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Police Response Time and Injury Outcomes

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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, 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 will result in an injury. To overcome the endogeneity of more severe calls being assigned higher priority, which requires a faster response, we take several steps. First, we focus on the 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 incident at the time it is received by the call center. When controlling for beat, month, and 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 victims, 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

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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 pursuing this goal has been evaluating crime prevention strategies implemented by the police.[1] While it seems reasonable that deterrence or incapacitation of criminals could increase 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 a long-term effect on community safety.

Minimizing police response times is the goal of rapid-response policing (Kelling et al. 1989) 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 because of 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 about rapid-response policing is that it comes at the expense of other policing strategies (such as neighborhood policing, hotspot 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 scene of the incident or if officers who arrive earlier at the scene are able to collect better evidence from the crime scene (Hess and Hess-Orthmann 2012). Blanes i Vidal and Kirchmaier (2018) provide causal

[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), police response times 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 (2021) 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.

evidence that a 10 percent increase in police response time leads to a 4.7 percent decrease in the probability of making an arrest in connection with 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 in which 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 a future injury at a given residence.

We are not the first to examine the possible role of police officers in crime escalation. Miller and Segal (2018) find that the integration of women in US policing results in decreased rates of subsequent nonfatal 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 and 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."

[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 fifty minutes after she placed the call and left when there was no answer. Her body was found at the house by her family two 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 could imply that if officers arrive in the heat of the moment they may be able to help prevent 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 in which 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 20,933 emergency 911 calls for service placed to the Dallas Police Department (DPD) in 2009 that were classified as Major Disturbance—Violence incidents (priority level 2). While the starting evaluation of all of these calls was identical, the crime outcomes ranged from "a threat of violence" to "murder" to "intention to kill." Focusing on 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 can 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 dispatch officers faster to incidents that are more likely to result in an injury, this would bias the estimated response-time effect toward 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 precise information both from DPD call data on the time and location of the incident (latitude and longitude coordinates) and from the automated vehicle locator (AVL) system data on the real-time location of police vehicles. In 2009, AVL systems were active in all 873 DPD police patrol vehicles and data on their locations were saved and stored. These data were used by dispatchers to

[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 in which officers received erroneous information it led to more negative outcomes.

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

optimally assign officers to 911 calls. Our instrument takes advantage of these roughly one hundred 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 1.6 percent (s.e. 0.10). This instrument is motivated by the fact that despite the intentions of the dispatcher, response times will be slower during periods in which officers are not located near the incident. We carefully discuss concerns regarding the exclusion restriction throughout the paper. To ensure that police availability within a 2.5-mile radius is not directly correlated with the occurrence of an injury, we include controls for beat (the geographic patrol area where the incident took place), month, day-of-week, and time-of-day 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 because of expectations regarding violence, or incidents may develop differently when an officer is nearby. To address these concerns we also run our analysis 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 small and statistically insignificant effects of police response time on the probability of an injury. Specifically, a 10 percent increase in police response time increases the probability of an injury by 0.08 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 1.3 percentage points (s.e. 0.4). This result is robust to alternative definitions of police availability and response time and to including beat-by-hour controls, beat-by-month controls, dispatcher fixed effects, 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 we find no effect of response time for this same category of incidents that were reported to 911 after they had already occurred. Lastly, we find that faster responses to calls are associated with a lower likelihood of repeat offenses at the same residence, implying an intertemporal dividend from prompt responses.

This paper proceeds as follows. In the next section, we introduce our data. 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 victims 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 will result 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: its estimated population of 1.345 million in 2018 makes 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 (2010–14).

Given the population size and total area, Dallas employs a relatively large law enforcement agency. As of 2013, 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 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 calls-for-service flow diagram).

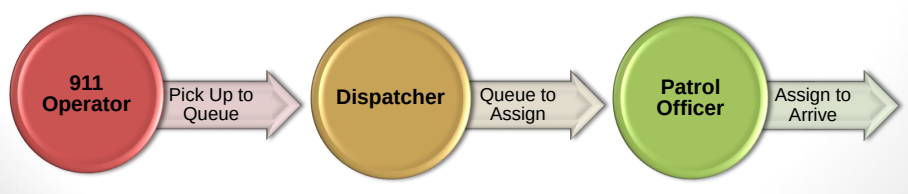

Figure 1: Flow Diagram of Calls for Service (Brown 2016)

The priority of the call is determined from the information received by the 911 call taker using the preset priority ranking displayed in figure 2. The lower the priority number, the more urgent the call priority. For example, for priority-1 calls (e.g., active shooting) the aim is for law enforcement to respond in eight 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 three main DPD databases. The first is the Calls for Service database, which 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 AVL data, which record the precise latitude-longitude points of each Dallas police patrol vehicle throughout 2009.

The most severe incidents in the 911 call database are classified as priority-1 or priority-2 calls for service. These calls typically involve events that are described as major disturbances, car accidents, burglaries, robberies, shootings, etc. In panel A of figure 3 we present the distribution of the twelve most common calls for service (which make up over 90 percent of high-priority calls). While all of these incident types could end with an injury occurring, this outcome is quite low for most calls. For example, calls coded as "CIT" indicate the need for a crisis-intervention team to be deployed. While such calls for service sound alarming, they result in an injury approximately 6 percent of the time. Major-disturbance violence, car accidents, and robbery incidents are the calls most likely to result in physical violence, with injury rates of over 20 percent (see figure 3 panel B).

Our main analysis focuses on "Major Disturbance—Violence" calls for service, which constitute nearly half of all priority-1 and priority-2 calls for service. These calls have an injury rate of roughly 30 percent and are unique in that there is potential for violence, and they are thus given a ranking of priority 2, but the violence has not yet occurred

(otherwise they would have likely received the "Major Disturbance—Ambulance" classification).[9] This stands in contrast to car accidents, for example, which have a relatively high injury rate but for which much of the damage probably occurred prior to calling 911.[10] Focusing on one specific category of incidents strengthens our goal of examining calls that all received an identical classification by a 911 call taker. We further examine the importance of the timing of the 911 call in relationship to the incident in section 4 when we present results for burglary, theft, and robbery calls.

We used the Calls for Service database to focus on 137,376 calls that are classified as "Major Disturbance—Violence." Calls in this category are always assigned priority 2, which has a response-time goal of under twelve minutes. In addition to providing information on the category of the incident, the Calls for Service database also includes information on the precise latitude-longitude location of the call, the time the 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 at which the first officer arrived at the scene of the incident. These data allowed 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 was joining the calls data with the crime data. We were able to use a service-number identifier to join 25,348 of these 911 calls with reported crimes. While this match rate of roughly 20 percent is not necessarily surprising since most 911 calls do not result in crime reports (Neusteter et al. 2019), it still raises the question of whether the write-up of a 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 will be resolved not only without an injury but also without a crime report, then confining our sample to calls that include a crime report would understate the effect of response time on injury outcomes. Alternatively, if when officers arrive faster 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.

[9] In the Dallas 911 call data, we focus on calls that are classified as "6X—Major Dist (Violence)" as opposed to "6XA—Major Dist Ambulance," which are "Major Disturbance—Violence" incidents that require an ambulance.

[10] Importantly, police officers may also play an important role in providing medical assistance that lowers injury severity. For example, a fast arrival time may decrease the level of injury incurred from an attempted suicide or drug overdose. Unfortunately, because of data limitations, examining this outcome is beyond the scope of this paper.

In figure 4 we show that the distribution of actual response times is similar for both calls that result in crime reports and those that do not. Additionally, when we ran our analysis on the entire sample of "Major Disturbance—Violence" calls while instrumenting for response time with police availability and examined how this affects the probability of a crime report, we found 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 0.02 percentage points (s.e. 0.62)).[11] Lastly, figure 5 displays the correlation between the observable characteristics of the call and the probability that the call will result in a crime report. While most characteristics fail to predict a crime report, reports tend to be less likely on weekends and holidays and more likely during rush hour.

The crime-data records provide an opportunity to classify whether the call resulted in an injury based on both the injury field in the data and the officer description of the incident.[12] 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, kick, assault, shot, kneed, bit, strik(e), stab, slap, fight, fire, penetrate, beat, strangle, headlock, or physical altercation.[13]

The third step in constructing the database involves the use of AVL data. The AVL data are 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 thirty-second intervals with the precise latitude-longitude coordinates of where the vehicle is located.[14] When an officer is assigned to a call, the database also includes a master incident identifier that can be joined to the call database.[15] This database was used to count the number of officers within a 2.5-mile (4-kilometer) radius of the 911 call. We focused on a 4-kilometer cutoff as this was the average distance between an assigned officer and a priority-2 incident in Dallas in 2009. On average, a distance of 4 kilometers amounts to a five-minute drive in Dallas. Additionally, we calculated officer counts within 3- and 5-kilometer radii to ensure

[11] See appendix table A.1 for reduced-form, first-stage, and two-stage least squares results.

[12] 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 in which an injury occurred to the officer and one incident in which the injury was caused by the officer. While response times may impact officer misconduct, we were not able to obtain access to these data for this period.

[13] We used a regular-expressions extraction to identify these terms and also identify negated terms (e.g., "did not kick") to prevent misclassifications.

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

[15] This provided an opportunity for us to calculate an alternative response-time value based on when the assigned officer first appears within two hundred meters of the incident, which we discuss in section 4.

that there is not a specific distance cutoff that drives our results.[16]

To control for other factors that may be correlated with both response time and injuries, we collected additional information on weather characteristics, such as average daily temperature and precipitation. We also merged in data on the timing of sunrise and sunset in Dallas to determine whether the incident occurred after nightfall. We took 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 20,933 calls that include a police-coded arrival time, as this is likely to achieve the most accurate measure of response time.[17] Table 1 presents descriptive statistics of our data broken down by the seven divisions of the DPD. There are approximately twice as many relevant incidents in the Northeast, South Central, Southeast, and Southwest Divisions compared with the Central, North Central, and Northwest Divisions. The likelihood that an incident will result in an injury is fairly constant at 20–30 percent 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 comes from the availability of officers at the time of a call. Specifically, the Central Division has, on average, roughly seventeen available officers within a 2.5-mile radius of an incident, whereas every other division has approximately four to eight available officers. This result is driven by the fact that beats in the Central Division average 0.8 square miles, which is about half the average beat size 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 are fairly similar to those 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

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

[17]In section 4 we discuss the results of running our analysis on a larger sample of 25,058 calls by introducing our own measure of police arrival time for those calls with missing values of police arrival times. We found similar results.

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 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 and Results

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

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

$Injury_{ibh}$ 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 in to 911 and when 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 will result in an injury, such as darkness, weather, and holidays. We include month (δ_m), hour (γ_h), and beat (η_b) fixed effects to absorb unobserved variation within specific months, 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 will result in an injury.[18] $\widehat{\beta_1}$ estimates the causal effect of response time on injury outcomes 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 in which 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 toward zero.

