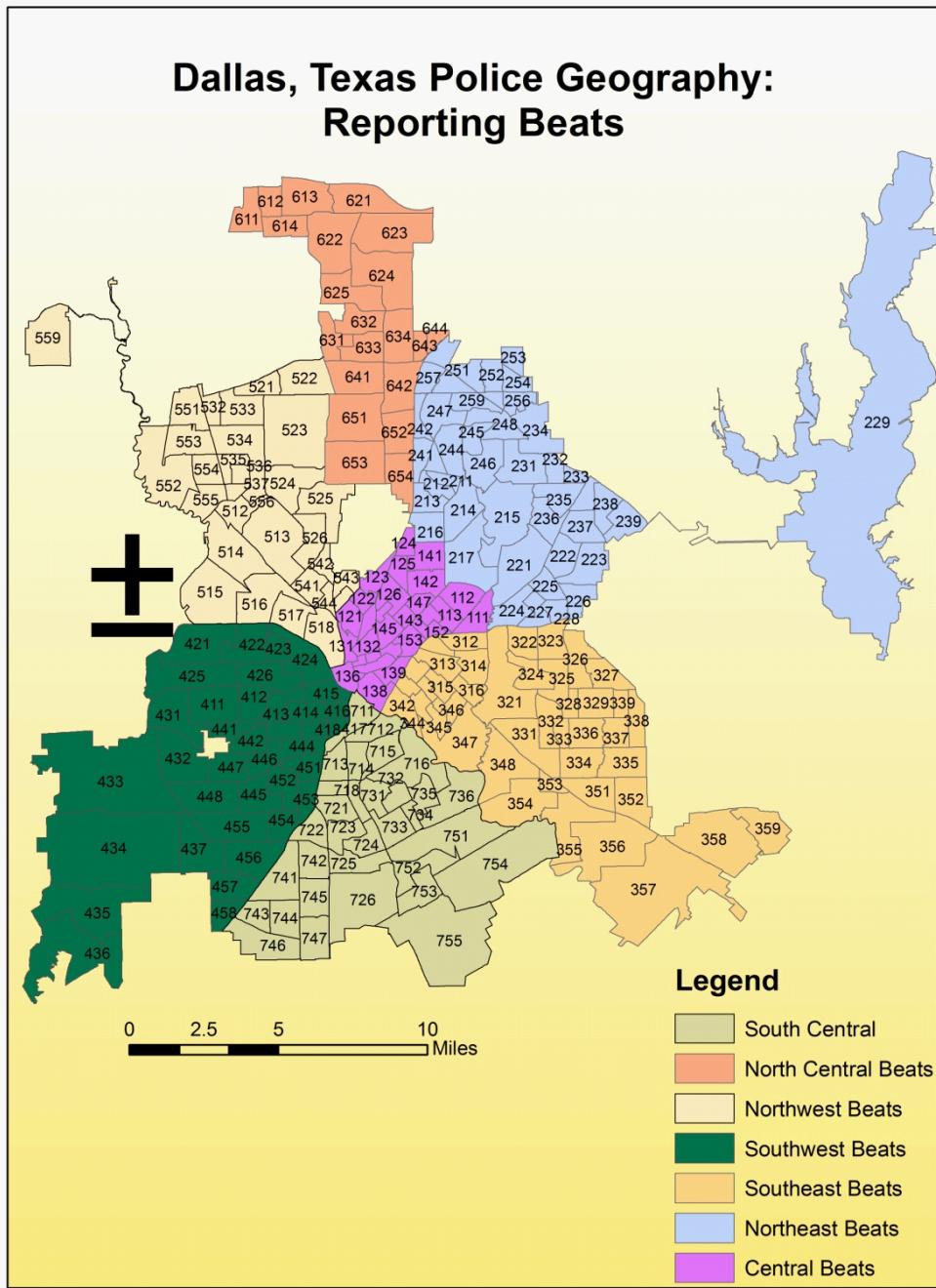


Table 1: Monthly Means for Reporting Areas Summarized by Division

	Central	NC	NE	NW	SC	SE	SW
<b>Accidents:</b>							
Minor	1.680 (2.241)	2.611 (3.894)	1.828 (2.659)	2.614 (3.802)	0.929 (1.723)	1.238 (2.013)	1.148 (1.646)
Major	0.660 (1.002)	1.052 (1.687)	0.784 (1.257)	0.943 (1.392)	0.466 (0.885)	0.720 (1.179)	0.609 (0.992)
Major Freeway	0.395 (1.181)	0.648 (2.420)	0.378 (1.308)	0.659 (2.290)	0.315 (1.001)	0.188 (0.649)	0.283 (0.865)
<b>Police Vehicles Per Hour:</b>							
Total Cars	4.109 (4.016)	3.925 (2.876)	3.279 (2.262)	3.360 (3.335)	2.498 (2.339)	2.970 (2.611)	2.387 (2.106)
Stationary	0.976 (1.902)	0.816 (1.240)	0.637 (1.059)	0.712 (1.182)	0.468 (1.027)	0.554 (1.139)	0.460 (0.891)
Traffic	0.0676 (0.0315)	0.0296 (0.0215)	0.0287 (0.0216)	0.0395 (0.0273)	0.0154 (0.0162)	0.0269 (0.0225)	0.0192 (0.0169)
<b>Tickets:</b>							
Tickets Per Beat	49.30 (39.04)	36.31 (28.22)	50.10 (29.88)	46.43 (35.38)	39.20 (24.34)	48.09 (29.93)	51.43 (34.54)
<b>Civilian Call-Ins:</b>							
Speeding	0.128 (0.386)	0.261 (0.571)	0.301 (0.691)	0.302 (0.777)	0.155 (0.503)	0.353 (0.821)	0.235 (0.579)
Violent Crime	0.604 (1.012)	0.813 (1.304)	1.099 (1.840)	1.075 (1.876)	0.749 (1.415)	1.105 (1.641)	0.678 (1.184)
Property Crime	3.417 (3.871)	7.946 (10.29)	7.334 (10.08)	6.056 (6.824)	4.166 (6.841)	5.930 (8.324)	4.469 (6.078)
Disorder	18.61 (18.40)	31.55 (38.37)	32.64 (41.20)	25.42 (25.93)	20.91 (28.59)	31.13 (34.37)	22.33 (24.60)
<b>RA Characteristics:</b>							
Acres	62.08 (48.87)	278.0 (204.7)	353.5 (2057.1)	228.5 (220.1)	188.9 (235.9)	223.9 (318.1)	208.4 (352.5)
Population	546.1 (689.1)	2,256.0 (2471.8)	1,691.8 (1652.7)	1,111.8 (1592.0)	623.0 (647.4)	891.3 (1073.6)	880.4 (1042.9)
Average Speed Limit	28.89 (2.868)	27.75 (2.390)	28.27 (3.405)	28.92 (3.609)	28.21 (4.650)	28.41 (3.476)	27.93 (3.787)
