DISCUSSION PAPER SERIES

DP14536
(v. 4)

POLICE RESPONSE TIMES AND INJURY OUTCOMES

Gregory DeAngelo, Marina Toger and Sarit Weisburd

INDUSTRIAL ORGANIZATION

PUBLIC ECONOMICS

ISSN 0265-8003

POLICE RESPONSE TIMES AND INJURY OUTCOMES

Gregory DeAngelo, Marina Toger and Sarit Weisburd

Discussion Paper DP14536
First Published 27 March 2020
This Revision 27 August 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

POLICE RESPONSE TIMES AND INJURY OUTCOMES

Abstract

The delayed response of law enforcement to calls for service has become a hot button issue when evaluating police department performance. While it is often assumed that faster response times could play an important role in quelling potentially violent incidents, to date there is no empirical evidence to support this claim. In this paper, we measure the effect of police response time on the likelihood that an incident results in an injury. To overcome the endogeneity between more severe calls being assigned higher priority, which requires a faster response, we take several steps. First, we focus on a subset of calls for service categorized as ``Major Disturbance - Violence'' that all receive the same priority level. Second, we instrument for police response time with the number of vehicles within a 2.5 mile radius of the call at the time it is received by the call center. When controlling for beat \& time of day fixed effects, this instrumenting strategy allows us to take advantage of the geographical constraints faced by a dispatcher when assigning officers to an incident. In contrast to the OLS estimates, our two-stage least squares analysis establishes a strong causal relationship whereby increasing response time increases the likelihood that an incident results in an injury. The effect is concentrated among female callers, suggesting that faster response time could potentially play an important role in reducing injuries related to domestic violence.

JEL Classification: N/A

Keywords: Rapid Response, Injuries, Policing, Safety

Gregory DeAngelo - gregory.deangelo@cgu.edu
Claremont Graduate University

Marina Toger - marina.toger@kultgeog.uu.se
Uppsala University

Sarit Weisburd - saritw@post.tau.ac.il
Tel Aviv University and CEPR

Police Response Time and Injury Outcomes

Gregory DeAngelo[*], Marina Toger[†], Sarit Weisburd[‡]

August 27, 2020

Abstract

The delayed response of law enforcement to calls for service has become a hot button issue when evaluating police department performance. While it is often assumed that faster response times could play an important role in quelling potentially violent incidents, to date there is no empirical evidence to support this claim. In this paper, we measure the effect of police response time on the likelihood that an incident results in an injury. To overcome the endogeneity between more severe calls being assigned higher priority, which requires a faster response, we take several steps. First, we focus on a subset of calls for service categorized as "Major Disturbance - Violence" that all receive the same priority level. Second, we instrument for police response time with the number of vehicles within a 2.5 mile radius of the call at the time it is received by the call center. When controlling for beat & time of day fixed effects, this instrumenting strategy allows us to take advantage of the geographical constraints faced by a dispatcher when assigning officers to an incident. In contrast to the OLS estimates, our two-stage least squares analysis establishes a strong causal relationship whereby increasing response time increases the likelihood that an incident results in an injury. The effect is concentrated among female callers, suggesting that faster response time could potentially play an important role in reducing injuries related to domestic violence.

Keywords: Rapid Response, Injuries, Policing, Public Safety

[*]Department of Economic Sciences, Claremont Graduate University; email: gregory.deangelo@cgu.edu
[†]Department of Social and Economic Geography, Uppsala University; email: toger.marina@gmail.com
[‡]Department of Economics, Tel Aviv University; email: saritw@tauex.tau.ac.il

1 Introduction

Law enforcement agencies are charged with providing one of the most important public goods: community safety. The primary focus of both public discourse and the economics of crime literature in achieving this goal has been evaluating crime prevention strategies implemented by the police.[1] While it seems reasonable that deterrence or incapacitation of criminals could lead to an increase in community safety, the role of police response times in determining the outcome of an ongoing emergent incident has been largely overlooked. This paper fills this void by examining whether faster response time by police officers can have both an immediate and long term effect on community safety.

Minimizing police response times is the goal of rapid response policing and a major focus for many police departments. Rapid response statistics are published publicly and different agencies are praised or criticized based on how their numbers compare with those of similar cities.[2] The effectiveness of this policy remains a source of friction between criminologists and law enforcement agencies. This strategy has often come under attack due to the lack of evidence regarding its benefits (Spelman and Brown (1981), Bayley (1996), and Sherman (2013)). Thus, while analyzing police response times is a popular data driven strategy to evaluate police effectiveness, these numbers can be misleading if fast response times have no known benefits for the communities that law enforcement agencies aim to protect. The underlying concern with rapid response policing is that it comes at the cost of other policing strategies (such as neighborhood policing, hot-spots policing, etc.) whose crime reduction benefits have been well established in the literature.[3]

Recent research has revisited the claim that faster response times can reduce crime by increasing the probability of arresting the suspect.[4] Rapid response may impact arrest rates if the officers arrive before the perpetrator of the crime has fled the location of the incident, or if officers who arrive earlier at the scene of the incident are able to collect better evidence from the crime scene (Hess and Hess-Orthmann 2012). Blanes i Vidal and Kirchmaier (2018) provide causal evidence that a 10 percent increase in police response time

[1] See works by Levitt (1997), Evans and Owens (2007), Vollaard and Hamed (2012), DeAngelo and Hansen (2014), Chalfin and McCrary (2017), and Mello (2019).

[2] As noted in Shults (2019), response time does play a big role in public satisfaction [with law enforcement].

[3] A summary of this literature can be found in Braga (2001), Weisburd and Eck (2004), and Telep and Weisburd (2012). Weisburd (forthcoming) finds that assigning officers in Dallas to 911 calls outside of their patrol beat (in the interest of providing faster response times) increases crime in the beats that were left behind.

[4] See Ater et al. (2014), Buonanno and Raphael (2013), and Barbarino and Mastrobuoni (2014) regarding the incapacitation effect of arrests.

leads to a 4.7 percent decrease in the probability of making an arrest in relation to the crime. Similarly, Mastrobuoni (2019) finds a decrease in the probability of an arrest for crimes that occur during police shift changes. He attributes this effect to longer response times as the officers taking over the new shift are in transit to their patrol location.

If faster response times can provide an opportunity to capture a suspect before he/she flees the incident, perhaps faster response times can also impact the severity of the criminal incident? There are some well publicized incidents where slow response times resulted in grave consequences.[5] This paper examines whether more subtle changes in response times can impact how an incident unfolds, specifically relating to the occurrence of injuries at incidents. Additionally, even if a fast response today prevents an immediate injury, a concern might be that injuries are simply being displaced to a later period. On the other hand, a faster response time today may contribute to long term deterrence.[6] Our data provide an opportunity to better understand this long term relationship by measuring the impact of faster response times on the probability of both a future call and future injury at a given residence.

We are not the first to examine the possible role of police officers in crime escalation. Specifically, Miller and Segal (2018) find that the integration of women in US policing results in decreased rates of subsequent non-fatal domestic abuse and intimate partner homicide. They show that the mechanism driving this result is increased reporting, which increases the probability of police involvement and criminal penalties. While Miller and Segal (2018) examine the role of police intervention on the escalation of crime over the life-cycle, our paper examines both the immediate impact of police intervention on current crime escalation, as well as the impact on future criminal engagement and violence.

The literature on the immediate role of emotions in decision making suggests that the timing of police arrival may play an important role in crime outcomes. Loewenstein and Lerner (2003) point out that even when people have a realistic understanding of their own self-interest, immediate emotions can cause people to lose control of their own behavior. This could imply that if officers arrive in the heat of the moment they may be able to help prevent

[5] For example, on August 17, 2012 Deanna Cook called Dallas 911 to report that she was being attacked by her abusive ex-husband (Administrator 2012). Officers first arrived at the scene 50 minutes after she placed the call and left when there was no answer. Her body was found at the house by her family 2 days later.

[6] A deterrence effect would arise if residents avoid committing a violent act in the future as they are concerned about the repercussions from an officer arriving quickly. Additionally, stopping the first injury at a residence may disrupt what could have become a long term escalation into a cycle of violence, as there is no need to avenge an injury that did not occur.

this loss of control.[7] Previous research has already found that external events can have an immediate effect on violent crime outcomes. Dahl and DellaVigna (2009) find that mass viewings of violent movies provide an outlet for violent emotions and decrease violent crime. Similarly, Card and Dahl (2011) report that an unexpected football loss by the home-team results in an immediate increase in the rate of at-home violence against wives and girlfriends in that location. In such instances where individuals lose control and engage in criminal conduct, the public calls on law enforcement to provide safety, which is what our research aims to examine.

In this paper we focus on 21,068 emergency 911 calls for service placed to the Dallas Police Department (DPD) in 2009 that were classified as priority level 2 (Major Disturbance Violence). While the starting evaluation of all of these calls was identical, the crime outcome ranges from a threat of violence to murder or intention to kill. Focusing within this specific call category, we analyze the role of response time in determining whether the incident results in an injury. We define response time as the time that elapsed between when the call was first answered at the 911 call center and when the first officer arrived at the scene of the incident.

Regressing injury outcomes on response time will only provide a causal estimate of the relationship if we are able to assume that response times are exogenously determined. However, at the time of the call some of these incidents may have begun with a higher potential for violence than others. If the call taker or dispatcher made use of this additional information to send officers more quickly to more injury prone incidents, this would bias the estimated response time effect towards zero. We therefore instrument for actual response time with police availability at the time of the call in a 2.5 mile (4 kilometer) radius surrounding the incident.[8]

We calculate the instrument of police availability using both precise information from the DPD Call Data on the time and location of the incident (latitude/longitude coordinates) and from the Automobile Vehicle Locator System data (AVL) on the real-time location of police vehicles. During 2009, AVL systems were active in all 873 DPD police patrol vehicles and data on their location was saved and stored. These data were used by dispatchers to optimally assign officers to 911 calls. Our instrument takes advantage of these

[7]While arriving at the scene of the incident quickly could reduce the likelihood of an injury, there may be a concern that officers arriving unprepared at an incident could make the situation worse. Indeed, Taylor (2020) finds that despite the fact that priming of information about an incident usually enhances the quality of policing, in situations where officers received erroneous information it led to more negative outcomes.

[8]In Dallas this distance approximately translates to a 5 minute drive.

roughly 100 million pings of information to count the number of officers within a 2.5 mile radius at the time of the call.

Our first stage results suggest that each additional police vehicle in a 2.5 mile radius of the incident decreases response time by 1.4 percent (s.e. 0.10). This instrument is motivated by the fact that despite the intentions of the dispatcher, during periods where officers are not located nearby to the incident, response times will be slower. We carefully discuss concerns regarding the exclusion restriction throughout the paper. To ensure that police availability within a 2.5 mile (4 km) radius is not directly correlated with the occurrence of an injury, we include controls for beat, hour, and day of week fixed effects. Even after including these fixed effects, there may still remain concerns regarding the validity of the exclusion restriction. For example, cars may be assigned to a specific location at a specific time due to expectations regarding violence, or incidents may develop differently when an officer is nearby. To address these concerns we also run our analysis when excluding nearby cars (within a 0.5 km radius) that may have been seen or heard by individuals involved in the incident or sent to the area to address specific concerns.

Without instrumenting for police response time with officer availability we find very small and statistically insignificant effects of police response time on the probability of an injury. Namely, a 10 percent increase in police response time increases the probability of an injury by 0.001 percentage points (s.e. 0.06). When instrumenting for police response time with police availability, the effect of a 10 percent increase in response time grows to a 1.7 percentage point increase in the probability of an injury (s.e. 0.6). This result is robust to alternative definitions of police availability and response time and to including beat-by-hour controls, as well as dispatcher and officer fixed effects. We report a similar effect when applying the same analysis to "in-progress" robberies, burglaries, and incidents of theft reported to 911, and a zero effect of response time for this same category of incidents that were reported to 911 after they had already occurred. We also find that faster responses to calls are associated with a lower likelihood of repeat offenses and injuries at the same residence, implying an inter-temporal dividend is paid for prompt responses.