[18] Appendix figure A.1 illustrates how log response time can reduce the influence of the outlier response times observed in figure 4. In a robustness specification, we conducted our analysis with response-time levels and continued to find a significant effect of response time on the probability of an injury.

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 time it takes 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:

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

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

Panel A of appendix figure A.2 presents the distribution of police availability in our full sample. Availability ranges between zero and forty-nine cars within a 2.5-mile radius with a standard deviation of six. When excluding the incidents with the highest 1 percent of police availability, this number ranges from zero to twenty-six. Panel B of appendix figure A.2 maps the distribution of residualized officer availability after controlling for beat and time-of-day fixed effects. Police availability continues to range from negative seventeen to thirty-seven with a standard deviation of four (or negative nine to fifteen when excluding the first and ninety-ninth 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.) and policing tasks, such as responding to calls, appearing in court, or providing security at community events. 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: incidents with higher P_{ibh} (more surrounding police officers) have *lower* response times.[19] If police availability only impacts the occurrence of an injury via response time, then two-stage least squares (2SLS) 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

[19]Figure 6 excludes the 1 percent of calls with high levels of police availability (ranging between twenty-seven and forty-nine). These calls were included in our regression analysis.

officers 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 to reduce injuries, we would expect to see more officers surrounding locations where incidents ended in injury. Instead, figure 6 suggests the opposite relationship: even without additional controls, more surrounding officers are negatively correlated with injury outcomes.[20]

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 occurred during rush hour, whether it occurred 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 percent of homes that are vacant), and time-of-day, month, 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 -0.016 (s.e. 0.001) on police availability implies that having six more police vehicles within a 2.5-mile radius of a criminal incident (a one-standard-deviation increase in police availability) decreases response time by 9.6 percent, which is significant at the 1 percent level. Moreover, the F-test for the instrument is well over one hundred across these specifications, indicating that our instrument is both strong and relevant (Lee et al. 2020).

These first-stage results also provide an opportunity to consider other factors besides police availability that may 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 will result in an injury. Once again,

[20]Another potential explanation is that the most escalated types of encounters are deterred when there are more police available nearby. In section 4, we consider this more closely and continue to find that increased officer availability decreases injuries even when removing officers most likely to create deterrence (those within a 0.5-mile radius of the incident).

we included three specifications that increasingly saturate the regression model. Overall, we found that having six more police vehicles available within a 2.5-mile radius of a criminal incident (a one-standard-deviation increase in police availability) reduces the likelihood of the incident ending in an injury by 1.2 percentage points, which is statistically significant at the 1 percent 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.

A remaining concern with this specification could be that an upsurge in crime is driving the increase in injuries and decrease in police availability (as police are spread thinly across multiple incidents) or that a general increase in police presence is having a direct impact on injuries because of deterrence. We find it reassuring that the effect of police availability on injuries remained significant and of the same magnitude when holding call volume constant by including an additional control for the number of 911 calls received in that police division on that day. We also found that these results are robust to including a control for average police availability within a 2.5-mile radius of the incident at that hour and day of week for the three weeks leading up to the incident (see appendix table A.2).

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 monotonic relationship between the instrument (police availability) and police response times. While table 2 demonstrates that, on average, each additional car within a 2.5-mile radius decreases response time by 1.6 percent, figure 7 maps the relationship between these two variables. Thus, moving from zero cars within a 2.5-mile radius of the incident to one available car decreases response time by 13 percent (s.e. 2.5). This relationship appears strongly monotonic, such that moving from zero to two cars decreases response time by 20 percent (s.e. 2.3). When moving above six cars, increasing police availability continues to decrease 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 sixty-four incidents with twenty-six available cars).[21]

In table 3 we present both the OLS and 2SLS estimates for our main specification (equation (1)). Without including beat fixed effects, the OLS results are statistically significant at the 10 percent level but small in magnitude (a 10 percent increase in response time increases the probability of an injury by 0.1 percentage points). Once beat fixed effects

[21] We exclude incidents with more than twenty-six available cars (the top 1 percent) from the analysis that created this figure, as these estimates become increasingly imprecise because of the lack of observations.

are included, the OLS estimates do not yield a statistically significant relationship between response times and injury outcomes. As noted above, however, if officers are being sent faster to incidents with a higher potential to escalate, this will likely bias these estimates toward zero. Once we instrumented for police response time with police availability (columns (4)–(6)), we observed a stronger, statistically significant effect of longer response times on the likelihood of an injury. In specification (6), which includes all relevant controls and beat fixed effects, we found that a 10 percent increase in response time increases the likelihood of an injury by 1.3 percentage points (s.e. 0.4). Given the 30 percent injury rate in our data, a 1.3 percentage-point increase implies a 4.3 percent change in the injury rate. Thus, we find a strong, causal relationship between police response time and the likelihood that an incident will result in an injury.

4 Falsification and Robustness Tests

Our main estimate suggests that response time can affect the likelihood that an incident will result in an injury. The robustness of this result is examined in a number of ways. To start, we present alternative specifications of response time and officer availability using our most saturated specification. We focus on our definition of response time, selection concerns, and the definition of police availability. We also show that our results are robust to alternative classifications of injuries and to the inclusion of additional fixed effects regarding the call taker, responding officer, and within-beat time trends.

Column (1) of table 4 presents results with response time measured in levels as opposed to logs. We show that each additional minute of response time increases the probability of an injury by 0.9 percentage points, an effect that is statistically significant at the 1 percent level. Given the average injury probability of 30 percent and average response time of roughly fifteen minutes, this implies that a 10 percent increase in response time increases the probability of an injury by 4.5 percent, which is nearly identical to our main estimate of 4.3 percent. Given the distribution of response times shown in figure 4 and appendix figure A.1, log response time should be providing a more precise estimate by minimizing the impact of outliers.

Recall that when defining our sample, 4,415 observations did not have an officer arrival time coded in the data and, accordingly, 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 was not biasing our results, we used the AVL data to track the time at which the officer assigned to the incident appeared within two hundred meters of the call location. Applying this technique, we were able to match 4,125 out of the 4,415 missing observations. Column (2) presents the results of our analysis when filling in the missing data with these researcher-calculated response times; it reports similar results to those found in our main specification.

While column (2) of table 4 demonstrates that our results remain similar when we include all "Major Disturbance—Violence" incidents that are matched to crimes, column (3) applies the Heckman correction to address the concern that our analysis was being applied only to those 911 calls in which the incident results in a crime report (Heckman 1979). To implement this approach, we first estimated the probability of a crime report as a function of all our previous controls in addition to a new variable, *officer write-up*. This variable was calculated from the full database of 911 calls in 2009 as the fraction of 911 calls that this police officer was assigned to that resulted in a crime report. The 2,582 officers observed in our data have *officer write-up* values ranging between 0.125 and 1. We estimated that being assigned to an officer that is 10 percent more likely to write up a crime increases the probability of a crime report by 4 percent. We then included the inverse Mills ratio from this first stage in our main analysis and estimated a slightly larger impact of response time on injury outcomes (a 10 percent increase in response time increases the probability of an injury by 1.8 percentage points with s.e. 0.5).[22]

Throughout this paper we define police availability based on the number of officers within a 2.5-mile (4-kilometer) radius. Columns (4) and (5) replicate our results when defining police availability based on the number of officers within either a 3-kilometer radius (column (4)) or 5-kilometer radius (column (5)) of the incident. While both of these specifications produced results that are in line with our main specification, the result weakened when we focused only on officers within a 3-kilometer radius. This raises 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

[22]We calculated standard errors for this specification using the bootstrapping method with one thousand iterations.

the nearest officers may directly impact the probability of an injury.[23] 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 close may weaken the exclusion restriction.[24] Restricting our count only to officers within a three-kilometer 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 (6) 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 their presence precisely surrounding these locations. If these predictable events are more likely to result in violence, then this will bias our estimates toward zero. We therefore constructed an alternative measure of police availability by including all officers who are within a 2.5-mile (4-kilometer) radius of an incident while excluding the nearest officers (those within 0.5 kilometers of the incident). Indeed, using this newly constructed instrument, we conducted the same analysis as before and identified larger estimates than we observed in table 3.

Our results imply that shorter response times by police officers can reduce the probability that an incident will escalate into physical violence. Table 5 looks more closely at this escalation result by providing alternative definitions of escalation. When we broadened our categorization of injuries to include damage to property and verbal abuse, we estimated similar effects, but they were more noisily measured. While the magnitude of the measured effect is smaller when we constrained the definition of injury to gunshot wounds (a 10 percent increase in response time increases the probability of a gunshot injury by 0.3 percentage points (s.e. 0.1)), this translates to a 10 percent increase in the probability that an incident will result in a gunshot wound.[25]

Our identification strategy takes advantage of random changes in response times to avoid concerns that endogenous factors are driving police response times. Thus, while we

[23] 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), DeAngelo and Smith (2020), and Weisburd (2021) that explore the deterrent effect of police presence on crime.

[24] An additional concern about counting nearby officers is that they may directly impact whether a call is placed to 911. If having more officers nearby results in less severe calls being placed to 911, this will bias our results.

[25] Only 3 percent of incidents in our data set resulted in a gunshot wound.

may expect the expertise or experience of the 911 call operator to play a role in determining faster response times in situations in which injuries are more likely, this should not have any impact on our estimated effects. Similarly, while we may expect that some officers are better at preventing injuries than others and that these more effective officers are also better at responding promptly to incidents, this should not be a concern in our instrumental-variable (IV) specification. Indeed, in appendix table A.3 we include call-operator fixed effects (see column (1)), officer fixed effects (see column (2)), and then both call-operator and officer fixed effects (in column (3)) and show similar results to those reported in table 3.

The last two specifications of appendix table A.3 summarize our results when including beat-by-hour fixed effects (column (4)) and then beat-by-month fixed effects (column (5)). The estimates in column (4) identify the effect of a change in response time when looking within the same beat and hour of day to account for the possibility that different beats may face different levels of police availability and injury risks across different periods. We found that a 10 percent increase in response time results in a 1.1 percentage-point increase in the probability of an injury. Column (5) estimates the effect of response time when controlling for differences in seasonal trends across different beats and periods due to changes in policing strategies or civilian interactions with the police by including beat-by-month fixed effects. Accounting for potential unobserved variation over time continues to yield similar effects to those reported in table 3 such that a 10 percent increase in response time results in a 1.2 percentage-point increase in the probability of an injury, which is significant at the 5 percent level.

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

Our IV strategy predicts that faster response times change the outcome of an incident by reducing the likelihood that an injury will occur. One concern is that there exists an underlying correlation between officer availability and incident severity that would produce these same results, even in contexts in which we would not expect officer presence to impact the severity. For example, if police availability were to decrease because of an influx of severe incidents, the IV analysis would find a significant effect of police response time on injury outcomes even when those injuries clearly occurred prior to the officers' arrival time.