N	5,921,760	2,978,400	5,501,280	4,905,600	6,552,480	6,482,400	8,024,160

Standard deviation in parenthesis.

Table 2: The Effect of Police Expectations on Accidents (NW Division)

Days Counting Rule:	Days of Total Police>0 <sup>a,b</sup>	Days of Total Police>0 <sup>b</sup>	Days of Stat Police>0 <sup>b</sup>	Days of Stat Police > Median <sup>b</sup>
One Day (0/1) <sup>c</sup>	1.131* (0.684)	-0.112 (0.275)	-0.356*** (0.083)	-0.156 (0.105)
Two Days (0/1) <sup>c</sup>	0.95 (1.032)	-0.458 (0.3)	-0.483*** (0.08)	-0.472*** (0.108)
Three Days (0/1) <sup>c</sup>	1.094 (1.019)	-0.332 (0.27)	-0.374*** (0.085)	-0.531*** (0.108)
Four Days (0/1) <sup>c</sup>	1.314 (1.019)	-0.322 (0.255)	-0.294*** (0.092)	-0.747*** (0.108)
Five Days (0/1) <sup>c</sup>	1.522 (1.02)	-0.389 (0.238)	-0.248** (0.087)	-1.021*** (0.11)
Six Days (0/1) <sup>c</sup>	1.925* (1.019)	-0.264 (0.229)	-0.073 (0.101)	-1.286*** (0.11)
Full Week (0/1) <sup>c</sup>	2.288** (1.021)	-0.129 (0.226)	0.088 (0.099)	-1.633*** (0.107)
Precipitation (cms)	0.075*** (0.007)	0.076*** (0.007)	0.076*** (0.007)	0.078*** (0.007)
Morning Rush (6-9)	0.393*** (0.084)	0.390*** (0.085)	0.396*** (0.083)	0.289*** (0.092)
Daytime (9-4 PM)	0.615*** (0.071)	0.670*** (0.072)	0.650*** (0.075)	0.864*** (0.086)
Evening Rush (4-7 PM)	0.785*** (0.066)	0.851*** (0.067)	0.814*** (0.069)	0.975*** (0.081)
Night (7 PM-Midnight)	0.247*** (0.065)	0.305*** (0.063)	0.296*** (0.063)	0.393*** (0.071)
Holiday	-0.121 (0.081)	-0.215** (0.086)	-0.220*** (0.083)	-0.318*** (0.082)
Percent of Land Used for Parks	-0.022*** (0.007)			
Percent of Residential Land Use	-0.011*** (0.002)			
Location Fixed Effects	No	Yes	Yes	Yes
Observations	936342	936342	936342	936342

Standard errors account for clustering at the reporting area level.