This paper proceeds as follows. In the next section we introduce the data used for this project. Section 3 discusses the empirical strategy and presents estimates of the impact of response time on the probability of an injury. Section 4 explores falsification and robustness tests. Section 5 discusses heterogeneity across locations and callers and provides a closer look at the characteristics of compliers. We discuss the long-term effects of our analysis in Section 6 and conclude in Section 7.

2 Data

This project utilizes data from Dallas, Texas to estimate the impact of officer response time on the likelihood that an incident results in an injury. Dallas is an excellent location to examine for a variety of reasons related to this research question. It is a large city with an estimated population of 1.345 million people in 2018, making it the ninth most populous city in the United States. The city sprawls, covering nearly 390 square miles. Dallas is also a diverse city, with 29 percent of the population reporting as White, nearly 25 percent identifying as Black, and 42 percent identifying as Hispanic or Latino (of any race) according to the American Community Survey (2010-2014).

Given the size of the population and total area, Dallas employs a relatively large law enforcement agency. As of 2013, Dallas Police Department (DPD) employed 3,496 total sworn officers, with 2,064 officers assigned to patrol duties. Approximately 53 percent of the total sworn officers were White, 26 percent were Black and 19 percent were Hispanic. Approximately 83 percent of the sworn staff were male officers.

Within DPD, policing is divided across seven divisions. Each division contains approximately five sectors, and within each sector there are on average seven beats. The aim of the distribution of DPD officers is to ensure that each beat has at least one vehicle present at any point in time, although this objective is not always met. One of the main reasons to allocate at least one officer per beat is to ensure that law enforcement resources are available should a call for service be received.

As in most law enforcement agencies, calls for service are received and processed by the 911 call center and this information is then used by dispatchers to assign an officer to the incident. There were 684,584 911 calls recorded by DPD in 2009. As calls for service are received, a 911 operator answers the call and collects pertinent information about the incident to classify its location and determine its priority. Once this information is uploaded to the computer-aided dispatch (CAD) system, it is electronically routed to the dispatch queue of the relevant dispatcher based on the division where the call took place. The dispatcher then locates an available officer and assigns him/her to the incident (see Figure 1 for a visual outline of the call for service flow diagram).

The priority of the call is determined from the information received by the 911 call taker using the pre-set priority ranking displayed in Figure 2. The lower the priority number, the more emergent the call priority. For example, for priority 1 calls (e.g. active shooting)

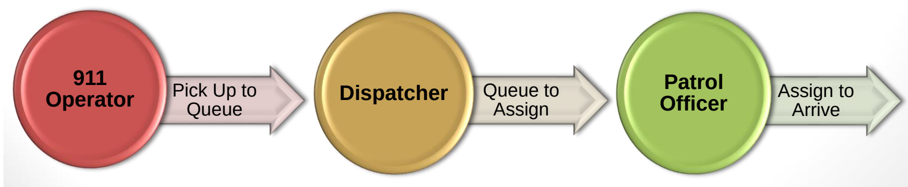


Figure 1: Flow Diagram of Calls for Service (Brown 2016)

the aim is for law enforcement to respond in 8 minutes or less. At the other end of the spectrum, priority 5 calls (e.g. lost property) likely do not even result in an officer arriving at the scene, but rather result in a follow-up phone call to discuss the incident. As one might expect, the response time is a function of the priority of the call, which is determined by the call taker's assessment of the incident and the availability of nearby officers.

Our analysis required us to combine information from 3 main DPD databases. The first is the Calls for Service Database that records all 911 calls that were placed to DPD in 2009. The second is the Crime Reports database which contains all crime records from 2009. The third is the Dallas Automated Vehicle Locator (AVL) data, which records the precise latitude-longitude points of each Dallas police patrol vehicle throughout 2009.

We use the Calls for Service Database to focus on 137,376 calls that are classified as "Major Disturbance - Violence." Calls in this problem category are always assigned a priority level of 2 with a response time goal of under 12 minutes. In addition to providing information on the problem category of the incident, the Calls for Service database also includes information on the precise latitude-longitude location of the call, the time this call was first answered by a call taker, the name of the person placing the call, the name of the call taker, and the time the first officer arrived at the scene of the incident. These data allow us to calculate response time as the difference between arrival time and the time the call was first answered by a 911 call operator.

The next step in creating our database is joining the calls data with the crime data. We are able to use a service number identifier to join 25,411 of these 911 calls with reported crimes. This is in line with general reports in the literature finding that most 911 calls do not result in crime reports (Neusteter et al. 2019). This still raises the question of whether the write-up of a crime report may have been impacted by the speed at which officers arrived at the scene of the incident. Thus, for example, if faster arrival times increase the probability that the incident is resolved not only without an injury but also without a crime report, then constraining our sample to calls that include a crime report would understate the effect of response time on injury outcomes. Alternatively, if when officers arrive more quickly at the scene of an incident they increase the probability of a crime report specifically for less serious outcomes, which otherwise would not have been reported, this would raise concerns that our results could be driven by a reporting change and not a behavioral change. In Figure 3 we show that the distribution of actual response times are very similar for both calls that result in crime reports and those that do not. Additionally, when we run our analysis on the entire sample of "Major Disturbance - Violence" calls instrumenting for response time with police availability and examining how this affects the probability of a crime report, we find no significant effect of response time on the probability of reporting (a 10 percent increase in response time increases the probability of a crime report by 0.09 percentage points (s.e. 0.33)).[9]

The crime data records provide an opportunity to classify whether or not the call resulted in an injury based on both the injury field in the data as well as the officer description of the incident.[10] We classify an incident as resulting in an injury if it includes any of the following words: injur, hit, pain, push, punch, choke, struck, wound, gsw (gun shot wound), blood, bleed, bruis(e), gash, twist, or kick.[11]

The third step in constructing the database involves the use of AVL data. The AVL data is used by the DPD dispatcher to track the location of officers and match officers to calls. For each police vehicle identifier, the system includes pings at roughly 30 second intervals with the precise latitude-longitude coordinates of where the vehicle is located.[12] When an officer is assigned to a call, the database also includes a master incident identifier that can be joined to the call database.[13] This database is used to count the number of officers within a 2.5 mile (4 km) radius of the 911 call. We focus on a 4 km cutoff as this is the mean distance between an assigned officer and a priority 2 incident in Dallas during 2009. On average, a distance of 4 kilometers amounts to a 5 minute drive in Dallas. Additionally, we calculate officer counts within a 3 and 5 km radius in order to ensure that there is not a

[9] See Appendix Table A.1 for reduced form, first stage, and 2SLS results.

[10] It is important to note that these fields primarily record injuries to either the complainant or suspect, not to or by the responding officer(s). Indeed, we have only identified one incident where an injury occurred to the officer and one incident where the injury was caused by the officer. While response times may impact officer misconduct, we were not able to obtain access to this data for this period.

[11] We use a regular expressions extraction to identify these terms and also identify negated terms (e.g. "...did not kick...") to prevent mis-classifications.

[12] These location pings are less frequent when the car is stationary.

[13] This provides an opportunity for us to calculate an alternative response time value based on when the assigned officer first appears within 200 meters of the incident that we discuss in our Robustness section.

specific distance cutoff that drives our results.[14]

To control for other factors that may be correlated with both response time and injuries, we collect additional information on weather characteristics, such as average daily temperature and precipitation. We also merge in data on the timing of sunrise and sunset in Dallas to determine whether the incident occurred after nightfall. We take advantage of Census block level data on race, earnings, and age to characterize the population residing in each of the beats in our sample.

Each observation in our final database is a 911 call reporting a major disturbance that has been linked to a crime and includes a count of the number of officers in a 2.5 mile radius at the time of the call. Our main analysis focuses on the 21,068 calls that include a police coded arrival time, as this is likely to achieve the most accurate measure of response time.[15] Table 1 presents descriptive statistics of our data broken apart by the 7 divisions of the DPD. There are approximately twice as many relevant incidents in the North East, South Central, South East and South West Divisions compared to the Central, North Central and North West Divisions. The likelihood that an incident results in an injury is fairly constant at 20-30% across all of the divisions in Dallas. Response times are somewhat similar as well, although response times appear to be slightly shorter in the Central, North Central, and South Central Divisions.

Perhaps the largest difference in variables of interest in our analysis come from the availability of officers at the time of a call. Specifically, the Central Division has, on average, nearly 17 available officers in a 2.5 mile radius around an incident, whereas every other division has approximately 4-8 available officers. This result is driven by the fact that beats in the Central Division average 0.6 square miles in size, which is roughly a third of the size of beats in other divisions. Interestingly, beats in the Central Division face the lowest average response time and have both the lowest injury rate and highest arrest rate.

Table 1 illustrates that while average income is much higher (nearly double other divisions) in the North Central Division, the injury rate, and average response time to incidents is fairly similar to that of other areas. Another characteristic that varies across locations is race, where beats in the South Central and Southeast Divisions tend to have a higher percentage of Black residents, and beats in the Northwest and Southwest Divisions have a higher percentage of Hispanic residents. These differences are important as one might

[14]For a detailed description of the steps taken to generate the data used in our analysis, see Appendix B.

[15]In Section 4 we run our analysis on a larger sample of 25,121 calls by introducing our own measure of police arrival time for those calls with missing values of police arrival times and find very similar results.

expect incidents in different neighborhoods to both follow different patterns of escalation, and be handled differently by the police. Finally, monthly arrests and crime calls vary across divisions, demonstrating the importance of including geographic fixed effects to control for underlying differences across locations.

3 Empirical Strategy & Results

In equation (1), we model the likelihood that an incident results in an injury as a function of log response time:

$$Injury_{ibh} = \beta_0 + \beta_1 ln(Response_{ibh}) + x_{ibh}\beta_2 + \gamma_h + \eta_b + \varepsilon_{ibh}, \tag{1}$$

where $Injury_{ibh}$ is a binary measure of whether an incident resulted in an injury and $Response_{ibh}$ is the length of time that elapsed between when the incident was called into 911 and an officer arrived at the scene. x_{ibh} is a vector of characteristics of the incident that can impact the probability that a reported crime results in an injury such as darkness, outside temperature, holidays, etc. We include hour (γ_h) and beat (η_b) fixed effects to absorb unobserved variation within specific hours of the day or police beats. The coefficient of interest is β_1, which aims to capture the impact of increases in police response time on the probability that the incident results in an injury.[16] $\widehat{\beta}_1$ estimates the causal effect of response time on an injury outcome as long as response time ($Response_{ibh}$) is not correlated with the remaining unobserved factors included in the error term (ε_{ibh}). Unfortunately, this is a difficult assumption to make since calls are given a priority precisely to drive faster responses to more serious calls. While all of the calls included in this sample are ranked as priority 2 calls, we cannot rule out a scenario where dispatchers further differentiate within the priority 2 group to allow faster responses to incidents with higher "damage potential." This negative correlation between response time and "damage potential" in ε_{ibh} would bias the response time effect towards zero.

Our identification strategy focuses on the environmental factors outside of a dispatcher's control that can result in different response times for incidents with identical characteristics. Specifically, after a call-taker determines priority, the amount of time it takes

[16] Figure 4 illustrates how log response time can reduce the influence of the outlier response times observed in Figure 3. In a robustness specification, we conduct our analysis with response time levels and continue to find a significant effect of response time on the probability of an injury, albeit smaller in size.

a car to arrive at the incident is a function of police availability in the surrounding area. Equation (2) describes the first stage relationship between the location of officers and log response time,

$$ln(Response_{ibh}) = \alpha_0 + \alpha_1 P_{ibh} + x_{ibh}\alpha_2 + \theta_h + \rho_b + \delta_{ibh}, \tag{2}$$

where P_{ibh} provides a count of the number of police vehicles in a 2.5 mile radius surrounding the 911 incident at the time of the call.