To look more closely at the mechanism driving our results, we applied 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 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 an injury occurred on response time, when including beat, time-of-day, weekend, month, 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 present estimates of a similar first-stage effect of police availability for these two different call categories. Specifically, each additional officer within a 2.5-mile radius of the call decreases response time by 1.6 to 1.7 percent regardless of whether 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 1 percentage point (s.e. 0.5), the same analysis resulted in an estimate of a -0.05 percentage-point change (s.e. 0.3) for incidents within the same category that are no longer in progress. In other words, while a 10 percent decrease in response times reduces the probability of an injury by 8 percent for burglaries, thefts, and robberies that are in progress, this relationship does not hold for incidents that have already occurred.[26]

5 Heterogeneity and Local Average Treatment Effect

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, whether there are specific types of victims 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 race, age, gender, whether the 911 caller is the victim, residential-call history, and whether the officer responding to the call is at the beginning or end of his/her shift.

[26]Note that the injury rate for burglary, theft, and robbery calls is 12 percent.

The impact of response time on incident escalation may be a function of the vulnerability of the victim and the victim's perception of police fairness and effectiveness. Different groups within the population may face different injury risks or have different interactions with the police. This could be driven either by the perception these victims have of the police or, alternatively, by police behavior toward these different groups. The differences in injury risks across groups are apparent when comparing the mean of the dependent variable (Injury Rate) in row (iv) of table 7. When examining race, nonwhite victims are 22 percent more likely to be involved in an injury and seem to benefit more from fast response time (see panel A). Younger victims (under age thirty) are 39 percent more likely than older victims to be involved in an incident that results in an injury (see row (iv) of panel B), but it is older victims who seem to benefit most from faster response times. We also find that response times tend to be most important for incidents in which the victim of the crime was responsible for calling 911. Perhaps victims can report incidents at an earlier stage of escalation than incidents that are called in by neighbors.[27]

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 percent of calls that end up being coded as domestic-violence crimes in our data set are reported by female victims. When we split our data by the gender of the victim, we found that faster response times are more important for female than male victims. Thus, we found that a 10 percent increase in response time increases the probability of an injury by 1.3 percentage points (s.e. 0.7) for crimes reported by women, with a noisier measure of 0.4 (s.e. 0.9) for crimes reported by men (see panel D of table 7). When we further confined this sample to focus on incidents in which the victim of the crime was responsible for calling 911, the gender gap widened.[28] Specifically, a 10 percent increase in response time increases the probability of an injury by 3.9 percentage points (s.e. 1.8) for female victims and 0.3 percentage points (s.e. 1.9) for male victims (see panel E). One interpretation of this result is that the reduction in violence associated with faster responses to female callers in need of assistance could be decreasing more severe violence associated with domestic disputes.

We next examined the impact of longer response times on the likelihood of injury at residences that placed many (three or more) high-priority 911 calls in 2009 relative to

[27]We determined whether the victim of the crime was responsible for reporting the incident to 911 by the degree of similarity between the name given to the 911 operator and the name used in the official crime report. We do this using the bigram method with a cutoff of 0.4.

[28]This may be especially relevant for domestic violence occurring within the home.

those with few (one or two) high-priority calls for service.[29] Panel F of table 7 demonstrates that longer response times have a large, statistically significant impact on injury outcomes for residences that place fewer than three high-priority calls. 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 hotspots of crime.

Finally, panel G of table 7 focuses 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 characteristics of the responder should have little effect. To shed light on this issue, we broke our data apart based on whether the responding officer happens to be at the beginning (first four hours) or end (five or more 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 will occur. 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 Local Average Treatment Effect

Local average treatment effect (LATE) is another important factor to consider in interpreting our results, as our 2SLS estimates provide the average effect for incidents in our sample whose response time would have been different if officer availability had been higher/lower at the time of the call. Using a similar strategy to Dobbie et al. (2018), we estimated the fraction of compliers in our sample as a whole and across different subgroups.[30] We define compliers as calls for which response time would have been different if it had occurred in a period with the highest amount of police availability rather than one with 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 a priority-2 call (twelve minutes). We define the fraction of always takers

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

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

(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 in which 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 set 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 (in which the sample is confined to include only incidents that occurred with either minimal police presence $(\underline{a})$ or maximum police presence $(\overline{a})$) or the 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	$\hat{\pi}_a = \hat{\psi}_0$	$\hat{\pi}_a = \hat{\gamma}_0 + \hat{\gamma}_1(\underline{a})$

$H_{ibh} = 1$ when this incident occurred during a period of maximum police presence. In both the local linear and full linear models, beat, month, 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 to define minimum and maximum police availability. In table A.4 we show this distribution using cutoffs of 1 percent, 1.5 percent, and 2 percent. We show that the fraction of compliers ranges between 30 percent when applying the local linear model and 20 percent when apply-

ing 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 roughly 30 percent of the sample are never takers and the remainder are always takers. These results remain fairly consistent across different cutoffs for minimum and maximum police availability.

To better understand the characteristics of incidents that are identified as compliers, we can calculate the degree to which each subgroup is represented within the compliant population ($P[X = x|Complier]$) and how this compares with their representation in the entire sample (P[X=x]).[31] Table A.5 provides a summary of the different characteristics of incidents in our data and the degree to which they are represented within the complier group.[32] We generally found that the characteristics of complier incidents are similar to those of the general sample with the exception that they are more likely to be located farther away from their local police department (defined as over the median distance of 4.3 kilometers).

While our discussion so far has focused on observed differences between complier incidents and the general population of calls, an additional concern has to do with the unobserved factors that determine both the response to the instrument (i.e., being a complier) and the effect of a faster response time on injury outcomes. Specifically, are compliers precisely those incidents that benefit the most from fast response times? In appendix table A.6 we show the results of applying the marginal-treatment-effect framework, which enabled us to test the extent to which heterogeneity in the treatment effect can be explained by unobserved heterogeneity in the probability of receiving a fast response (see the original study by Bjorklund and Moffitt (1987) and extended work by Heckman and Vytlacil (1999; 2005) and Heckman and Vytlacil (2007)). We did not find evidence of selection into treatment based on unobserved gains (those most likely to benefit from a fast response are not most likely to receive a fast response). This suggests that the estimated LATE is similar in magnitude to the average treatment effect and that expanding fast response to more calls should have a significant impact on reducing injury outcomes.

[31] 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.

[32] For this analysis we use the linear model and 1 percent cutoff.

6 The Long-Term Effects of Response Time

Thus far our analysis has focused on the effect of officer response time on contemporaneous injuries. In table 8 we show the results of extending our analysis to identify the effect of the time to respond to the first call received at any address on the likelihood of repeat offenses and future injuries. Because we were looking at repeat offenses and not specifically at injury outcomes on a given offense, we were able to take advantage of the full database of "Major Disturbance—Violence" incidents, including those that did not end up with a crime report. The first step of running this analysis was restructuring our data so that the unit of observation is a residence (unique address). Because we were now using the full database of major disturbance calls, this expanded our data set from 20,933 to 38,016 observations and enabled us to determine whether a residence experienced repeat "Major Disturbance—Violence" calls and any injuries associated with future calls during our data-sample period. Approximately 36 percent of residences that reported a "Major Disturbance—Violence" incident in 2009 ended up with at least one repeat call of this type, with less than 10 percent of all locations calling five or more times.

In table 8 we report the results of an analogous analysis to that reported in table 3, except that we focused on the impact of time to respond to the first call on the likelihood that a future "Major Disturbance—Violence" call or injury will occur.[33] Column 1 of table 8 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 time to respond to the first call on the likelihood of a repeat call for service. The naïve OLS results show a small, negative relationship between a longer response time for the first call and the probability of a future call for service, which could be in line with a displacement effect. Specifically, a 10 percent increase in response time is correlated with a 0.2 percentage-point (s.e. 0.01) decrease in the probability of a future call. However, the reduced-form analysis suggests a negative relationship between availability of officers at the first call and the likelihood of a repeat offense. Indeed, our IV results indicate that a 10 percent increase in the time it takes police to respond to the first call increases the likelihood of a repeat offense by 1 percentage point (s.e. 0.43). The effect of longer time responding to the first call at a residence on the probability of a future injury is similar in magnitude to our measured effect when examining repeat calls, but it is not statistically significant from zero. We find

[33] It is worthwhile to note that the identification assumption for this analysis no longer requires that police availability be uncorrelated with injury outcomes in this period, but rather, in later periods.

that a 10 percent increase in response time increases the probability of a future call by 3 percent (a 0.99 percentage-point increase at a baseline repeat-call rate of 36 percent) and the probability of a future injury by 3 percent (a 0.19 percentage-point increase at a baseline repeat-injury rate of 7 percent).[34] These results suggest 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 will be received and, even if they are received, could reduce the likelihood that future injuries will occur.[35]

7 Conclusion

In 2020, twelve cities including Seattle, New York, Los Angeles, San Francisco, and Washington, DC, announced that they will be defunding their police departments and decreasing the size of their police force (McEvory 2020).[36] Understanding the benefits provided by patrol officers is especially important in a climate in which 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 not yet been addressed.[37] Naïve attempts to measure the impact of police response time on safety outcomes are complicated by law enforcement's 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 applied an instrumenting strategy that takes advantage of a factor outside of the dispatcher's control: the geographic availability

[34]Recall that because this database includes all calls, even those in which a crime was not reported, injuries are more noisily measured.

[35]Indeed, in appendix table A.7 we show the results of running this analysis when focusing on any repeat high-priority 911 call (without constraining our sample to "Major Disturbance—Violence" calls) at an address. We found slightly stronger results.

[36]While our database tracks police behavior in 2009 during the Great Recession, in which we may have expected large budget cuts in police funding, 2009 looks similar to previous years in terms of crime and police budgets for communications and dispatch (see City of Texas Annual Budgets for years 2007–8, 2009–10, and 2011–12 and https://www.macrotrends.net/cities/us/tx/dallas/crime-rate-statistics/Dallas TX Crime Rate 1999-2018).

[37]Interestingly, our results when focusing specifically on incidents with the potential for escalation suggest an opposite result regarding arrests, as a decrease in escalation could remove the necessity of making an arrest. Indeed, the arrest rate is 18 percentage points (s.e. 0.7) higher for incidents in our data set that record an injury, and when applying our IV analysis to arrest outcomes, we were unable to reject the hypothesis that the coefficient on response time is zero (see appendix table A.8).

of officers. Because the location of officers is dynamic across space and time, we were able to examine incidents that occur within the same neighborhood but face different response times as a result of the number of nearby officers at the time of the call. The results of our analysis identified a causal effect of slower response times on the likelihood that an injury will occur. Specifically, we found that a 10 percent increase in response times (approximately two minutes) leads to a 4.3 percent increase in the injury rate. These results are robust to alternative specifications and sensitivity checks on the metric used to identify officer availability. Additionally, our analysis suggests that faster response times today do not displace injuries to later periods, and they may actually reduce injury risks at a 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 an 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 focused on a specific category of calls, namely "Major Disturbance—Violence." We showed that this category, which makes up roughly 50 percent of high-priority calls (priority-1 and priority-2 calls) and 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 for all calls may be less informative than focusing on specific calls that are likely to contribute to community safety.