<sup>a</sup>We also include controls for RA characteristics such as: % land used for retail, # of schools, classified as high risk accident location (0/1), size, and population.

<sup>b</sup>We include time varying controls: weekday travel, average daily temperature, and visibility.

<sup>c</sup>"X Days" is a dummy variable equal to 1 if there were X days of presence in the last 7 days.

\* p<0.1, \*\* p<0.05, \*\*\* p<0.01

Table 3: The Effect of Policing on Accidents (NW Division)

Category of Current Police Presence:	All Vehicles	All Vehicles	All Vehicles	RPatrol Vehicles <sup>a</sup>
All Police Vehicles <sup>b</sup>	0.035** (0.014)			
Stationary Police Vehicles <sup>b</sup>		-0.045** (0.02)		
At least one Stat Police Vehicle Present (0/1) <sup>b</sup>			-0.164*** (0.034)	-0.160*** (0.050)
Moving Police Vehicles <sup>b</sup>		0.087*** (0.018)	0.091*** (0.019)	0.143*** (0.028)
1 Day of Stationary Presence > Median (0/1) <sup>c</sup>	-0.158 (0.104)	-0.158 (0.104)	-0.156 (0.105)	-0.156 (0.105)
2 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-0.474*** (0.107)	-0.477*** (0.108)	-0.476*** (0.109)	-0.473*** (0.108)
3 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-0.530*** (0.107)	-0.537*** (0.108)	-0.542*** (0.108)	-0.535*** (0.108)
4 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-0.744*** (0.107)	-0.756*** (0.108)	-0.765*** (0.109)	-0.753*** (0.108)
5 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-1.014*** (0.109)	-1.031*** (0.111)	-1.047*** (0.111)	-1.029*** (0.109)
6 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-1.276*** (0.11)	-1.298*** (0.112)	-1.320*** (0.113)	-1.298*** (0.11)
7 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-1.617*** (0.107)	-1.645*** (0.109)	-1.676*** (0.109)	-1.648*** (0.106)
Additional Controls <sup>d</sup>	Yes	Yes	Yes	Yes
Location Fixed Effects	Yes	Yes	Yes	Yes
Observations	936342	936342	936342	936342

Standard errors account for clustering at the reporting area level.

<sup>a</sup>Random Patrol vehicles are police vehicles that are responding to a call at a different location. In this specification stationary police vehicles refer to RPatrol stationary police vehicles and moving police vehicles refer to RPatrol moving police vehicles.

<sup>b</sup>These are measures of current police presence at given time  $t$  and location  $r$ .

<sup>c</sup>"X Days of Stationary Presence>Median" is a dummy variable equal to 1 if there were X days where police presence exceeded the median (for that location and time of day over 2009) in the last 7 days.

<sup>d</sup>Analysis includes additional controls for: time of day, temperature, precipitation, visibility, holiday, and weekend/weekday travel.

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

Table 4: The Effect of Policing on Accidents (By Division)