Panel A of Figure 5 presents the distribution of police availability in our full sample. Availability ranges between 0 and 49 cars in a 2.5 mile radius with a standard deviation of 6. When excluding the incidents with the highest 1% of police availability, this number ranges from 0 to 26. Panel B of Figure 5 maps the distribution of residualized officer availability after controlling for beat and time of day fixed effects. Police availability continues to range from -17 to 26 with a standard deviation of 3 (or -8 to 10 when excluding the first and 99th percentiles). The remaining variation in police availability is likely driven by staffing constraints on that date (how many officers are on vacation, sick days, training etc.) as well as policing tasks, such as responding to calls, court appearances, providing security at community events, etc. Each of these different incidents is heterogeneous in terms of its location and time investment.

We expect police availability (P_{ibh}) to have a negative effect on response time as it increases the probability that there is an officer nearby that can be assigned to the incident ($\alpha_1 < 0$). The left side of Figure 6 demonstrates this relationship in the raw data where incidents with higher P_{ibh} (more surrounding police officers) have *lower* response times.[17] If police availability only impacts the occurrence of an injury via response time, then two-stage least squares analysis will allow us to estimate the causal impact of response time on severity. Even after controlling for beat and hour fixed effects, we may expect more police in an area where a crime has recently taken place or the police have reason to believe that a crime may soon take place. While police departments are known to focus on allocating officers in an effort to minimize response time and maximize deterrence, we argue that an injury is more complicated to predict in advance. The right side of Figure 6 graphs the reduced form relationship between police availability (P_{ibh}) and an injury outcome ($Injury_{ibh}$) in the raw data. If officer assignment was being carried out in an effort to reduce injuries, we

[17]Figure 6 excludes the 1% of calls with high levels of police availability (ranging between 27 and 49). These calls are included in our regression analysis.

would expect to see more officers surrounding incidents that ended up with injury outcomes. Instead, Figure 6 suggests the opposite relationship where even without additional controls, more surrounding officers are negatively correlated with an injury outcome. We address this issue further in Section 4 by exploring different measures of police availability and discussing how this choice impacts the strength of the exclusion restriction and our results.

The first three columns of Table 2 present the first-stage estimates of the impact of police availability (P_{ibh}) on log response time, as defined in equation (2). Column 1 includes no controls, while column (2) includes a series of date and time characteristics (whether an incident occurs during rush hour, in darkness, precipitation level, temperature), beat-level controls (household income, population, square miles, percent of the population that is Black or Hispanic, percent of the population that are teens, and the percent of vacant homes), as well as time of day, holiday, and weekend fixed effects. In column (3) we further saturate the model by including beat fixed effects. The estimates of the effect of police availability on response time are robust to the degree that we saturate the model. The coefficient of -0.014 (s.e. 0.001) on police availability implies that having 6 more police vehicles in a 2.5 mile radius surrounding a criminal incident (a one standard deviation increase in police availability) decreases response time by 8.4%, which is significant at the 1 percent level. Moreover, the F-test for the instrument is well over 100 across these specifications, indicating that our instrument is both strong and relevant.

The first three columns of Table 2 provide an opportunity to consider other factors besides police availability that can also play a role in determining response times. Generally, response times tend to be longer during rush hour (when there is traffic congestion) and on the weekends (when there is a larger volume of calls for service). Perhaps unsurprisingly, wealthier beats experience faster response times, which could be a product of economic or political pressure to minimize criminal activity in these regions. Finally, beats with larger square mileage experience longer response times.

The last three columns of Table 2 present the reduced form estimates of the effect of officer availability on the likelihood that an incident results in an injury. Once again, we include three specifications that increasingly saturate the regression model. Overall, we find that having 6 more police vehicles available in a 2.5 mile radius surrounding a criminal incident (a one s.d. increase in police availability) reduces the likelihood of the incident ending in an injury by 1.2%, which is statistically significant at the 1% level. Injuries are less likely to occur during rush hour (when people are commuting) and more likely to occur in beats with a larger teen population and more vacant homes.

Thus far we have discussed two of the three assumptions necessary for interpreting our 2SLS estimates as the causal effect of police response times on injury outcomes. The third assumption requires a monotone relationship between the instrument (police availability) and police response times. While Table 2 demonstrates that on average, each additional car in a 2.5 mile radius decreases response time by 1.4 percent, Figure 7 maps out the nonlinear relationship between these two variables. Thus, moving from 0 cars in a 2.5 mile radius of the incident to 1 available car decreases response time by 11 percent (s.e. 2.3). This relationship appears strongly monotonic, whereby moving from 0 to 2 cars decreases response time by 18 percent (s.e. 2.2). When moving above 6 cars, increasing police availability continues to decreases response time, but the effect is weaker. The precision of the estimates decrease when looking at higher levels of police availability, which are less common in the data (there are only 65 incidents with 26 available cars).[18]

In Table 3 we present both the OLS and 2SLS estimates for our main specification (equation (1)). The OLS estimates do not yield a statistically significant relationship, regardless of the specification. As noted above, however, if officers are being sent more quickly to incidents with a higher potential to escalate, this will likely bias these estimates toward zero. It is only when instrumenting for police response time with police availability (columns (4)-(6)) that we observe a statistically significant positive effect of longer response times on the likelihood of an injury. In specification (6), which includes all relevant controls including beat fixed effects, we find that a 10 percent increase in response time increases the likelihood of an injury by 1.7 percentage points (s.e. 0.6). Given the 27 percent injury rate in our data, a 1.7 percentage point increase implies a 6.3 percent change in the injury rate. Thus, we find a strong, causal relationship between police response time and the likelihood that an incident results in an injury.

4 Falsification & Robustness Tests

Our main estimate suggests that response time can affect the likelihood that an incident results in an injury. We examine the robustness of this result in a number of ways. To start, in Table 4 we present alternative specifications of response time and officer availability using our most saturated specification. The first two specifications focus on our definition of response time, while the second two specifications focus on our definition of police availability.

[18]We exclude incidents with more than 26 available cars (the top 1%) from our analysis as these estimates become increasingly imprecise due to the lack of observations.

The fifth column removes officers that are nearby to the incident to account for potential concerns regarding both the reason for their precise location and how people may respond to observing officers nearby.

Column (1) presents results with response time measured in levels as opposed to logs. We find that each additional minute of response time increases the probability of an injury by 0.6 percentage points, an effect that is statistically significant at the 5% level. Given the average injury probability of 27% and response time of roughly 17 minutes, this implies that a 10% increase in response time increases the probability of an injury by 3.8% which is lower than our main estimate of 6.3%. Given the distribution of response times explored in Figures 3 and 4, log response time should be providing a more precise estimate by minimizing the impact of outliers.

Recall that when defining our sample, 4,343 observations did not have an officer arrival time coded in the data and, as such, were removed from our analysis. A priori, it is unclear how these observations should be treated. One explanation for the lack of arrival time is that an officer never arrived at the scene of the incident. Alternatively, an officer may have arrived but for some reason the call database was never updated. To ensure that selecting only those observations with recorded response times is not biasing our results we use the AVL data to track the time at which the officer assigned to the incident appeared within 200 meters of the call location. Applying this technique we are able to match 4,053 out of the 4,343 missing observations. Column (2) presents the results of our analysis when filling in the missing data with these researcher calculated response times and reports similar results to those found in our main specification.

Throughout this paper we define police availability based on the number of officers within a 2.5 mile (4 km) radius. Columns (3) and (4) replicate our results when defining police availability based on the number of officers within either a 3 km radius (column 3) or 5 km radius (column 4) of the incident. While both of these specifications produce results that are in line with our main specification it is relevant to note that the result weakens when focusing only on officers within a 3 km radius. This begs the question, which officers are the "right" officers to count in defining police availability?

The validity of our instrument depends on the assumption that police availability impacts response time but has no direct effect on the outcome of an incident. Since we know that the location of officers can impact the occurrence of a crime, this raises the concern that the nearest officers may directly impact the probability of an injury.[19] Thus, while counting officers that are too far away from the location of the incident could result in weakening the first stage, counting officers that are too nearby may weaken the exclusion restriction. Restricting our count only to officers within a 3 km radius may disregard precisely those officers who can arrive quickly at the scene of an incident but would have no direct deterrence effect on crime.

To further strengthen the exclusion restriction, in column (5) of Table 4 we focus only on officers who are within a 2.5 mile radius of the call but are not located in the direct vicinity of the incident. Assuming that the police may sometimes have fairly precise information on the location of a crime risk (e.g. an apartment where there have been repeat domestic violence calls or gang related incidents) they may increase presence precisely surrounding these locations. If these predictable events are more prone to violence, then this would bias our estimates towards zero. We therefore construct an alternative measure of police availability by summing all officers who are within a 2.5 mile (4 km) radius of the incident while excluding the nearest officers (those within 0.5 km of the incident). Indeed, using this newly constructed instrument, we conduct the same analysis as before and identify larger estimates than we observed in Table 3.

Our identification strategy takes advantage of random changes in response times to avoid concerns regarding endogenous factors driving police response times. Thus, while we may expect the expertise or experience of the 911 call operator to play a role in determining faster response times in situations where injuries are more likely, this should not have any impact on our estimated effects. Similarly, while we may expect some officers to be better at preventing injuries than others, and that these more effective officers may also be better at responding promptly to incidents, this should not be a concern in our IV specification. Indeed, in columns (1) and (2) of Table 5 we include 911 call operator fixed effects and officer fixed effects, respectively and find similar results to those reported in Table 3.

The last specification of Table 5 summarizes our results when including beat-by-hour fixed effects. While our main specification separately controls for beat and hour fixed effects, this cannot account for the fact that different beats may face different levels of police availability and injury risks across different hours of the day. Column (3) of Table 5 estimates the effect of a change in police availability when looking within the same beat and hour of

[19] See works by Sherman and Weisburd (1995), Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), Gould and Stecklov (2009), Draca et al. (2011), Bushway et al. (2013), MacDonald et al. (2015), and Weisburd(forthcoming) that explore the deterrent effect of police presence on crime.

the day. We continue to find that a 10 percent increase in response time results in a 1.6 percentage point increase in the probability of an injury.

4.1 The Effect of Police Response Time on Injuries: The Case of 911 Burglary, Theft, and Robbery Reports

Our instrumental variable strategy predicts that faster response times change the outcome of an incident by reducing the likelihood that an injury occurs. One concern is that there exists an underlying correlation between officer availability and incident severity that would produce these same results, even in contexts where we would not expect officer presence to impact the outcome of the incident.

To look more closely at the mechanism driving our results we apply our analysis to 911 calls reporting burglaries, thefts, and robberies. These categories are interesting as the call classification system labels the calls differently based on whether or not the incident is currently in progress. The first three columns of Table 6 focus on 911 calls reporting incidents that are currently in progress, while the last three columns focus on incidents in the same category that have already occurred.

Columns (1) and (4) of Table 6 provide estimates from regressing the binary outcome of whether or not an injury occurred on response time, when including beat, time of day, weekend, and holiday fixed effects. Thus, without addressing the endogeneity concerns regarding response time, we cannot reject the null hypothesis that response time has no effect on injury outcomes for either "in-progress" or "not-in-progress" burglary, theft, and robbery reports. In columns (2) and (5), we estimate a similar first stage effect of police availability for these two different call categories. Namely, each additional officer within a 2.5 mile radius of the call decreases response time by 2.1 to 2.3 percent regardless of whether or not this call pertains to a crime that is currently in progress. However, while the 2SLS estimate for incidents that are in-progress is statistically significant at the 5 percent level and suggests that a 10 percent increase in response time increases the probability of an injury by 2.8 percentage points (s.e. 1.4), the same analysis results in an estimate of 0.02 (s.e. 0.5) for incidents within the same category that are no longer in progress. In other words, while fast response times can have a large and statistically significant effect on crimes that are in-progress, this relationship does not hold for incidents that have already occurred.