Our data allowed us to look closer at our results to further understand the populations that can benefit the most from faster response times. We found that the effects are largest for female-victim 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-victim 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.

While this research fills an important void related to the speed of response times and public safety, it also identifies important areas for future research. Given resource constraints, identifying the most appropriate response to calls for service remains unanswered. Although this research found that faster responses reduce injurious outcomes, there is a trade-off in reducing response times. Additionally, our analysis is confined to incidents that are called in to 911. Would a policy intervention of faster response times impact people's propensity to

call 911 for assistance? If previously unreported incidents became reported incidents, would this weaken or strengthen the results in our analysis? Lastly, our results regarding whether the responding officer is at the beginning or end of his/her shift suggest that police behavior and preparedness may also play an important role in the evolution of an emergency incident. Thus, we may expect to find different impacts of response times in police departments following different protocols regarding civilian interactions. Such policy implications and management decisions are beyond the scope of the current analysis but merit consideration in future research.

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Table 1: Summary statistics

	Central	*North Central*	*Northeast*	*Northwest*	*South Central*	*Southeast*	*Southwest*
Injury	0.23	0.26	0.33	0.24	0.31	0.34	0.30
	(0.42)	(0.44)	(0.47)	(0.43)	(0.46)	(0.47)	(0.46)
Response Time	12.12	13.16	15.83	15.30	14.38	15.38	15.15
	(9.02)	(8.84)	(11.51)	(10.46)	(9.80)	(9.92)	(10.00)
Availability	17.02	4.31	5.67	7.62	5.91	7.02	6.26
	(6.93)	(2.94)	(3.55)	(4.62)	(3.60)	(5.39)	(4.40)
Income ($10,000)	3.67	6.89	4.17	3.58	2.88	2.87	3.49
	(1.39)	(2.10)	(1.33)	(1.60)	(1.09)	(1.11)	(1.04)
Black (%)	0.18	0.17	0.28	0.16	0.67	0.44	0.28
	(0.16)	(0.14)	(0.17)	(0.18)	(0.24)	(0.28)	(0.24)
Hispanic (%)	0.36	0.36	0.36	0.52	0.26	0.44	0.58
	(0.23)	(0.21)	(0.17)	(0.27)	(0.18)	(0.24)	(0.25)
Teens (%)	0.04	0.06	0.06	0.06	0.07	0.08	0.08
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Vacant Houses (%)	0.14	0.11	0.14	0.12	0.12	0.13	0.09
	(0.04)	(0.03)	(0.06)	(0.04)	(0.04)	(0.06)	(0.03)
Population (Beat)	4234.05	9166.68	6364.26	5395.71	3524.02	4202.80	5966.09
	(2927.87)	(3795.60)	(2515.80)	(3146.24)	(1972.88)	(2130.31)	(3135.65)
Square Miles (Beat)	0.78	1.59	1.12	1.29	1.38	1.54	1.93
	(1.00)	(1.08)	(2.29)	(1.41)	(1.42)	(1.69)	(2.48)
Monthly Arrests (Beat)	44.13	17.57	28.66	36.09	19.48	22.70	24.36
	(23.90)	(10.03)	(15.05)	(20.80)	(10.55)	(11.14)	(11.48)
Weekend 911 Calls (Division)	178.43	146.61	282.77	192.18	224.27	286.91	290.90
	(25.35)	(15.82)	(33.56)	(24.92)	(36.42)	(48.28)	(44.34)
Weekday 911 Calls (Division)	142.49	123.66	241.61	161.49	206.86	234.67	230.46
	(26.11)	(18.49)	(31.08)	(25.37)	(30.12)	(37.11)	(36.09)
Weekend Patrol Cars (Division)	81.72	81.46	95.99	82.35	90.21	99.13	89.95
	(8.45)	(6.61)	(9.46)	(7.25)	(6.12)	(7.41)	(6.02)
Weekday Patrol Cars (Division)	91.85	95.32	118.68	97.21	103.23	110.88	108.93
	(10.27)	(7.15)	(9.33)	(9.48)	(7.65)	(9.02)	(7.50)
Beats	29	22	41	31	37	39	33
Observations	2156	1751	3983	2210	3390	3918	3525

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	-0.017***	-0.016***	-0.016***	-0.004***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rush Hour		0.152***	0.149***		-0.060***	-0.062***
		(0.024)	(0.024)		(0.021)	(0.021)
Weekend		0.025***	0.026***		0.021***	0.022***
		(0.009)	(0.009)		(0.006)	(0.007)
Holiday		0.013	0.014		0.049**	0.049**
		(0.025)	(0.025)		(0.019)	(0.020)
Darkness		-0.021**	-0.021**		-0.011	-0.011
		(0.010)	(0.010)		(0.008)	(0.008)
Precipitation (cm)		0.003	0.004		-0.002	-0.001
		(0.005)	(0.005)		(0.004)	(0.004)
Percent Black		-0.055			0.098**	
		(0.060)			(0.045)	
Percent Hispanic		-0.011			0.074	
		(0.064)			(0.055)	
Percent Teens		0.315			0.942*	
		(0.628)			(0.507)	
Percent Vacant Houses		0.088			0.284**	
		(0.158)			(0.113)	
Household Income ($10,000's)		-0.015**			0.003	
		(0.006)			(0.005)	
Population (per 10,000)		0.000			0.043**	
		(0.027)			(0.019)	
Square Miles		0.008**			-0.003	
		(0.003)			(0.002)	
N	20,933	20,933	20,933	20,933	20,933	20,933
Mean of dependent variable	2.51	2.51	2.51	0.30	0.30	0.30
Beat FE	No	No	Yes	No	No	Yes
Time of Day FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	Yes	Yes	No	Yes	Yes

Columns (1)-(3) present the first stage estimates to determine the relationship between officer availability and log(response time). Columns (4)-(6) present the reduced form estimates for linear probability models to determine the relationship between officer availability and the probability of an injury. "Availability of Officers" is a count of the number of police vehicles located within a 2.5 mile (4 km) radius of the incident at the time of the call. Percent Black, Hispanic, teens, vacant houses, household income, population and square miles are characteristics of the beat where the call took place. Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: The Effect of Police Response Time on Injury

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Response Time (log)	0.013**	0.011*	0.008	0.251***	0.142***	0.127***
	(0.006)	(0.006)	(0.006)	(0.035)	(0.036)	(0.044)
Rush Hour		-0.061***	-0.064***		-0.081***	-0.081***
		(0.021)	(0.021)		(0.022)	(0.022)
Weekend		0.021***	0.023***		0.017***	0.019***
		(0.006)	(0.007)		(0.006)	(0.007)
Holiday		0.051***	0.051**		0.047**	0.047**
		(0.019)	(0.020)		(0.019)	(0.020)
Darkness		-0.011	-0.011		-0.008	-0.008
		(0.008)	(0.008)		(0.008)	(0.008)
Precipitation (cm)		-0.002	-0.001		-0.002	-0.001
		(0.004)	(0.004)		(0.004)	(0.004)
Percent Black		0.113**			0.106***	
		(0.046)			(0.041)	
Percent Hispanic		0.084			0.076	
		(0.056)			(0.050)	
Percent Teens		1.012*			0.897**	
		(0.515)			(0.441)	
Percent Vacant Houses		0.261**			0.272**	
		(0.113)			(0.114)	
Household Income ($10,000's)		0.005			0.005	
		(0.005)			(0.005)	
Population		0.045**			0.043**	
		(0.019)			(0.019)	
Square Miles		-0.002			-0.004**	
		(0.002)			(0.002)	
N	20,933	20,933	20,933	20,933	20,933	20,933
Mean of dependent variable	0.30	0.30	0.30	0.30	0.30	0.30
First Stage F-Statistic				229.37	235.31	213.06
Beat FE	No	No	Yes	No	No	Yes
Time of Day FE	No	No	Yes	No	No	Yes
Month FE	No	Yes	Yes	No	Yes	Yes

This table presents the OLS and 2SLS estimates from a linear probability model of the effect of police response times on injuries associated with calls for service. Columns (1)-(3) present the OLS results, while columns (4)-(6) instrument for response time with the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. Percent Black, Hispanic, teens, vacant houses, household income, population and square miles are characteristics of the beat where the call took place. * 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)	Response Time - Alt (2)	Heckman Correction (3)	3km Radius (4)	5km Radius (5)	Omit 0.5km Radius (6)
Response Time (log)		0.111***	0.182***	0.076*	0.231***	0.221***
		(0.041)	(0.046)	(0.041)	(0.043)	(0.038)
Response Time (levels)	0.009***					
	(0.003)					
Rush Hour	-0.084***	-0.066***	-0.076***	-0.074***	-0.095***	-0.094***
	(0.022)	(0.020)	(0.021)	(0.022)	(0.022)	(0.022)
Weekend	0.018***	0.020***	-0.014	0.021***	0.013**	0.014**
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)
Holiday	0.045**	0.056***	0.003	0.049**	0.044**	0.044**
	(0.020)	(0.020)	(0.022)	(0.020)	(0.020)	(0.020)
Darkness	-0.007	-0.001	-0.006	-0.009	-0.005	-0.006
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Precipitation (cm)	-0.001	-0.001	-0.002	-0.001	-0.003	-0.003
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
N	20,933	25,058	20,818	20,933	20,933	20,933
Mean of dependent variable	0.30	0.30	0.30	0.30	0.30	0.30
First Stage F-Statistic	196.13	219.16		258.89	168.56	189.28
Beat FE	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports alternative specifications for our 2SLS estimates of the effect of police response times on injuries. In specifications (1)-(3), we instrument for response time with the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. In specification (1), Response time (levels) measures the response time in levels rather than our main specification, in logs. In specification (2), we fill in missing values of response time based on when the assigned officer arrives within 200 meters of the incident. In specification (3), we apply the Heckman Correction method to account for the selection concern regarding whether or not a call appears in our data (i.e. was matched to a crime report) by computing an inverse mills ratio which is a function of *officer write-up* (the propensity of the assigned officer to end a call with a crime report) and including it as a control in the analysis. In specifications (4) and (5), the instrumental variable is defined as the number of police vehicles in a 3km and 5km Radius of the incident. In specification (6), the instrumental variable is a count of the number of vehicles in a 4 km radius of the incident when excluding the closest officers (those within a 0.5km of the incident). Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: The Effect of Police Response Time on the Outcome Severity of an Incident

Dep var:	Injuries, Property & Verbal (1)	Injuries & Property (2)	Injuries (3)	Severe Injury (4)
Response Time (log)	0.101*	0.096*	0.127***	0.028**
	(0.053)	(0.050)	(0.044)	(0.013)
Rush Hour	-0.086***	-0.096***	-0.081***	-0.010
	(0.023)	(0.023)	(0.022)	(0.007)
Weekend	0.021***	0.027***	0.019***	-0.001
	(0.007)	(0.007)	(0.007)	(0.002)
Holiday	0.047**	0.052***	0.047**	0.004
	(0.020)	(0.020)	(0.020)	(0.007)
Darkness	0.002	-0.005	-0.008	0.000
	(0.008)	(0.008)	(0.008)	(0.003)
Precipitation (cm)	-0.006	-0.004	-0.001	0.003*
	(0.004)	(0.004)	(0.004)	(0.002)
N	20,933	20,933	20,933	20,933
Mean of dependent variable	0.41	0.35	0.30	0.03
Beat FE	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