	Central	North Central	North East	South Central	South East	South West
Stationary Police Rpatrol Vehicle (0/1) <sup>a</sup>	-0.004 (0.049)	-0.160*** (0.052)	-0.091** (0.04)	-0.177*** (0.051)	-0.126*** (0.046)	-0.220*** (0.058)
Moving Police RPatrol Vehicles <sup>a</sup>	0.080*** (0.027)	0.086*** (0.031)	0.060** (0.024)	0.021 (0.037)	0.042 (0.03)	0.039 (0.034)
1 Day of Stationary Presence > Median (0/1) <sup>b</sup>	-0.057 (0.149)	0.106 (0.161)	-0.106 (0.105)	-0.385*** (0.074)	-0.404*** (0.082)	-0.226** (0.071)
2 Days of Stationary Presence > Median (0/1) <sup>b</sup>	-0.214 (0.167)	-0.146 (0.176)	-0.422*** (0.113)	-0.559*** (0.077)	-0.671*** (0.089)	-0.588*** (0.079)
3 Days of Stationary Presence > Median (0/1) <sup>b</sup>	-0.344** (0.15)	-0.303 (0.173)	-0.611*** (0.107)	-0.823*** (0.095)	-0.834*** (0.091)	-0.833*** (0.074)
4 Days of Stationary Presence > Median (0/1) <sup>b</sup>	-0.496*** (0.145)	-0.546*** (0.185)	-0.829*** (0.11)	-1.125*** (0.094)	-1.217*** (0.093)	-1.107*** (0.08)
5 Days of Stationary Presence > Median (0/1) <sup>b</sup>	-0.755*** (0.144)	-0.786*** (0.182)	-1.131*** (0.118)	-1.290*** (0.098)	-1.418*** (0.091)	-1.308*** (0.079)
6 Days of Stationary Presence > Median (0/1) <sup>b</sup>	-0.974*** (0.145)	-1.106*** (0.185)	-1.284*** (0.125)	-1.559*** (0.107)	-1.635*** (0.089)	-1.559*** (0.078)
7 Days of Stationary Presence > Median (0/1) <sup>b</sup>	-1.250*** (0.143)	-1.381*** (0.182)	-1.645*** (0.119)	-1.883*** (0.11)	-2.006*** (0.115)	-1.910*** (0.092)
Precipitation (cms)	0.057*** (0.009)	0.074*** (0.012)	0.063*** (0.012)	0.109*** (0.013)	0.057*** (0.01)	0.085*** (0.01)
Morning Rush (6-9)	0.435*** (0.056)	0.644*** (0.073)	0.595*** (0.075)	0.508*** (0.072)	0.317*** (0.06)	0.458*** (0.064)
Daytime (9-4 PM)	0.871*** (0.046)	1.224*** (0.086)	1.202*** (0.064)	1.214*** (0.076)	1.040*** (0.071)	1.109*** (0.061)
Evening Rush (4-7 PM)	1.011*** (0.054)	1.517*** (0.091)	1.455*** (0.068)	1.283*** (0.077)	1.379*** (0.06)	1.326*** (0.061)
Night (7 PM-Midnight)	0.447*** (0.05)	0.814*** (0.089)	0.723*** (0.072)	0.708*** (0.07)	0.878*** (0.066)	0.788*** (0.06)
Holiday	-0.295** (0.11)	-0.349** (0.12)	-0.384*** (0.089)	-0.044 (0.092)	-0.17 (0.095)	-0.004 (0.091)
Weekend	0.103** (0.033)	-0.06 (0.043)	0.079* (0.036)	0.132** (0.041)	0.263*** (0.031)	0.220*** (0.035)
Location Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1496266	608779	1050811	982918	1110601	1226635

Standard errors account for clustering at the reporting area level.

All specifications also control for temperature and visibility.

<sup>a</sup>A vehicle is defined as an RPatrol vehicle if it is en route to another location.

<sup>b</sup>"X Days of Stationary Presence>Median" is a dummy variable equal to 1 if there were X days where police presence exceeded the median (for that location and time of day over 2009) in the last 7 days.

\* p<0.1, \*\* p<0.05, \*\*\* p<0.01

Table 5: The Effect of Police Presence at High versus Low Risk Accident Locations (NW Division)

	Low Risk Accident Location <sup>a</sup>	High Risk Accident Location <sup>a</sup>
At Least 1 Stationary RPatrol	-0.065	-0.247***
Vehicle Present (0/1) <sup>b</sup>	(0.058)	(0.069)
Number of RPatrol Moving Police Vehicles <sup>b</sup>	0.185***	0.107***
1 Day of Stationary Presence > Median (0/1) <sup>c</sup>	-0.312***	0.054
2 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-0.723***	-0.174
3 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-0.737***	-0.285
4 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-0.876***	-0.575***
5 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-1.190***	-0.825***
6 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-1.379***	-1.156***
7 Days of Stationary Presence > Median (0/1) <sup>c</sup>	-1.693***	-1.536***
Precipitation (cms)	0.077*** (0.011)	0.077*** (0.009)
Morning Rush (6-9)	0.184 (0.165)	0.411*** (0.09)
Daytime (9-4 PM)	0.689*** (0.14)	1.027*** (0.107)
Evening Rush (4-7 PM)	0.797*** (0.131)	1.104*** (0.103)
Night (7 PM-Midnight)	0.291*** (0.089)	0.453*** (0.123)
Holiday	-0.369*** (0.116)	-0.265** (0.119)
Weekend	0.058 (0.079)	-0.012 (0.069)
Location Fixed Effects	Yes	Yes
Observations	474936	461406

Standard errors account for clustering at the reporting area level.

All specifications also control for temperature and visibility.

<sup>a</sup>High Risk= reporting areas that include accident hotspots as defined by the Dallas Police Department. All other reporting areas are defined as Low Risk.

<sup>b</sup>Random Patrol vehicles are police vehicles that are responding to a call at a different location.

<sup>c</sup>"X Days of Stationary Presence>Median" is a dummy variable equal to 1 if there were X days where police presence exceeded the median (for that location and time of day over 2009) in the last 7 days.

\* p<0.1, \*\* p<0.05, \*\*\* p<0.01