5 Heterogeneity & LATE

5.1 Heterogeneity

Our results suggest that police response times can play an important role in preventing the escalation of an incident. However, the question remains whether this effect applies to the entire population, or alternatively, if there are specific types of callers or responders for whom response times are especially important for predicting injury outcomes. We examine this question in Table 7 by running our 2SLS analysis separately by gender, age, residential call history, and whether the officer responding to the call is at the beginning or end of his/her shift.

The impact of response time on incident escalation may be a function of the vulnerability of the caller as well as the caller's perception of police fairness and effectiveness. Different groups within the population may face different injury risks and/or have different interactions with the police. This could be driven either by the perception these callers have of the police, or alternatively, police behavior towards these different groups. The differences in injury risks across groups are apparent when comparing the mean of the dependent variable (probability of injury) in Table 7. Thus, younger callers (under age 30) are 20 percent more likely than older callers to be involved in an incident that results in an injury (see columns (1) and (2)). Interestingly, it is older callers who seem to benefit most from faster response times.

One of the most important issues pertaining to police response time is domestic violence (Townsend et al. 2006; Thorndyke 2015). While we cannot conduct our analysis on domestic violence calls, as this is an outcome by itself, it is worth noting that 84% of calls that end up being coded as domestic violence crimes in our data are reported by female callers. When splitting our data by the gender of the caller, our results suggest that faster response times are especially important for female versus male callers. A 10 percent increase in response time increases the probability of an injury by 2.7 percentage points (s.e. 1.0) for female callers, with a much smaller effect of 0.05 (s.e. 1.1) among male callers (see columns (3) and (4)). One interpretation of this result is that the reduction in violence associated with faster responses to female callers could be decreasing more severe violence associated with domestic violence.

We next examine the impact of longer response times on the likelihood of injury by residences that have many (3+) high priority 911 calls in 2009 relative to few (1-2) high priority calls for service.[20] Columns (5) and (6) of Table 7 demonstrate that longer response times have a large, statistically significant impact on injury for residences that have fewer than 3 high priority calls as opposed to residences that tend to record more crimes. Thus, it is the locations that are less incident prone that seem to benefit the most from faster response times. This result provides support for the Rapid Response policing strategy of allocating police officers in an effort to provide fast response times for all areas of the city as opposed to focusing on hot-spots of crime.

Finally, columns (7) and (8) of Table 7 focus not on the characteristics of the caller, but rather on the characteristics of the responder. If the mechanism driving our result is that when officers arrive at the scene they exert effort to prevent the escalation of an incident, then we might expect them to be most effective at the start of their shift when they are most alert. Alternatively, if it is the arrival of the officer that prevents escalation, regardless of officer conduct, then the characteristic of the responder should have little effect. To shed light on this issue, we break our data apart based on whether the responding officer happens to be at the beginning (first four hours) or end (5+ hours) of his/her shift. Longer response times specifically in the first half of an officer's shift have a large and statistically significant effect on the likelihood that an injury occurs. In other words, when interpreting our results it is important to think carefully not only about how quickly officers are arriving, but also about their conduct (or de-escalation ability) upon arrival.

5.2 LATE

LATE is another important factor to consider in interpreting our results as our two stage least square estimates provide the average effect for incidents in our sample whose response time would have been different, had officer availability been higher/lower at the time of the call. Using a similar strategy to Dobbie et al. (2018) we estimate the fraction of compliers in our sample as a whole and across different subgroups.[21] We define compliers as calls for which response time would have been different had it occurred in a period with the highest amount of police availability as opposed to the lowest amount of police availability. Let a fast response (F) equal 1 if police respond to the call within the suggested response time of

[20]The cutoff for many versus few high priority calls is determined by the median number of priority 1 and 2 calls made to 911 per address in our data during 2009.

[21]Their analysis was based on work by Abadie (2003) and Dahl et al. (2014).

a priority 2 call (12 minutes). We define the fraction of always takers (π_a) as,

$$\pi_a = \Pr(F_i = 1|A_i = \underline{a})$$

Where $\underline{a}$ defines situations with the minimum level of police availability for that division. Thus, π_a captures the fraction of calls that would receive a fast response regardless of how many officers are nearby. We can then define the fraction of our sample who are compliers (π_c) as,

$$\pi_c = \Pr(F_i = 1|A_i = \overline{a}) - \Pr(F_i = 1|A_i = \underline{a}),$$

where $\overline{a}$ defines situations with the maximum level of police availability for that division. In other words, to calculate compliers, we subtract the fraction of always takers from the fraction of incidents where high availability results in fast response times.

Lastly, we define the fraction of never takers using calls that did not result in a fast response despite having the maximum level of police availability for that division at the time of the call (π_n) as,

$$\pi_n = \Pr(F_i = 0|A_i = \overline{a}).$$

We estimate these groups within our data by using our first stage regression (see equation (2) when focusing on the binary outcome of fast response (F) either when applying a local linear model (where the sample is constrained to include only incidents that occurred with either minimal police presence ($\underline{a}$) or maximum police presence ($\overline{a}$)) or full linear model.

Calculating Fraction of Compliers, Always Takers, Never Takers

	Local Linear Model $F_{ibh} = \psi_0 + \psi_1 H_{ibh} + \delta_{ibh}$	Linear Model $F_{ibh} = \gamma_0 + \gamma_1 P_{ibh} + \delta_{ibh}$
Compliers	$\hat{\pi}_c = \hat{\psi}_1$	$\hat{\pi}_c = \hat{\gamma}_1(\overline{a} - \underline{a})$
Never Takers	$\hat{\pi}_n = 1 - (\hat{\psi}_0 + \hat{\psi}_1)$	$\hat{\pi}_n = 1 - (\hat{\gamma}_0 + \hat{\gamma}_1(\overline{a}))$
Always Takers	$\hat{\pi}_a = \hat{\psi}_0$	$\hat{\pi}_a = \hat{\gamma}_0 + \hat{\gamma}_1(\underline{a})$

Where $H_{ibh} = 1$ when this incident occurred during a period of maximum police presence. In both the local linear and full linear models beat, hour, weekend, holiday, rush-hour, darkness, and precipitation are partialled out of the equation.

To calculate the share of compliers, always takers, and never takers it is necessary for us to define minimum and maximum police availability. In Table 8 we show this distribution using cutoffs of 1%, 1.5%, and 2%. We find that the fraction of compliers ranges between 30%

when applying the local linear model and 20% when applying the full linear specification. Thus, for roughly a quarter of our sample moving from low police availability to high police availability has a significant effect on police response times. The remainder of the sample is split such that there are roughly 5% more never takers than always takers for both the local linear and full linear specifications. These results remain fairly consistent across different cutoffs for minimum and maximum police availability.

To better understand the characteristics of incidents that are characterized as compliers we can calculate the degree at which each subgroup is represented within the compliant population ($P[X = x|Complier]$) and how this compares to their representation in the entire sample (P[X=x]).[22] Table 9 provides a summary of the different characteristics of incidents in our data and the degree of which they are represented within the complier group.[23] We find that complier incidents are significantly more likely to be located farther away from their local police department (defined as over the median of 3km distance) and to occur outside of rush hour traffic. We do not find any significant differences in compliance based on caller characteristics such as race, gender, age or the number of high priority 911 calls received from this residence.

6 The Long Term Effects of Response Time

Thus far our analysis has focused on the effect of officer response time on injuries contemporaneously. In Table 10 we extend our analysis to identify the effect of response time to the first call received at any address on the likelihood of repeat offenses and future injuries. To do this, we first re-structure our data so that the unit of observation is a residence (unique address). This reduces our data from 21,068 to 13,384 observations, and enables us to determine whether a residence experienced repeat "Major Disturbance - Violence" calls, as well as any injuries associated with future calls, during our data sample. Approximately 50% of residences that report a "Major Disturbance - Violence" incident in 2009 end up with at least one repeat call, with fewer than 5% of all locations calling 5 or more times.

In Table 10 we run an analogous analysis to Table 3, except that we now focus on

[22] We calculate $P[X = x|Complier]$ as $\frac{P[X=x][\hat{\pi}_c|X=x]}{\hat{\pi}_c}$. The numerator is equal to the fraction of compliers from this group within the full population and calculated as the fraction of the group within the full population multiplied by the fraction of compliers within the group. We calculate the fraction of compliers from this group out of all compliers by dividing the numerator by the fraction of compliers within the full population.

[23] For this analysis we use the linear model and 1% cutoff.

the impact of response time to the first call on the likelihood that a future call for service or injury occurs.[24] Column 1 of Table 10 shows the strong, negative first-stage relationship between the availability of officers and their response time at the first call for service from that address. Columns 2-4 display the OLS, reduced form and 2SLS analyses, respectively, to measure the effect of response time to the first call on the likelihood of a repeat call for service. The naïve OLS results show no relationship between a longer response time at the first call and the probability of a future call for service. However, the reduced form analysis displays a strong negative relationship between availability of officers at first call and the likelihood of a repeat offense. Thus, it is not surprising that our IV results indicate that a 10% increase in the response time of police to the first call increases the likelihood of a repeat offense by 3.6 percentage points (s.e. 1.08).

We further explore the effect of response time to the first call for service on future outcomes by examining the likelihood of a future call that results in an injury.[25] Once again, naïve OLS results do not display any statistically significant effect of response times on the probability that a future call results in an injury. However, our IV results indicate that a 10% increase in the response time of police to the first call increased the likelihood of an injury in a future call for service by 1.06 percentage points (s.e. 0.57). While, this effect is noisily measured (statistically significant at the 10% level), it suggests that the benefit of fast response times is not isolated to current calls for service, but rather may pay dividends in the future by reducing the likelihood that 911 calls are received and, even if they are received, could reduce the likelihood that future injuries occur.

7 Conclusion

This year 12 cities including Seattle, New York, Los Angeles, San Francisco, and Washington, DC have announced that they will be defunding their police departments and decreasing the size of their police force (McEvory 2020). Understanding the benefits provided by patrol officers is especially important in a climate where large policy changes are quickly going into effect. While previous research has provided evidence that longer response times may reduce the likelihood that crimes are cleared, the question of whether law enforcement arriving at the scene of an incident faster impacts the evolution of the incident has yet to be addressed. Naïve

[24]In Table A.2 we conduct the analysis from Table 3 when focusing on only the 13,384 first calls at each residence and find estimates that are consistent with our main findings.

[25]If there was no future call from that residence we set the variable future injury to zero.

attempts to measure the impact of police response time on safety outcomes are complicated by law enforcement patrolling decisions, officer dispatch decisions, and a number of other unobservable factors that would likely lead to an uninformative analysis.

To overcome these endogeneity concerns we apply an instrumenting strategy that takes advantage of a factor outside of the dispatchers control, namely, the geographic availability of officers. Because the location of officers is dynamic across space and time we are able to examine incidents that occur within the same neighborhood but face different response times as a result of the number of officers nearby at the time of the call. The results of our analysis identify a causal effect of slower response times on the likelihood that an injury occurs. Specifically, we find that a 10 percent increase in response times (approximately 2 minutes) leads to a 6.3 percent increase in the injury rate. These results are robust to alternative specifications as well as sensitivity checks of the metric used to identify officer availability. Additionally, our analysis suggests that faster response times today do not displace injuries to later time periods, and may actually reduce injury risks at this residence in the future.

Our results stand in contrast to much of the existing literature on rapid response policing (see Weisburd and Eck (2004)). While we argue that part of the explanation for the lack of effect in prior research is the underlying correlation between response times and incident characteristics, another important factor that differentiates our analysis from that of prior research is that we focus on a specific category of calls, namely "Major Disturbance - Violence." We show that these priority 2 calls that make up roughly 20 percent of all 911 calls can be impacted by officer arrival times. Therefore, our results suggest that judging police departments based on response times to all calls may be less informative than focusing on specific calls that are likely to contribute to community safety.