This table reports the 2SLS estimates of the effect of police response time on various measures of severity outcomes. All specifications instrument for response time with the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. The outcome variable in column (1) includes any escalation such as verbal threats, property damage, or physical damage. Column (2) restricts an escalation to only include physical damage to person or property. The result in Column (3) is identical to our main results where escalation is defined as injury to person. Column (4) further restricts the definition of escalation to only include injuries involving gun shot wounds. Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

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

	In Progress			Not In Progress		
	OLS	First Stage	2SLS	OLS	First Stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Response Time (log)	0.002		0.097**	-0.003		-0.005
	(0.006)		(0.048)	(0.003)		(0.028)
Availability of Officers		-0.017***			-0.016***	
		(0.002)			(0.001)	
Rush Hour	-0.012	0.282***	-0.039	0.012	0.347***	0.013
	(0.027)	(0.059)	(0.032)	(0.015)	(0.032)	(0.018)
Weekend	0.015*	0.097***	0.005	0.005	0.044***	0.005
	(0.008)	(0.017)	(0.009)	(0.004)	(0.010)	(0.004)
Holiday	-0.014	-0.021	-0.013	-0.005	-0.015	-0.005
	(0.022)	(0.057)	(0.023)	(0.011)	(0.026)	(0.011)
Darkness	0.006	0.028	0.004	0.005	0.006	0.005
	(0.011)	(0.021)	(0.011)	(0.004)	(0.011)	(0.004)
Precipitation (cm)	-0.006	-0.004	-0.006	-0.000	-0.001	-0.000
	(0.004)	(0.009)	(0.004)	(0.002)	(0.005)	(0.002)
N	6,284	6,284	6,284	27,960	27,960	27,960
Mean of dependent variable	0.12	2.29	0.12	0.11	2.97	0.11
First Stage F-Statistic		65.54			199.89	
Beat FE	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports OLS, first stage, and 2SLS estimates for calls for service involving burglary, theft or robbery. We further divide this subset of the data into calls for service that are and are not in progress as defined by the 911 call-taker at the time of call. "Availability of Officers" is defined as the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. The 2SLS specifications in columns (3) and (6) instrument for "Response Time (log)" with "Availability of Officers." 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 Caller Characteristics

			Yes (1)	No (2)
Panel A: White				
	(i)	Coefficient	0.011	0.193***
	(ii)	Standard Error	(0.102)	(0.066)
	(iii)	First Stage F-Statistic	[60.02]	[114.73]
	(iv)	Injury Rate	{0.32}	{0.39}
	(v)	Observations	3,667	12,835
Panel B: 30 & Older				
	(i)	Coefficient	0.155*	0.058
	(ii)	Standard Error	(0.081)	(0.072)
	(iii)	First Stage F-Statistic	[71.24]	[133.81]
	(iv)	Injury Rate	{0.31}	{0.43}
	(v)	Observations	7,970	7,920
Panel C: Victim Caller				
	(i)	Coefficient	0.309***	0.044
	(ii)	Standard Error	(0.114)	(0.048)
	(iii)	First Stage F-Statistic	[48.80]	[202.01]
	(iv)	Injury Rate	{0.36}	{0.26}
	(v)	Observations	8,783	11,277
Panel D: Female				
	(i)	Coefficient	0.131*	0.042
	(ii)	Standard Error	(0.069)	(0.085)
	(iii)	First Stage F-Statistic	[111.83]	[66.68]
	(iv)	Injury Rate	{0.41}	{0.31}
	(v)	Observations	10,388	5,513
Panel E: Female & Victim Caller†				
	(i)	Coefficient	0.389**	0.027
	(ii)	Standard Error	(0.180)	(0.187)
	(iii)	First Stage F-Statistic	[32.03]	[16.86]
	(iv)	Injury Rate	{0.41}	{0.29}
	(v)	Observations	5,973	2,444
Panel F: 3 or more Calls for Service				
	(i)	Coefficient	0.051	0.157***
	(ii)	Standard Error	(0.065)	(0.057)
	(iii)	First Stage F-Statistic	[120.42]	[105.03]
	(iv)	Injury Rate	{0.31}	{0.30}
	(v)	Observations	8,079	11,981
Panel G: Start Shift				
	(i)	Coefficient	0.181***	0.047
	(ii)	Standard Error	(0.068)	(0.053)
	(iii)	First Stage F-Statistic	[112.44]	[149.85]
	(iv)	Injury Rate	{0.30}	{0.31}
	(v)	Observations	10,742	9,318

This table reports 2SLS estimates of the effect of police response times on injuries by caller characteristics. Each estimate is the coefficient of response time in predicting injury outcomes from our main analysis when constraining the sample to the category defined by the relevant row and column (e.g. the first estimate in column (1) corresponds to a victim who is white whereas column (2) is estimated using only non white victims). Cluster robust standard errors appear in parenthesis and first stage F-statistics appear in brackets. * p<0.10, ** p<0.05, *** p<0.01.

† The subset of observations in column (1) contain calls for service for female and victim callers, where the subset of data in column (2) include male and victim callers.

Table 8: The Effect of Police Response Time on Future (Major Disturbance - Violence) 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 (log)		-0.017***		0.099**	-0.001		0.019
		(0.004)		(0.043)	(0.002)		(0.022)
Availability of Officers at 1st Call	-0.014***		-0.001**			-0.0003	
	(0.001)		(0.001)			(0.0003)	
Rush Hour	0.144***	0.003	0.001	-0.013	-0.013*	-0.013*	-0.016**
	(0.018)	(0.013)	(0.013)	(0.014)	(0.007)	(0.007)	(0.008)
Weekend	0.017**	-0.014***	-0.015***	-0.016***	-0.001	-0.001	-0.002
	(0.007)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Holiday	0.112***	0.004	0.001	-0.011	0.023***	0.022**	0.020**
	(0.019)	(0.011)	(0.011)	(0.013)	(0.009)	(0.009)	(0.009)
Darkness	-0.017**	0.004	0.004	0.006	-0.001	-0.001	-0.001
	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Precipitation (cm)	-0.001	0.007**	0.006**	0.007**	0.001	0.001	0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
N	38,016	38,016	38,016	38,016	38,016	38,016	38,016
Mean of dependent variable	2.53	0.36	0.36	0.36	0.07	0.07	0.07
Beat FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Column (1) of this table reports the first stage estimate of the effect of officer availability on "Response Time of 1st Call (log)" for the first call at any residential address. Columns (2) - (4) present the OLS, reduced form and 2SLS effects of officer availability/response time for the first call at an address on the probability of a repeat "Major Disturbance - Violence" offense at this address. Columns (5) - (7) report the OLS, reduced form and 2SLS estimates of the effect of officer availability/response time on future injuries related to a "Major Disturbance - Violence" incident reported at a residence. "Availability of Officers at 1st Call" is defined as the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the first call. The 2SLS specifications in columns (4) and (7) instrument for "Response Time of 1st Call (log)" with "Availability of Officers at 1st Call." Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

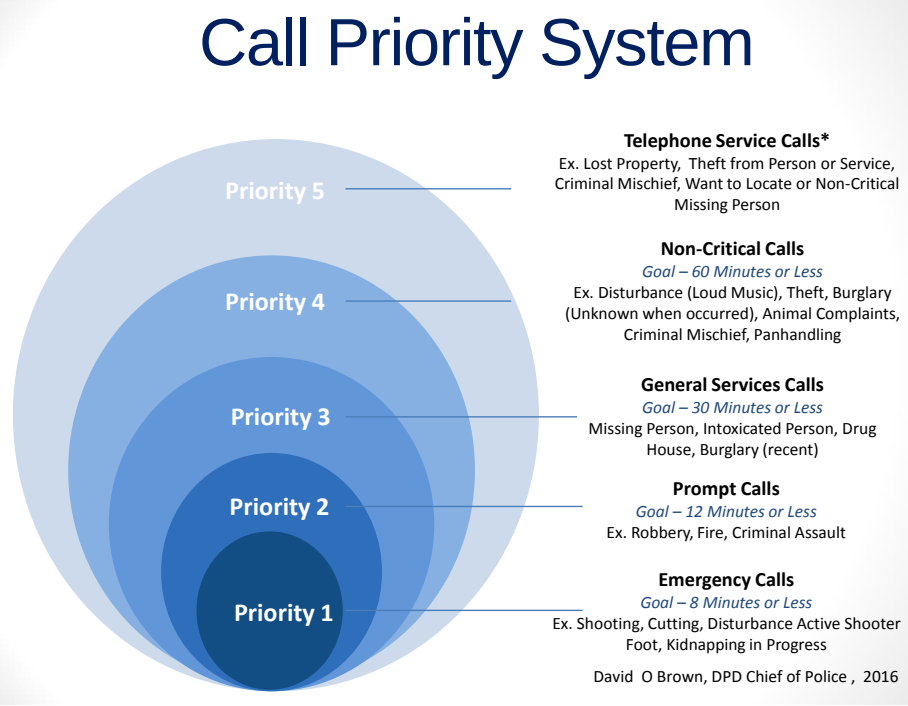
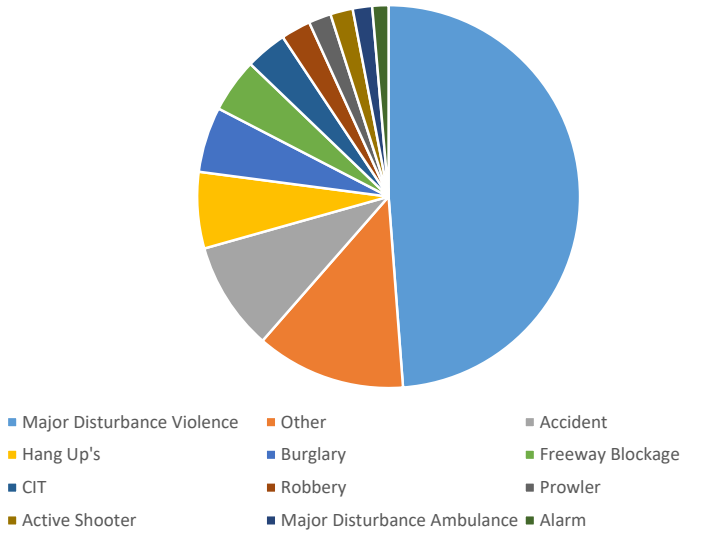


Figure 2: Explaining Priority Numbers (Brown, 2016)

Panel A: High Priority Call Categories (Priority 1 & 2)