Our data allow us to take a closer look at our results to further understand the populations that can benefit the most from faster response times. We find that our effects are largest for female callers and that our effects do not seem to be driven by specific high crime locations. Although data restrictions prevent us from knowing all of the details related to each call for service, a possible interpretation of the stronger effect on female callers is that response time is especially important in domestic disputes. This finding is policy relevant given increased concerns regarding the heavy toll of domestic abuse on society.

References

Abadie, A. (2003). Semiparametric Instrumental Variable Estimation of Treatment Response Models. *Journal of Econometrics*, 113(2):231 – 263.

Administrator, D. N. (2012). Dallas Woman Found Murdered 2 Days After Her Screams for Help to 911. *The Dallas Morning News*.

Ater, I., Givati, Y., and Rigbi, O. (2014). Organizational Structure, Police Activity and Crime. *Journal of Public Economics*, 115:62–71.

Barbarino, A. and Mastrobuoni, G. (2014). The Incapacitation Effect of Incarceration: Evidence from Several Italian Collective Pardons. *American Economic Journal: Economic Policy*, 6(1):1–37.

Bayley, D. (1996). *Police for the Future*. Studies in Crime and Public Policy. Oxford University Press.

Blanes i Vidal, J. and Kirchmaier, T. (2018). The Effect of Police Response Time on Crime Clearance Rates. *The Review of Economic Studies*, 85(2):855–891.

Braga, A. A. (2001). The Effects of Hot Spots Policing on Crime. *The ANNALS of the American Academy of Political and Social Science*, 578(1):104–125.

Brown, D. (2016). Communications Operations Center (Handling Calls for Service). *Memorandum*.

Buonanno, P. and Raphael, S. (2013). Incarceration and Incapacitation: Evidence from the 2006 Italian Collective Pardon. *American Economic Review*, 103(6):2437–65.

Bushway, S., DeAngelo, G., and Hansen, B. (2013). Deterability by Age. *International Review of Law and Economics*, 36:70 – 81.

Card, D. and Dahl, G. B. (2011). Family violence and football: The effect of unexpected emotional cues on violent behavior. *The Quarterly Journal of Economics*, 126(1):103–143.

Chalfin, A. and McCrary, J. (2017). Criminal Deterrence: A Review of the Literature. *Journal of Economic Literature*, 55(1):5–48.

Dahl, G. and DellaVigna, S. (2009). Does Movie Violence Increase Violent Crime?*. *The Quarterly Journal of Economics*, 124(2):677–734.

Dahl, G. B., Kostl, A. R., and Mogstad, M. (2014). Family Welfare Cultures *. *The Quarterly Journal of Economics*, 129(4):1711–1752.

DeAngelo, G. and Hansen, B. (2014). Life and Death in the Fast Lane: Police Enforcement and Traffic Fatalities. *American Economic Journal: Economic Policy*, 6(2):231–57.

Di Tella, R. and Schargrodsky, E. (2004). Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack. *American Economic Review*, 94(1):115–133.

Dobbie, W., Goldin, J., and Yang, C. S. (2018). The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges. *American Economic Review*, 108(2):201–40.

Draca, M., Machin, S., and Witt, R. (2011). Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks. *American Economic Review*, 101(5):2157–81.

Evans, W. N. and Owens, E. G. (2007). Cops and Crime. *Journal of Public Economics*, 91(1):181 – 201.

Gould, E. D. and Stecklov, G. (2009). Terror and the Costs of Crime. *Journal of Public Economics*, 93(11-12):1175–1188.

Hess, K. and Hess-Orthmann, C. (2012). Criminal Investigation.

Klick, J. and Tabarrok, A. (2005). Using Terror Alert Levels to Estimate the Effect of Police on Crime. *The Journal of Law and Economics*, 48(1):267–279.

Levitt, S. D. (1997). Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *The American Economic Review*, 87(3):270–290.

Loewenstein, G. and Lerner, J. (2003). *The Role of Affect in Decision Making*, pages 619–642. Oxford University Press, Oxford.

MacDonald, J., Klick, J., and Grunwald, B. (2015). The Effect of Private Police on Crime: Evidence from a Geographic Regression Discontinuity Design. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 179.

Mastrobuoni, G. (2019). Police Disruption and Performance: Evidence from Recurrent Redeployments Within a City. *Journal of Public Economics*, 176:18 – 31.

McEvory, J. (2020). At Least 12 Cities Are Defunding Their Police Departments. *Forbes*, pages 1 – 4.

Mello, S. (2019). More Cops, Less Crime. *Journal of Public Economics*, 172:174 – 200.

Miller, A. R. and Segal, C. (2018). Do Female Officers Improve Law Enforcement Quality? Effects on Crime Reporting and Domestic Violence. *The Review of Economic Studies*, 86(5):2220–2247.

Neusteter, R., Mapolski, M., Khogali, M., and O'Toole, M. (2019). The 911 call processing system: A review of the literature as it relates to policing. *Vera Institute of Justice*.

Sherman, L. and Weisburd, D. (1995). General deterrent effects of police patrol in crime "HOT SPOTS": A randomized, controlled trial. *Justice Quarterly*, 12:625–648.

Sherman, L. W. (2013). The Rise of Evidence-Based Policing: Targeting, Testing, and Tracking. *Crime and Justice*, 42(1):377–451.

Shults, J. (2019). Do Police Response Times Matter? *Police One Newsletter*.

Spelman, W. and Brown, D. (1981). Calling the Police: Citizen Reporting of Serious Crime. *Police Executive Research Forum*.

Taylor, P. L. (2020). Dispatch Priming and the Police Decision to Use Deadly Force. *Police Quarterly*, 0(0):1098611119896653.

Telep, C. W. and Weisburd, D. (2012). What is Known About the Effectiveness of Police Practices in Reducing Crime and Disorder? *Police Quarterly*, 15(4):331–357.

Thorndyke, B. (2015). Police Response Time to Domestic Violence Calls and its Effects. *Working Paper*.

Townsend, M., Hunt, D., Kuck, S., and Baxter, C. (2006). Law Enforcement Response to Domestic Violence Calls for Service. *National Institute of Justice Report 215915*.

Vollaard, B. and Hamed, J. (2012). Why the Police Have an Effect on Violent Crime After All: Evidence from the British Crime Survey. *The Journal of Law and Economics*, 55(4):901–924.

Weisburd, D. and Eck, J. E. (2004). What can police do to reduce crime, disorder, and fear? *The ANNALS of the American Academy of Political and Social Science*, 593(1):42–65.

Weisburd, S. Police Presence, Rapid Response Rates, and Crime Prevention. *The Review of Economics and Statistics*, Forthcoming:1–45.

Table 1: Summary statistics

	Central	***North Central***	***North East***	***North West***	***South Central***	***South East***	***South West***
Injury	0.21	0.24	0.31	0.23	0.28	0.31	0.27
	(0.41)	(0.43)	(0.46)	(0.42)	(0.45)	(0.46)	(0.44)
Response Time	14.99	16.88	18.41	17.72	16.92	17.60	17.29
	(25.03)	(72.31)	(32.60)	(12.42)	(33.91)	(11.74)	(10.80)
Availability	17.04	4.32	5.67	7.67	5.91	7.04	6.27
	(6.94)	(2.94)	(3.55)	(4.67)	(3.60)	(5.39)	(4.41)
Income ($10,000)	3.60	7.43	4.25	3.50	2.71	2.69	3.40
	(1.22)	(1.64)	(1.27)	(1.56)	(0.74)	(0.82)	(0.80)
Black (%)	0.15	0.15	0.27	0.14	0.73	0.46	0.27
	(0.11)	(0.09)	(0.15)	(0.14)	(0.16)	(0.27)	(0.24)
Hispanic (%)	0.35	0.29	0.36	0.54	0.24	0.45	0.62
	(0.22)	(0.20)	(0.15)	(0.27)	(0.15)	(0.24)	(0.24)
Teens (%)	0.04	0.05	0.06	0.06	0.08	0.08	0.08
	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Vacant Houses (%)	0.15	0.10	0.14	0.12	0.12	0.13	0.09
	(0.04)	(0.03)	(0.06)	(0.04)	(0.04)	(0.06)	(0.02)
Monthly Arrests (Beat)	48.81	15.43	28.39	36.84	17.82	22.00	23.85
	(23.60)	(6.01)	(14.19)	(20.64)	(7.39)	(9.23)	(9.42)
Population (Beat)	3766.79	9766.86	6537.03	5400.54	3249.79	3985.97	6044.22
	(2666.01)	(3510.28)	(2515.80)	(3144.84)	(1429.91)	(1749.57)	(3074.78)
Square Miles (Beat)	0.58	1.59	1.05	1.29	1.35	1.55	2.01
	(0.32)	(1.04)	(2.20)	(0.98)	(1.39)	(1.68)	(2.62)
Weekend 911 Calls (Division)	175.87	144.78	280.79	190.84	221.40	282.14	290.35
	(24.93)	(17.28)	(34.58)	(25.69)	(34.31)	(49.31)	(42.99)
Weekday 911 Calls (Division)	144.27	123.61	242.63	161.52	205.14	240.48	238.17
	(35.39)	(25.20)	(50.34)	(33.67)	(40.77)	(59.22)	(51.27)
Weekend Patrol Cars (Division)	88.59	87.08	99.38	82.11	91.54	102.30	93.65
	(10.52)	(9.65)	(6.75)	(10.42)	(5.17)	(12.46)	(14.87)
Weekday Patrol Cars (Division)	83.19	91.50	112.24	91.87	97.54	104.00	103.96
	(8.70)	(7.65)	(12.17)	(11.68)	(10.98)	(10.80)	(9.91)
Beats	29	22	41	31	37	39	33
Observations	2178	1763	3999	2226	3415	3944	3543

Table 2: First-Stage and Reduced Form Estimates of the Effect of Police Availability on Response Time and Injuries

Dep var:	Response Time (logs)			Injury		
	(1)	(2)	(3)	(4)	(5)	(6)
Availability of Officers	-0.014***	-0.014***	-0.014***	-0.004***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rush Hour		0.145***	0.144***		-0.063***	-0.061***
		(0.021)	(0.021)		(0.019)	(0.019)
Weekend		0.032***	0.033***		0.010	0.011
		(0.009)	(0.009)		(0.007)	(0.007)
Holiday		0.027	0.030		0.031*	0.029
		(0.022)	(0.022)		(0.018)	(0.018)
Darkness		-0.010	-0.010		-0.012*	-0.013*
		(0.009)	(0.009)		(0.007)	(0.007)
Precipitation (cm)		0.002	0.003		-0.006*	-0.005
		(0.004)	(0.004)		(0.004)	(0.004)
Percent Black		-0.088			0.043	
		(0.056)			(0.033)	
Percent Hispanic		-0.036			0.048	
		(0.063)			(0.040)	
Percent Teens		0.445			0.656*	
		(0.639)			(0.357)	
Percent Vacant Houses		0.181			0.273***	
		(0.141)			(0.096)	
Household Income ($10,000's)		-0.021***			-0.002	
		(0.006)			(0.004)	
Population (per 10,000)		0.010			0.029*	
		(0.025)			(0.016)	
Square Miles		0.011***			-0.003	
		(0.003)			(0.002)	
N	21,068	21,068	21,068	21,068	21,068	21,068
Mean of dependent variable	2.68	2.68	2.68	0.27	0.27	0.27
Beat FE	No	No	Yes	No	No	Yes
Time of Day FE	No	Yes	Yes	No	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 3: OLS & 2SLS Estimates of the Effect of Police Response Time on Injury

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Response Time (logs)	0.007	0.006	0.0001	0.275***	0.244***	0.168***
	(0.006)	(0.006)	(0.006)	(0.038)	(0.043)	(0.062)
Rush Hour		-0.064***	-0.062***		-0.098***	-0.086***
		(0.019)	(0.019)		(0.021)	(0.021)
Weekend		0.009	0.010		0.003	0.006
		(0.007)	(0.007)		(0.007)	(0.007)
Holiday		0.033*	0.031*		0.024	0.024
		(0.018)	(0.018)		(0.019)	(0.019)
Darkness		-0.013*	-0.013*		-0.010	-0.011
		(0.007)	(0.007)		(0.008)	(0.007)
Precipitation (cm)		-0.006*	-0.005		-0.007*	-0.006
		(0.004)	(0.004)		(0.004)	(0.004)
Percent Black		0.074**			0.064**	
		(0.035)			(0.028)	
Percent Hispanic		0.068			0.056*	
		(0.042)			(0.034)	
Percent Teens		0.803**			0.547**	
		(0.383)			(0.263)	
Percent Vacant Houses		0.229**			0.229**	
		(0.099)			(0.097)	
Household Income ($10,000's)		0.002			0.003	
		(0.004)			(0.003)	
Population		0.036**			0.027*	
		(0.016)			(0.016)	
Square Miles		-0.002			-0.006**	
		(0.003)			(0.003)	
N	21,068	21,068	21,068	21,068	21,068	21,068
Mean of dependent variable	0.27	0.27	0.27	0.27	0.27	0.27
First Stage F-Statistic				185.96	168.93	162.42
Beat FE	No	No	Yes	No	No	Yes
Time of Day FE	No	Yes	Yes	No	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 4: 2SLS Estimates of the Effect of Police Response Time on Injury (Alternative Specifications)

	Response Time - Levels (1)	Police-Research Response Time (2)	3km Radius (3)	5km Radius (4)	Omit 0.5km Radius (5)
Response Time (logs)		0.146***	0.108**	0.311***	0.303***
		(0.052)	(0.054)	(0.047)	(0.043)
Response Time (levels)	0.006**				
	(0.003)				
Rush Hour	-0.078***	-0.075***	-0.077***	-0.108***	-0.106***
	(0.020)	(0.019)	(0.021)	(0.022)	(0.021)
Weekend	-0.002	0.012**	0.007	0.000	0.001
	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
Holiday	0.024	0.043**	0.026	0.022	0.022
	(0.019)	(0.018)	(0.018)	(0.020)	(0.019)
Darkness	-0.007	-0.004	-0.012	-0.009	-0.009
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Precipitation (cm)	-0.004	-0.004	-0.006	-0.007*	-0.007*
	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)
N	21,068	25,121	21,068	21,068	21,068
Mean of dependent variable	0.27	0.28	0.27	0.27	0.27
First Stage F-Statistic	137.24	197.99	150.61	145.26	140.08
Beat FE	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$
Response time - levels measures the response time in levels rather than our main specification, in logs. *Police-Research Response Time* utilizes a combination of response times reported by the police and, when no response time is reported by the police, a response time calculated by the researchers based on when the assigned officer arrives within 200 meters of the incident. *3km Radius* and *5km Radius* adjust the distance used in calculating the availability of officers. *Omit 0.5km Radius* is identical to the main specification (4km) except that all officers within 0.5km have been removed from this measure of police availability.

Table 5: 2SLS Estimates of the Effect of Police Response Time on Injury

	(1)	(2)	(3)
Response Time (logs)	0.154**	0.202***	0.155**
	(0.064)	(0.063)	(0.074)
Rush Hour	-0.099***	-0.090***	-0.335***
	(0.022)	(0.022)	(0.009)
weekend	0.003	0.007	0.004
	(0.007)	(0.007)	(0.008)
holiday	0.023	0.026	0.021
	(0.019)	(0.019)	(0.021)
Darkness	-0.011	-0.010	-0.012
	(0.008)	(0.007)	(0.009)
Precipitation (cm)	-0.004	-0.005	-0.005
	(0.004)	(0.004)	(0.004)
N	21,068	21,068	21,068
Mean of dependent variable	0.27	0.27	0.27
First Stage F-Statistic	153.17	155.97	117.11
Beat FE	Yes	Yes	No
Call Taker FE	Yes	No	No
Officer FE	No	Yes	No
Beat X Hour FE	No	No	Yes
Time of Day FE	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Burglary, Theft, & Robbery Calls: The Effect of Police Response Time on Injuries

	In Progress			Not In Progress		
	OLS	First Stage	IV	OLS	First Stage	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Response Time (logs)	-0.020		0.278**	-0.003		0.002
	(0.022)		(0.137)	(0.006)		(0.054)
Availability of Officers		-0.023***			-0.021***	
		(0.006)			(0.003)	
Rush Hour	-0.007	0.083	-0.035	-0.001	0.419***	-0.003
	(0.076)	(0.109)	(0.074)	(0.028)	(0.060)	(0.037)
Weekend	-0.021	0.014	-0.025	-0.005	0.051**	-0.005
	(0.025)	(0.041)	(0.023)	(0.008)	(0.022)	(0.009)
Holiday	0.006	-0.121	0.047	-0.008	-0.015	-0.007
	(0.056)	(0.111)	(0.058)	(0.019)	(0.051)	(0.018)
Darkness	0.004	0.028	0.000	-0.007	0.005	-0.007
	(0.032)	(0.045)	(0.031)	(0.010)	(0.023)	(0.010)
Precipitation (cm)	-0.002	0.030**	-0.011	0.001	0.011	0.001
	(0.009)	(0.015)	(0.007)	(0.004)	(0.009)	(0.004)
N	1,220	1,220	1,220	5,861	5,861	5,861
Mean of dependent variable	0.11	2.48	0.11	0.09	3.08	0.09
First Stage F-Statistic		14.88			64.34	
Beat FE	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 7: 2SLS Estimates of the Effect of Police Response Time on Injuries by Characteristic of Caller & Responder

	Under 30 **(1)**	**30 and Older** **(2)**	**Female** **(3)**	**Male** **(4)**	**1-2 Calls** **(5)**	**3+ Calls** **(6)**	**Start Shift** **(7)**	**End Shift** **(8)**
Response Time (logs)	0.085	0.210***	0.268**	0.005	0.205***	0.078	0.309***	0.053
	(0.093)	(0.074)	(0.104)	(0.112)	(0.077)	(0.093)	(0.109)	(0.078)
Rush Hour	-0.080**	-0.091***	-0.125***	-0.017	-0.090***	-0.073***	-0.101***	-0.072
	(0.036)	(0.022)	(0.033)	(0.042)	(0.030)	(0.028)	(0.024)	(0.065)
Weekend	-0.005	0.014*	0.013	0.005	0.005	0.009	0.007	0.007
	(0.012)	(0.008)	(0.011)	(0.013)	(0.009)	(0.011)	(0.010)	(0.010)
Holiday	0.006	0.031	-0.015	0.049	0.014	0.038	0.028	0.040
	(0.032)	(0.022)	(0.029)	(0.036)	(0.025)	(0.029)	(0.026)	(0.029)
Darkness	-0.006	-0.013	-0.019	0.011	-0.015	-0.004	0.012	-0.029***
	(0.013)	(0.009)	(0.012)	(0.014)	(0.010)	(0.011)	(0.012)	(0.011)
Precipitation (cm)	-0.009	-0.004	-0.004	-0.007	-0.004	-0.010	-0.003	-0.012**
	(0.006)	(0.005)	(0.006)	(0.007)	(0.004)	(0.006)	(0.005)	(0.006)
N	8,355	13,270	10,915	5,794	12,356	8,712	10,800	9,359
Mean of dependent variable	0.39	0.20	0.37	0.27	0.26	0.28	0.26	0.28
First Stage F-Statistic	95.03	105.44	103.84	51.05	114.70	58.77	65.61	92.32
Beat FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01
Under 30 and *30 and older* break the data apart by the age of the caller. Similarly, *Female* and *Male* break the data apart by the gender of the caller. *1-2 Calls* and *3+ Calls* break the data apart by the number of high priority calls to the residence during our data sample. *Start Shift* and *End Shift* break the data apart by whether the incident occurred in the first 4 hours or second half, respectively, of the responding officer's shift.

Table 8: Sample Share by Compliance Type

	Local Linear Model			Linear Model		
	1%	1.5%	2%	1%	1.5%	2%
Compliers	0.352	0.310	0.332	0.224	0.197	0.189
Never Takers	0.310	0.380	0.355	0.410	0.433	0.441
Always Takers	0.337	0.311	0.314	0.366	0.370	0.371

Table 9: Characteristics of Compliers

	P[X = x]	P[X = x|*complier*]	$\frac{P[X=x\|complier]}{P[X=x]}$
Near Department	0.483	0.416	0.862
	(0.025)	(0.031)	(0.064)
Far from Department	0.517	0.664	1.284
	(0.025)	(0.056)	(0.140)
Weekend	0.298	0.248	0.835
	(0.024)	(0.043)	(0.112)
Non-Weekend	0.702	0.759	1.081
	(0.027)	(0.034)	(0.052)
Rush Hour	0.285	0.204	0.714
	(0.024)	(0.045)	(0.123)
Non-Rush Hour	0.715	0.782	1.095
	(0.027)	(0.034)	(0.048)
Male	0.275	0.233	0.846
	(0.025)	(0.049)	(0.129)
Female	0.518	0.551	1.065
	(0.025)	(0.042)	(0.096)
Black	0.401	0.448	1.118
	(0.025)	(0.048)	(0.116)
White	0.158	0.125	0.792
	(0.025)	(0.066)	(0.183)
Hispanic	0.221	0.201	0.911
	(0.025)	(0.059)	(0.159)
Under 30	0.370	0.424	1.146
	(0.024)	(0.046)	(0.113)
30 and Older	0.630	0.594	0.943
	(0.026)	(0.030)	(0.053)
1-2 Calls	0.587	0.601	1.025
	(0.026)	(0.035)	(0.068)
3+ Calls	0.413	0.415	1.003
	(0.025)	(0.046)	(0.113)

Near Department and *Far from Department* are determined based on median distance to nearest police department (3 kms). *Male, Female, Black, White, Hispanic, Under 30,* and *30 and older* reflect the characteristics of the caller. *0-2 Calls* and *3+ Calls* reflect the number of level 1 & 2 (high priority) calls to this residence during 2009.