Panel B: Injury Probabilities across High Priority Calls

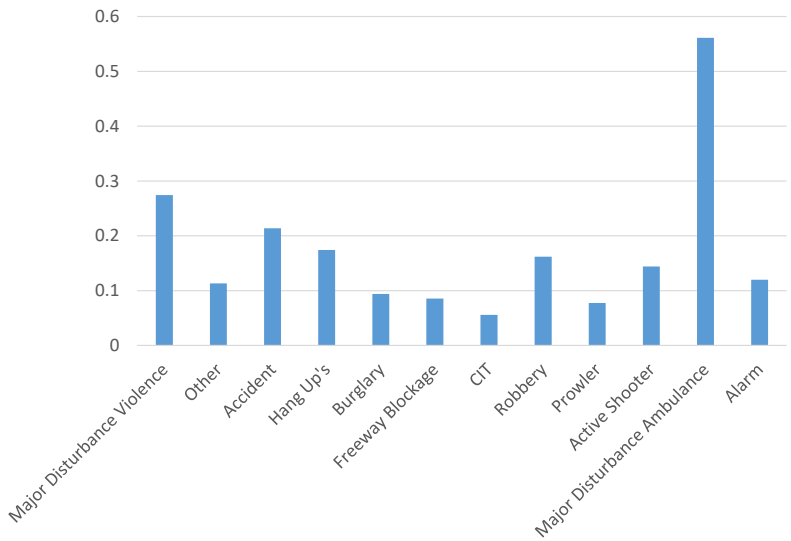


Figure 3: Composition & Probability of Injury of High Priority Calls for Service

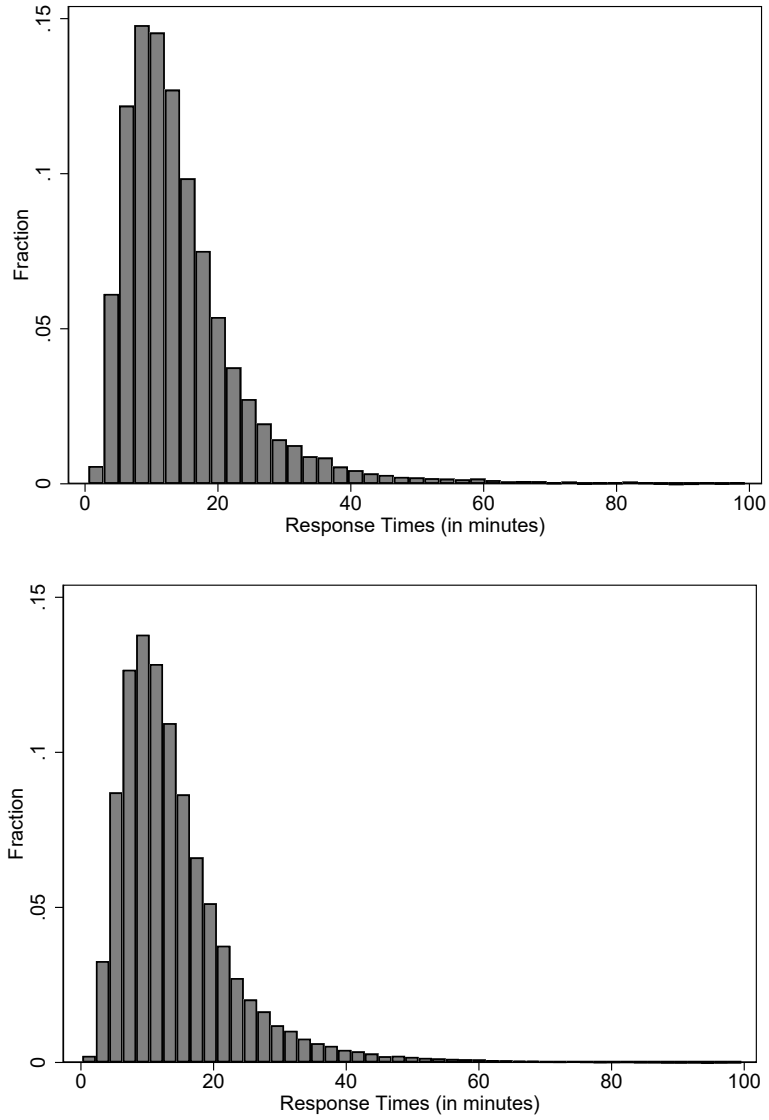


Figure 4: Distribution of officer response times for calls that ended with a crime report (top) and all calls (bottom). Although our analysis focuses on calls that end with a crime report, the distribution of officer response times do not appear to be different for calls that end in a crime report and calls that do not end in a crime report.

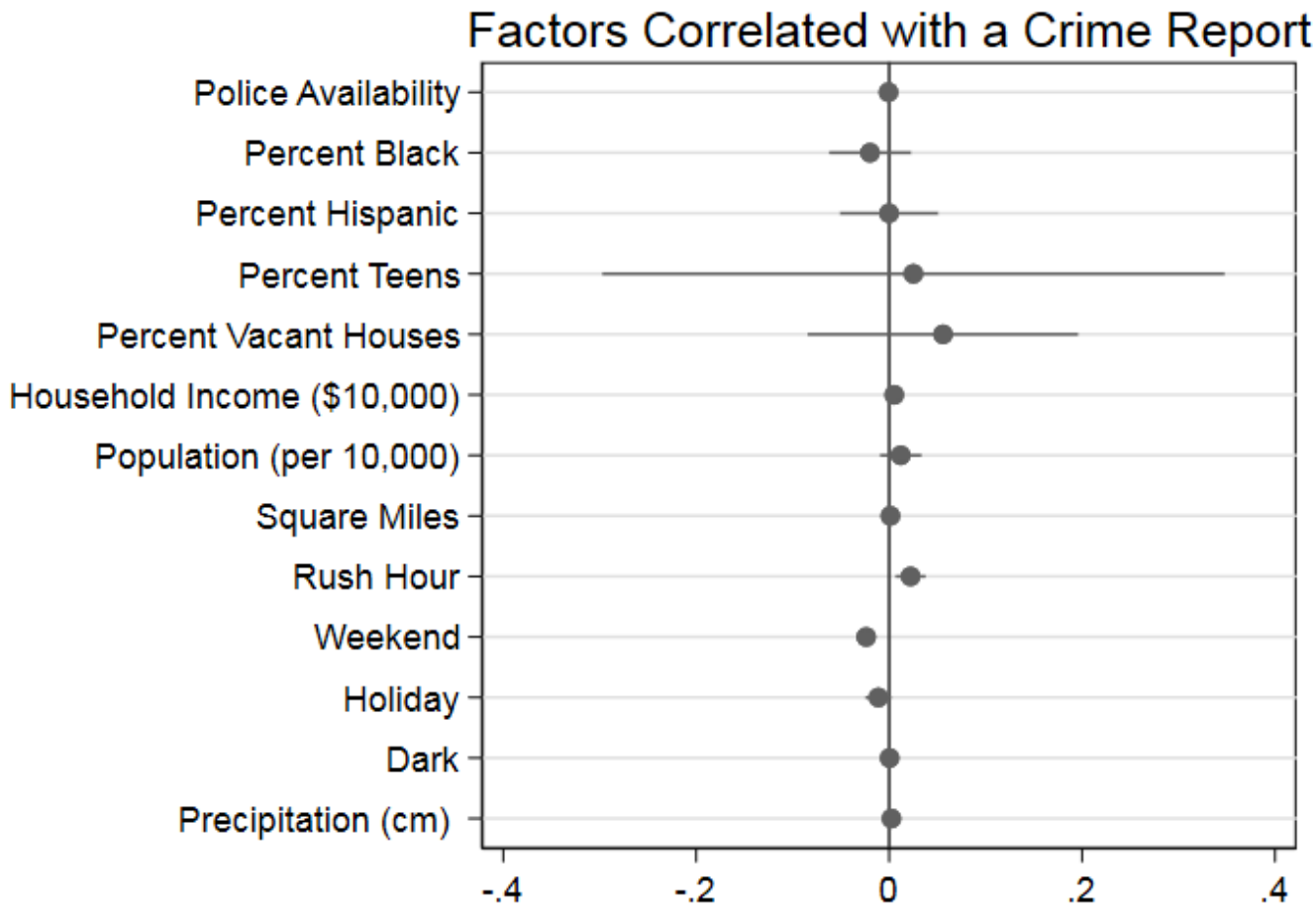


Figure 5: This figure presents the coefficient estimates for the likelihood that each factor listed on the vertical axis is associated with a crime report being filed. Regressions include beat, time of day and month fixed effects.

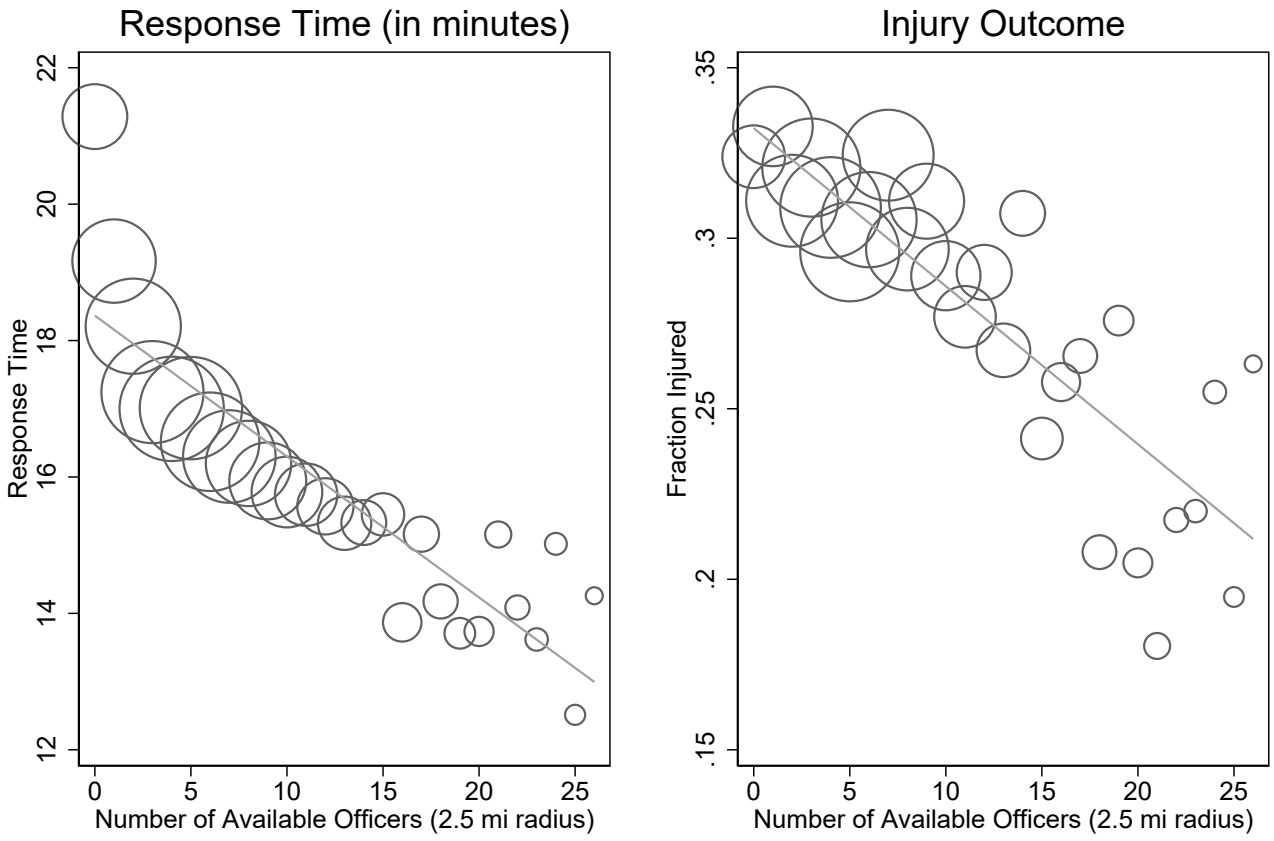


Figure 6: The left figure visualizes the first stage relationship between response times of responding police and the number of police available within a 2.5-mile radius of the call for service. The right panel visualizes the reduced form of the fraction of times that injuries occurred as a function of the number of police available within a 2.5-mile radius of the call for service.

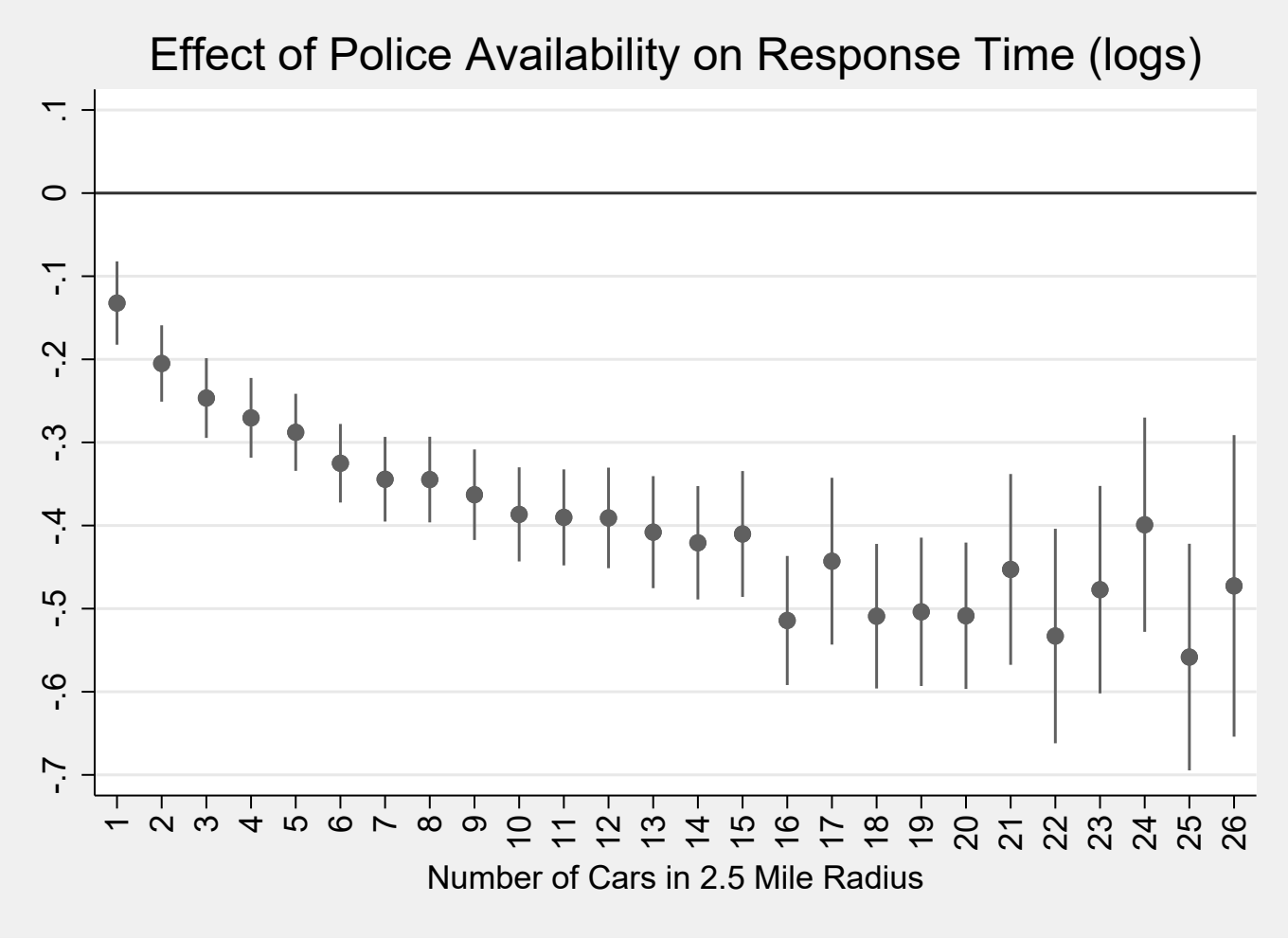


Figure 7: This figure visualizes the first stage used in our analysis. Specifically, it plots the natural log of response time as a function of the number of cars in a 2.5-mile radius.

A Appendix Tables

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 (log)			0.002
			(0.062)
Availability of Officers	-0.00003	-0.014***	
	(0.0008)	(0.001)	
Rush Hour	0.020**	0.134***	0.020
	(0.009)	(0.012)	(0.013)
Weekend	-0.022***	0.022***	-0.022***
	(0.003)	(0.005)	(0.003)
Holiday	-0.018**	0.028**	-0.018**
	(0.007)	(0.012)	(0.008)
Darkness	0.000	-0.008*	0.000
	(0.003)	(0.004)	(0.003)
Precipitation (cm)	0.003	-0.002	0.003
	(0.002)	(0.002)	(0.002)
N	98,759	98,759	98,759
Mean of dependent variable	0.21	2.50	0.21
Beat FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

In this table we run the reduced form, first stage and 2SLS analysis on the 98,759 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. "Availability of Officers" is defined as the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. The 2SLS specification in column (3) instruments for "Response Time (log)" with "Availability of Officers." Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.2: The Effect of Police Availability on Injuries

Dep var:	Reduced Form with Total Calls (1)	Reduced Form with Average Police Presence (2)
Police Availability	-0.002***	-0.002**
	(0.001)	(0.001)
Total Calls	0.0001	
	(0.0001)	
Average Police Presence (3 weeks)		0.001
		(0.001)
Rush Hour	-0.062***	-0.062***
	(0.021)	(0.022)
Weekend	0.020***	0.023***
	(0.007)	(0.007)
Holiday	0.049**	0.053**
	(0.020)	(0.023)
Darkness	-0.011	-0.008
	(0.008)	(0.008)
Precipitation (cm)	-0.001	-0.001
	(0.004)	(0.004)
N	20,933	19,033
Mean of dependent variable	0.30	0.30
Beat FE	Yes	Yes
Time of Day FE	Yes	Yes
Month FE	Yes	Yes

In this table we estimate the reduced form effect of officer availability on injuries, but include two controls to proxy for other factors that could be related to both police availability and injury outcomes. In column (1) we include total number of 911 calls received in that police division during that day (a proxy for the general crime level in that period), while in column (2) we include a control for average police availability in a 2.5 mile radius of the incident at that hour and day of week for the 3 weeks leading up to the incident (a proxy for expected police availability in that location which could drive deterrence). In column (2) we drop all calls that occurred in the first three weeks of January, as they lack information regarding police presence leading up to the incident. Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.3: 2SLS Estimates of the Effect of Police Response Time on Injury

	(1)	(2)	(3)	(4)	(5)
Response Time (log)	0.125***	0.128***	0.118***	0.107*	0.123**
	(0.044)	(0.043)	(0.038)	(0.055)	(0.048)
Rush Hour	-0.083***	-0.077***	-0.078***	-0.416***	-0.086***
	(0.022)	(0.023)	(0.023)	(0.016)	(0.023)
weekend	0.016**	0.022***	0.019***	0.011	0.016**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
holiday	0.045**	0.039*	0.040*	0.038*	0.041*
	(0.020)	(0.021)	(0.021)	(0.023)	(0.021)
Darkness	-0.009	-0.014*	-0.014*	-0.007	-0.009
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Precipitation (cm)	-0.002	-0.004	-0.004	-0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
N	20,933	20,933	20,933	20,933	20,933
Mean of dependent variable	0.30	0.30	0.30	0.30	0.30
First Stage F-Statistic	215.74	237.15	243.19	154.01	190.54
Beat FE	Yes	Yes	Yes	No	No
Call Taker FE	Yes	No	Yes	No	No
Officer FE	No	Yes	Yes	No	No
Beat X Hour FE	No	No	No	Yes	No
Beat X Month FE	No	No	No	No	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	No

In this table we estimate our main results when including a variety of alternative fixed effects. In all specifications we instrument for "Response Time (log)" with the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.4: Sample Share by Compliance Type

	Local Linear Model			Linear Model		
	1%	1.5%	2%	1%	1.5%	2%
Compliers	0.286	0.300	0.297	0.224	0.211	0.198
Never Takers	0.321	0.289	0.279	0.282	0.295	0.306
Always Takers	0.393	0.411	0.425	0.494	0.494	0.496

This table presents the estimated fraction of compliers, never takers, and always takers observed in the data. The first 3 columns estimate these fractions when applying a local linear model where minimum and maximum police availability are determined by the top/bottom 1% of incidents (column (1)), 1.5% of incidents (column (2)), and 2% of incidents (column (3)) in that division. The last 3 columns follow the same process when estimating a linear model on the full database.

Table A.5: Characteristics of Compliers

	P[X = x]	P[X = x|*complier*]	$\frac{P[X=x\|complier]}{P[X=x]}$
Near Department	0.5	0.42	0.835
	(0.026)	(0.045)	(0.089)
Far from Department	0.5	0.672	1.344
	(0.026)	(0.079)	(0.159)
Weekend	0.466	0.442	0.949
	(0.004)	(0.044)	(0.095)
Non-Weekend	0.534	0.607	1.138
	(0.004)	(0.060)	(0.111)
Rush Hour	0.283	0.256	0.905
	(0.004)	(0.038)	(0.134)
Non-Rush Hour	0.717	0.747	1.042
	(0.004)	(0.061)	(0.085)
Male	0.275	0.290	1.053
	(0.004)	(0.034)	(0.125)
Female	0.519	0.498	0.961
	(0.008)	(0.057)	(0.110)
Black	0.402	0.469	1.168
	(0.017)	(0.052)	(0.128)
White	0.158	0.148	0.934
	(0.009)	(0.025)	(0.16)
Hispanic	0.221	0.179	0.811
	(0.012)	(0.031)	(0.142)
Under 30	0.37	0.437	1.179
	(0.007)	(0.046)	(0.125)
30 and Older	0.63	0.576	0.915
	(0.007)	(0.053)	(0.085)
1-2 Calls	0.612	0.596	0.974
	(0.014)	(0.058)	(0.095)
3+ Calls	0.388	0.403	1.038
	(0.014)	(0.049)	(0.125)

This table presents the sample distribution, complier distribution, and relative likelihood for different subgroups. *Near Department* and *Far from Department* are determined based on median distance to nearest police department (4.3 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. Bootstrapped standard errors in parenthesis are obtained using 1000 replications.