Table 10: The Effect of Police Response Times on Future Calls & Injuries

			Repeat Offenses			**Future Injuries**	
	First-Stage	**OLS**	**Reduced Form**	**2SLS**	**OLS**	**Reduced Form**	**2SLS**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Response Time of 1st Call		-0.008		0.359***	0.009		0.106*
		(0.009)		(0.108)	(0.006)		(0.057)
Availability of Officers at 1st Call	-0.014***		-0.005***			-0.002*	
	(0.001)		(0.001)			(0.001)	
Rush Hour	0.178***	0.019	0.019	-0.045	-0.017	-0.015	-0.034*
	(0.025)	(0.027)	(0.027)	(0.031)	(0.018)	(0.018)	(0.020)
Weekend	0.029***	-0.005	-0.004	-0.014	0.017***	0.018***	0.015**
	(0.011)	(0.010)	(0.010)	(0.012)	(0.007)	(0.007)	(0.007)
Holiday	0.056**	-0.006	-0.011	-0.031	0.036*	0.036*	0.030
	(0.027)	(0.027)	(0.027)	(0.028)	(0.021)	(0.021)	(0.021)
Darkness	-0.014	0.009	0.009	0.014	-0.007	-0.007	-0.006
	(0.012)	(0.011)	(0.011)	(0.012)	(0.007)	(0.007)	(0.007)
Precipitation (cm)	0.002	-0.025***	-0.025***	-0.026***	-0.021***	-0.021***	-0.021***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
N	13,384	13,384	13,384	13,384	13,384	13,384	13,384
Mean of dependent variable	2.69	0.50	0.50	0.50	0.12	0.12	0.12
Beat FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

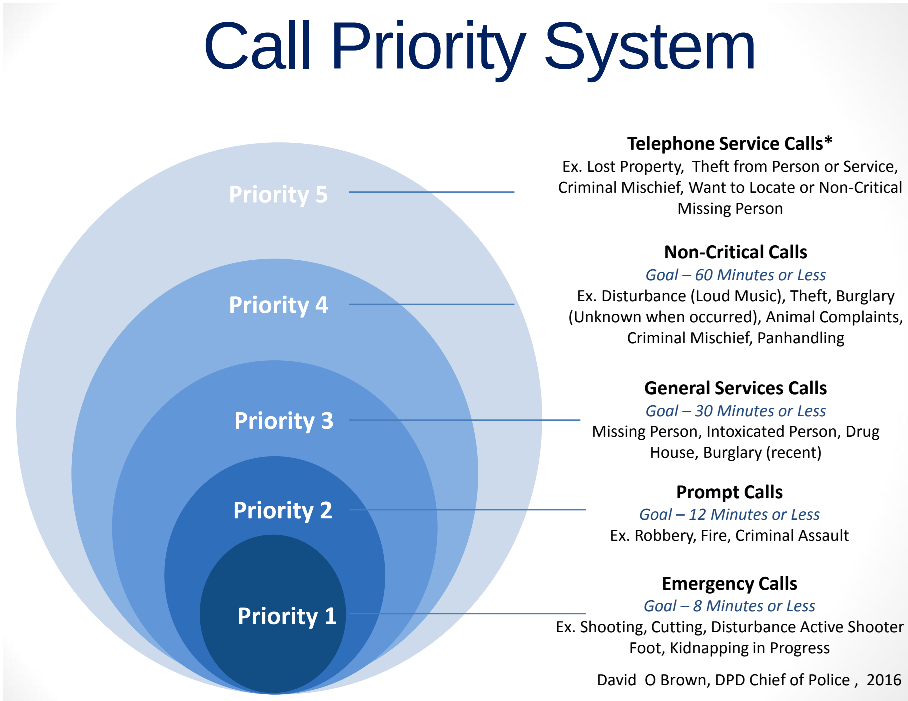


Figure 2: Explaining Priority Numbers (Brown,2016)

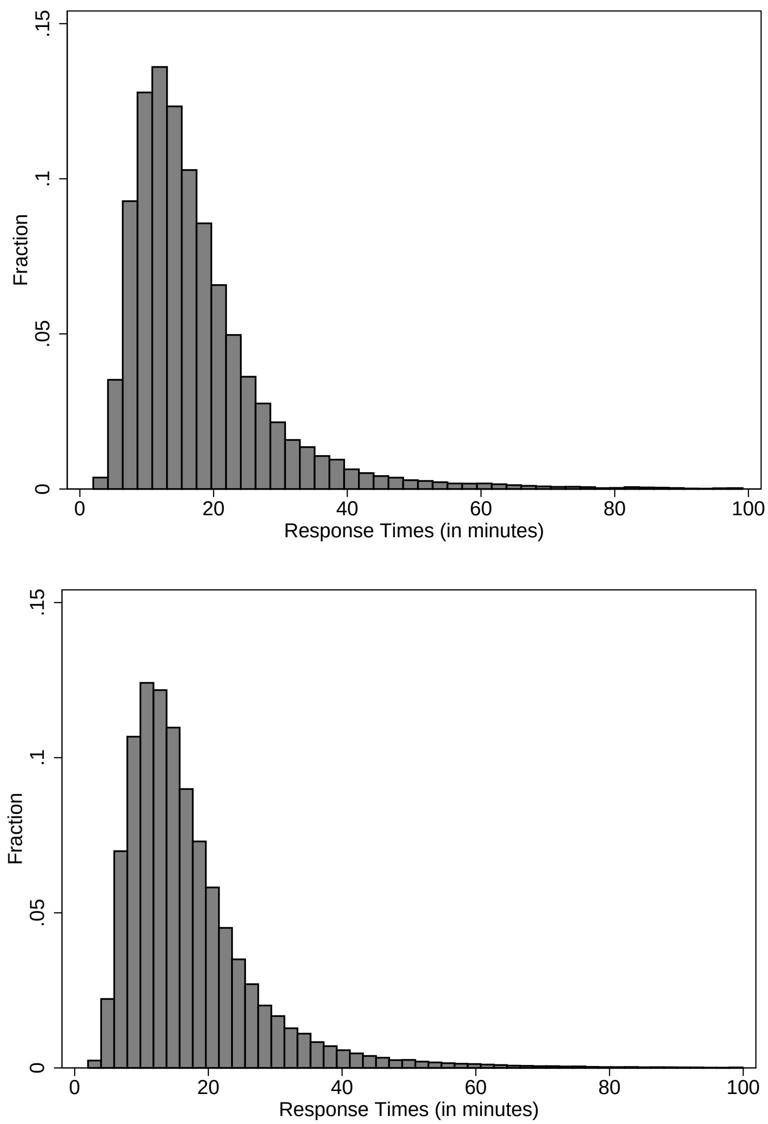


Figure 3: Distribution of Response Times for calls that ended with a crime report (top) and all calls (bottom)

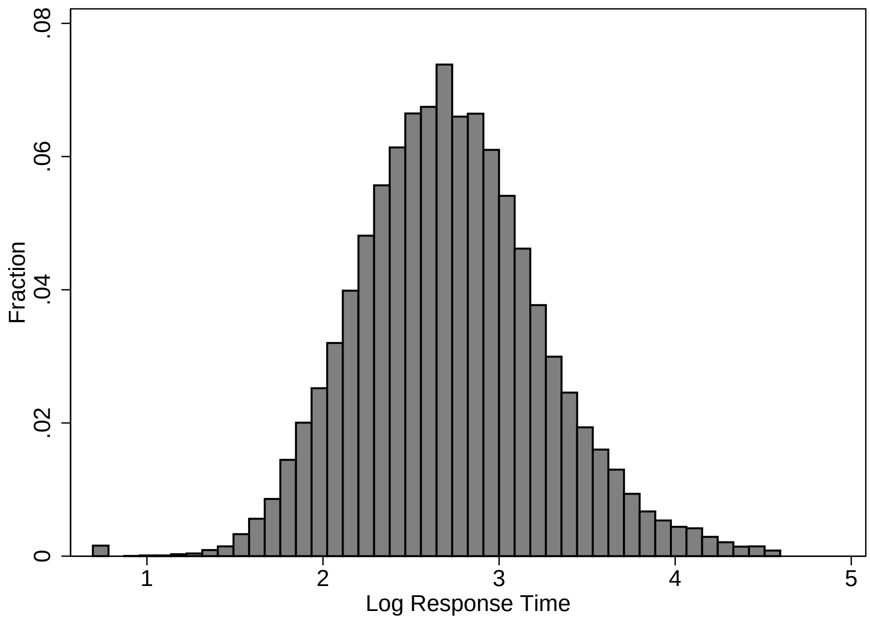


Figure 4: Distribution of Response Time in logs

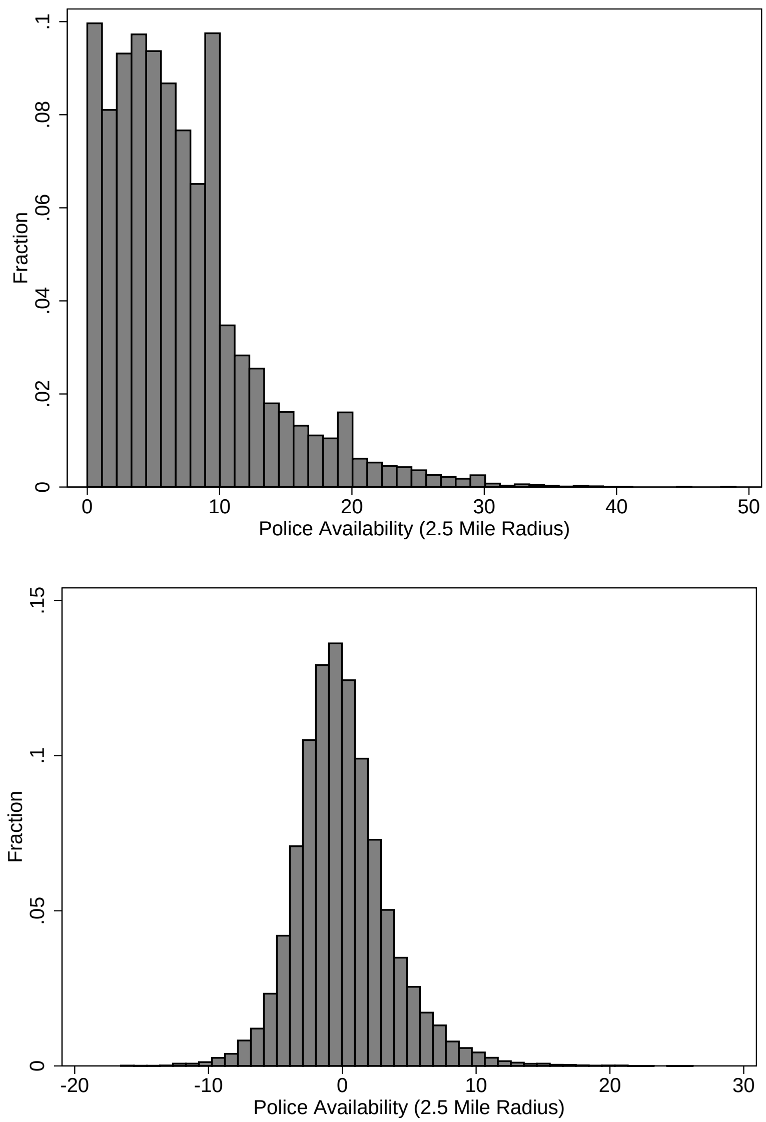


Figure 5: The full distribution of police availability (top) and the residualized distribution when including beat and time of day fixed effects (bottom)