Table A.6: MTE Table

	Selection Equation Response <= 12 Minutes (1)	Outcome Equation Injury (2)
Availability of Officers	0.032***	
	(0.002)	
Rush Hour	-0.332***	-0.045
	(0.054)	(0.037)
Weekend	-0.046	-0.0003
	(0.020)	(0.025)
Holiday	-0.043	0.149**
	(0.053)	(0.074)
Darkness	0.046**	0.008
	(0.022)	(0.029)
Precipitation (cm)	-0.005	-0.025*
	(0.012)	(0.013)
Propensity Score		-1.088
		(2.296)
Propensity Score^2		0.943
		(2.192)
Rush Hour x propensity score		-0.086
		(0.066)
Weekend x propensity score		0.039
		(0.050)
Holiday x propensity score		-0.223
		(0.152)
Darkness x propensity score		-0.033
		(0.059)
Precipitation (cm) x propensity score		0.049*
		(0.027)
N	20,933	20,933
p-value for test of heterogeneity		0.867
Beat FE	Yes	Yes
Month FE	Yes	Yes
Time of Day FE	Yes	Yes

Column (1) reports estimates from a probit selection model where the dependent variable is equal to one if an officer arrives at the incident within 12 minutes or less ("first stage"). Availability of officers (the instrument) is measured as the number of officers within a 2.5 mile radius of the incident. Column (2) displays estimates from the outcome equation, where the dependent variable is a binary indicator for whether or not an injury was recorded at the site of the incident. Coefficients of regressors that were not interacted with the propensity score measure the effect on injuries for incidents that did not receive a fast response time, whereas coefficients on regressors interacted with the propensity score measure the differential effect for incidents that received a fast response time. Bootstrapped standard errors clustered at the beat level are reported in parenthesis (1000 iterations). Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.7: The Effect of Police Response Time on Future High Priority 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 (log)		-0.024***		0.114**	-0.006*		0.013
		(0.004)		(0.056)	(0.003)		(0.029)
Availability of Officers at 1st Call	-0.014***		-0.001*			-0.0002	
	(0.001)		(0.001)			(0.0004)	
Rush Hour	0.144***	0.012	0.008	-0.008	0.003	0.002	-0.0001
	(0.018)	(0.014)	(0.015)	(0.017)	(0.009)	(0.009)	(0.010)
Weekend	0.017**	-0.023***	-0.024***	-0.026***	-0.005	-0.005	-0.005
	(0.007)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Holiday	0.112***	-0.005	-0.010	-0.023*	0.022**	0.021**	0.020**
	(0.019)	(0.011)	(0.011)	(0.013)	(0.010)	(0.010)	(0.010)
Darkness	-0.017**	0.000	0.001	0.003	0.001	0.001	0.001
	(0.007)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Precipitation (cm)	-0.001	0.007**	0.007**	0.007**	0.002	0.002	0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
N	38,016	38,016	38,016	38,016	38,016	38,016	38,016
Mean of dependent variable	2.53	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
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Column (1) of this table reports the first stage estimate of the effect of officer availability on "Response Time of 1st Call (log)" for the first call at any residential address. Columns (2) - (4) present the OLS, reduced form and 2SLS effects of officer availability/response time for the first call at an address on the probability of a repeat high priority offense (priority 1 or 2) at this address. Columns (5) - (7) report the OLS, reduced form and 2SLS estimates of the effect of officer availability/response time on future injuries related to a high priority incident reported at a residence. "Availability of Officers at 1st Call" is defined as the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the first call. The 2SLS specifications in columns (4) and (7) instrument for "Response Time of 1st Call (log)" with "Availability of Officers at 1st Call." Cluster robust standard errors by beat are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A.8: 2SLS Estimates of the Effect of Police Response Time on Arrests

	(1)	(2)	(3)	(4)
Injury	0.180***			
	(0.007)			
Response Time (log)		-0.010**		0.005
		(0.004)		(0.033)
Officer Availability			-0.0001	
			(0.001)	
Rush Hour	-0.045***	-0.055***	-0.056***	-0.057***
	(0.013)	(0.013)	(0.013)	(0.014)
weekend	-0.005	-0.000	-0.000	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)
holiday	0.004	0.013	0.013	0.013
	(0.014)	(0.014)	(0.014)	(0.014)
Darkness	-0.003	-0.005	-0.005	-0.005
	(0.005)	(0.006)	(0.006)	(0.006)
Precipitation (cm)	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
N	20,933	20,933	20,933	20,933
Mean of dependent variable	0.11	0.11	0.11	0.11
First Stage F-Statistic				213.06
Beat FE	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

In this table we examine the effect of injuries, police response times, and police availability on the likelihood that a call for service ends in an arrest. Column (1) examines the effect of an injury during a call for service on the likelihood of an arrest being made. Column (2) produces the OLS results of police response times on the likelihood of an arrest. Column (3) examines the reduced form effect of police availability on the likelihood of an arrest. "Officers Availability" is defined as the number of police vehicles observed within a 2.5 mile (4 km) radius of the location of the incident at the time of the call. Column (4) generates the 2SLS estimate of the effect of police response time on the likelihood of an arrest when instrumenting for "Response Time (log)" with "Officer Availability." Cluster robust standard errors by beat are shown in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

A Appendix Figures

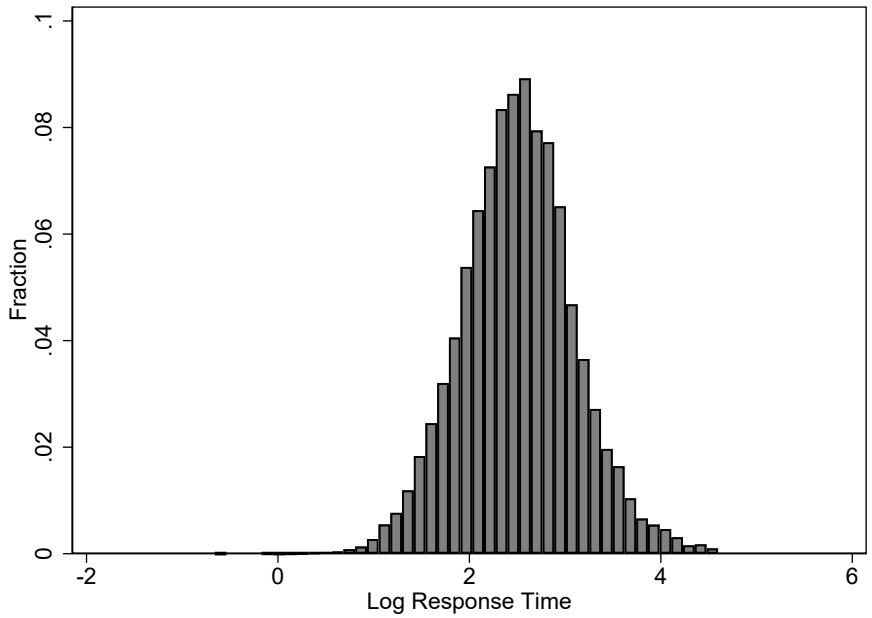


Figure A.1: Distribution of Response Time in logs for calls appearing in main database.

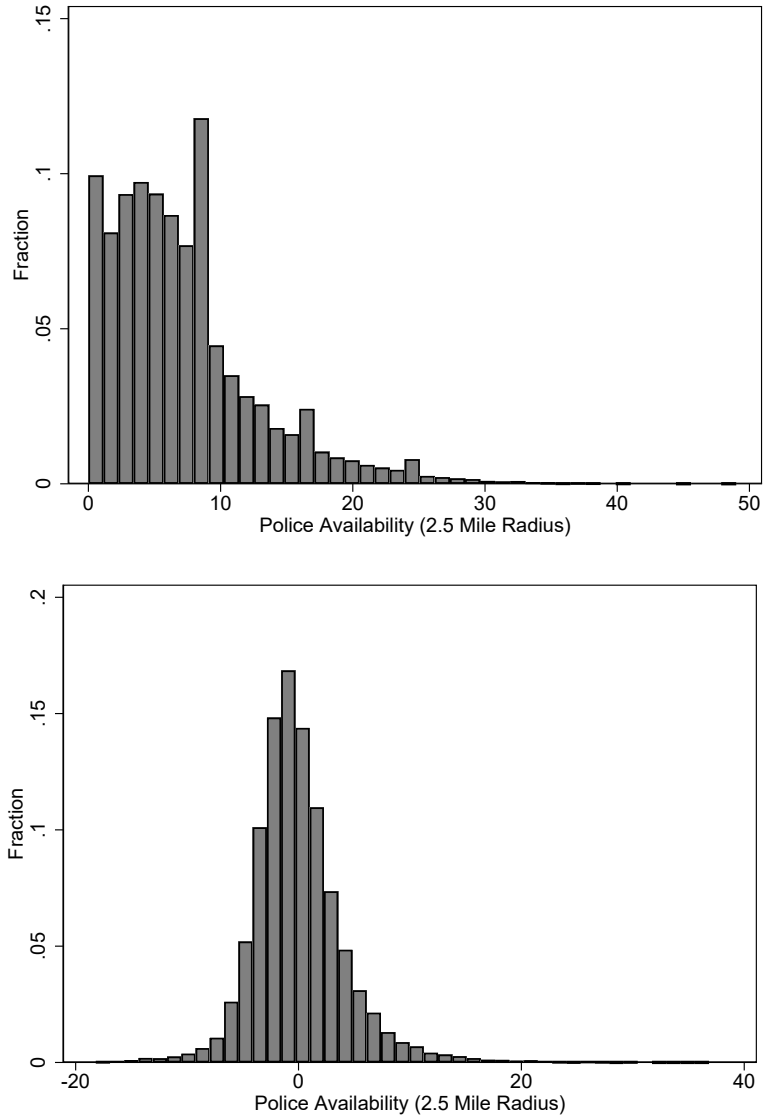


Figure A.2: The top figure present the distribution of the number of police available within a 2.5-mile radius of the call for service. The bottom panel presents the residualized distribution of the number of police available within a 2.5-mile radius of the call for service when beat, month, and time of day fixed effects are included.

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 a "Major Disturbance - Violence" (defined as $problem = 6X - MajorDist(Violence)$)
3. 117,572 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). In cases where the same call master incident ID appears multiple times due to multiple crime reports, the report is coded as an injury if an injury occurred in any of these reports. 98,759 of these calls have a coded arrival time by DPD.
4. 25,348 calls were matched to crimes using service number ID ($servicenum$) common to call and crime datasets.
5. Finally, 20,933 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 kilometers 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 $master\_inc\_id$.