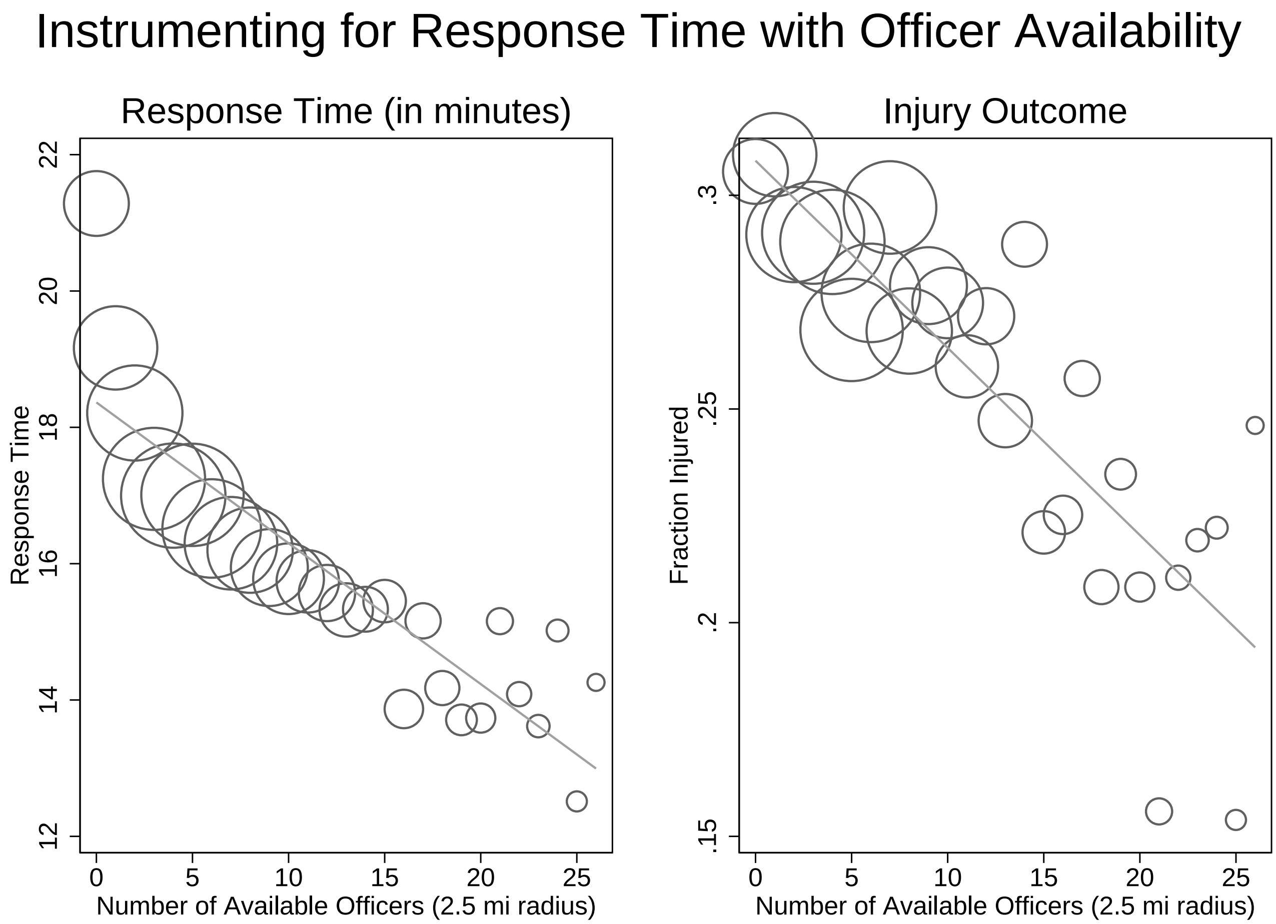
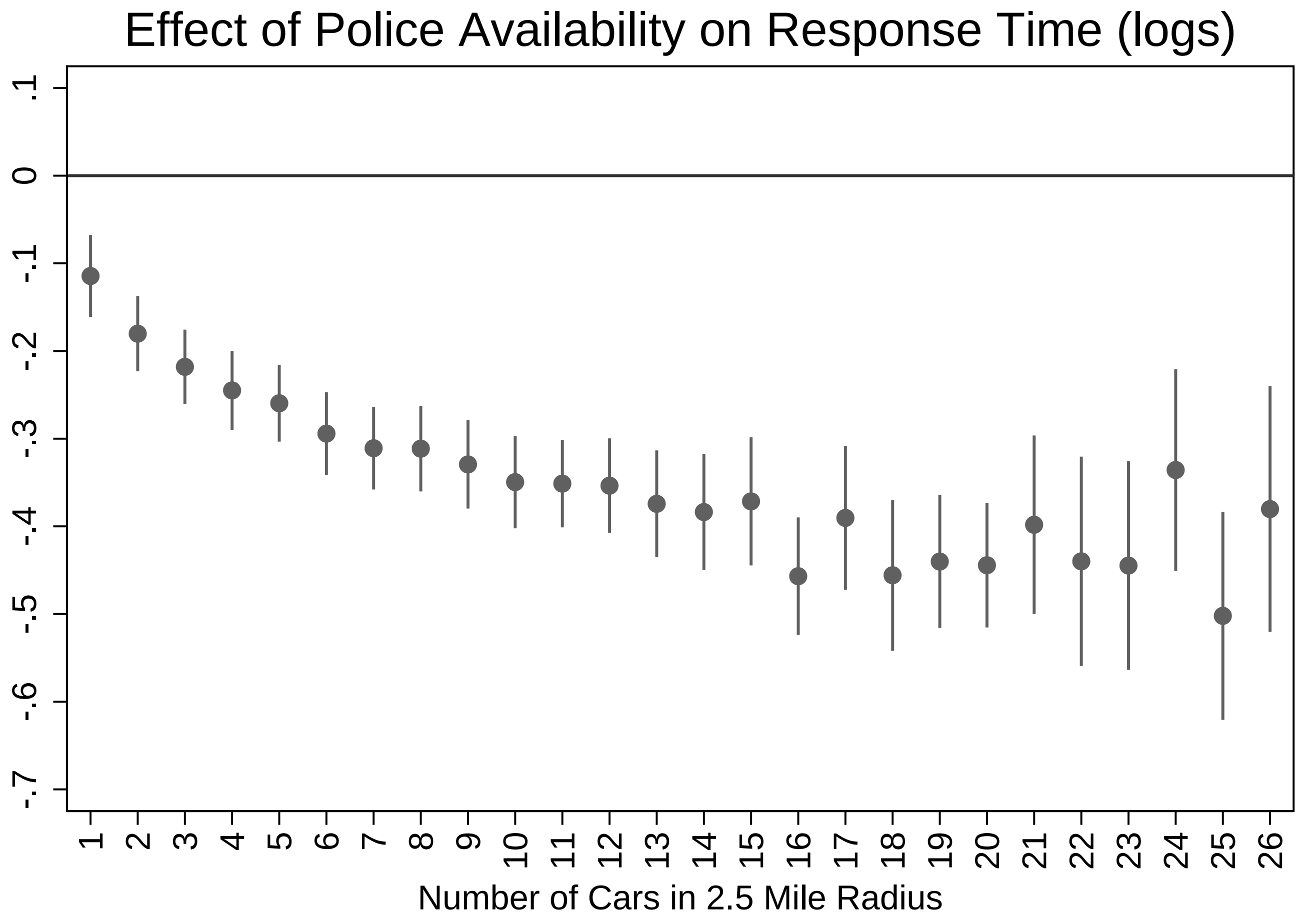

Instrumenting for Response Time with Officer Availability
Response Time (in minutes)
Response Time
12
14
16
18
20
22
0
5
10
15
20
25
Number of Available Officers (2.5 mi radius)
Injury Outcome
Fraction Injured
.15
.2
.25
.3
0
5
10
15
20
25
Number of Available Officers (2.5 mi radius)

Figure 6



Effect of Police Availability on Response Time (logs)
.1
0
-.1
-.2
-.3
-.4
-.5
-.6
-.7
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Number of Cars in 2.5 Mile Radius

Figure 7

A Appendix

Table A.1: The Effect of Police Response Time on the Reporting of a Crime

Dep var:	Reduced Form (1)	First Stage (2)	2SLS (3)
Response Time (logs)			0.009
			(0.033)
Availability of Officers	-0.0001	-0.013***	
	(0.0004)	(0.001)	
Rush Hour	0.021***	0.126***	0.020**
	(0.008)	(0.010)	(0.009)
Weekend	-0.023***	0.014***	-0.024***
	(0.003)	(0.004)	(0.003)
Holiday	-0.016**	0.025**	-0.016**
	(0.007)	(0.010)	(0.007)
Darkness	0.002	-0.002	0.002
	(0.003)	(0.004)	(0.003)
Precipitation (cm)	0.001	-0.002	0.001
	(0.002)	(0.002)	(0.002)
N	99,002	99,002	99,002
Mean of dependent variable	0.21	2.67	0.21
Beat FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

This analysis is run on the 99,002 observations that remain from the full sample of 137,376 911 calls reporting Major Disturbance Violence after removing duplicates and incidents with missing data on response times.

Table A.2: The Effect of Police Response Time on Injuries (First Call)

	OLS (1)	**Reduced Form** (2)	**2SLS** (3)
Response Time of First Call (logs)	-0.001		0.177**
	(0.007)		(0.075)
Availability of Officers at First Call		-0.003**	
		(0.001)	
Rush Hour	-0.065***	-0.065***	-0.096***
	(0.025)	(0.025)	(0.028)
Weekend	0.010	0.010	0.005
	(0.008)	(0.008)	(0.008)
Holiday	0.015	0.013	0.003
	(0.022)	(0.022)	(0.023)
Darkness	-0.011	-0.011	-0.009
	(0.010)	(0.010)	(0.010)
Precipitation (cm)	-0.005	-0.005	-0.005
	(0.004)	(0.004)	(0.004)
N	13,384	13,384	13,384
Mean of dependent variable	0.26	0.26	0.26
Beat FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes

Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

B Data Appendix

B.1 Matching Call Data to Crime Data

1. 684,584 911 calls reported to Dallas Police Department (DPD) in 2009
2. 137,376 calls reporting major disturbance ($problem = 6X - MajorDist(Violence)$)
3. 123,850 after data cleaning: removing duplicates and calls with missing location data. Duplicate calls were identified as calls with the same call master incident ID (mid_ca) and response date and time, or marked as duplicate, or same call master incident ID (mid_ca) and missing crime master incident ID (mid_cr).
4. 25,411 calls were matched to crimes using service number ID ($servicenum$) common to call and crime datasets.
5. Finally, 21,068 calls were left with coded arrival time by DPD ($time\_fir\_3$).

Table B.1: List of relevant variables Calls 911

Variable	Description
mid_ca	Call incident identifier master incident id (unique to each crime incident, so if there are multiple calls for the same crime they would have the same *mid_ca*)
servicenum	Incident identifier service number (used to match crimes to calls). For the first incident, it gets a value of 1 on 1st day of the year, and each next incident incrementally increases over the year. The year of the incident is added as a letter, 2009=W.
response_d and *response_t*	Recorded incident response date and time
problem	Description of the problem as coded by dispatch, used to select calls reporting major disturbance
$time\_fir\_3$	Recorded time of first arrival at the scene
beat and *division*	Beat and division of the call location
calltaking	Information on call-taker
priority	Priority, e.g. '2 - Urgent'

Each call is mapped to a beat and division. Time of incident is determined by the time the call was made to the police department ($response\_d$ and $response\_t$).

Table B.2: List of relevant variables Crimes

Variable	Description
mid_cr	Unique incident crime master incident ID
servicenum	Incident identifier service number (used to match crimes to calls)
mo_cr	A modus operandi description recorded by DPD, e.g. 'susp choked the comp causing her pain'
injuries	Recorded injuries related to the crime
comprace, *compage*, *compsex*, *compdob*	Complainant race, age, sex, date of birth

B.2 The Automated Vehicle Locator Data (AVL)

The Automated Vehicle Locator Data (AVL) contains location records for police vehicles, recording their position every 30 seconds for moving vehicles. 91,975,620 AVL observations were recorded in Dallas in 2009, averaging 7.6 million per month. Vehicles responded to, on average, 82,944 distinct incidents per month.

Table B.3: List of relevant variables AVL

Variable	Description
master_inc_id	Master incident identifier - when the vehicle has a non-null *master_inc_id* that means that it is responding to an incident. This marker was used to match responding officers to incidents (911 calls are successfully matched to recorded crimes).
vehicle_id	Unique vehicle identifier.
radio_name	Vehicle radio name, containing encoded shift and beat data. E.g. radioname B111 means second shift, beat 111. From this code can also be discerned if the vehicle is special (e.g. forensic identification) or a normal beat patrol car.
date_time	Timestamp of the location observation.

AVL records were joined to 911 calls for service in several ways. The assigned (responding) officers were obtained using *master_inc_id*s from the AVL data and then joined with the call data. The researcher calculated response time is determined based on the first time when the responding officer is observed within a 200 meter radius of the assigned incident. For each officer, the start of their shift was calculated using the earliest time that they are observed for this shift. A shift start is determined after a gap of at least 2 hours between two consecutive AVL pings. Officer availability was measured by a count of the number of officers within a given radius of the incident. We also calculate the distance of the assigned officers to each call at the time of the call. This provides a measure of the typical distance between officer locations and the incidents that they are assigned to respond to.

Table B.4: List of generated variables in the final dataset

Variable	Description
time_car_within_200m	Earliest time when responding officer (having matching *master_inc_id*) is observed within 200 meters distance after the call time.
n2m05km, *n2m3km*, *n2m4km*, *n2m5km*	Measure of officer availability - number of officers within 0.5, 3, 4, 5 km of when the call is received, respectively.
timeonshift	Time when responding officer started their shift.
cv_dist_m	Distance in meters from the call to the responding officer at the earliest time that officer has the matching *master_inc_id*.