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Traffic and the Provision of Public Goods*

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Abstract

We examine the relationship between traffic congestion and emergency response times by matching traffic data at a fine spatial and temporal scale to incident report data from fire departments in California. Our results show that traffic slows down fire trucks arriving at the scene of an emergency and increases the average monetary damages from fires. Allocating more funding to fire departments decreases response times, but not the marginal effect of traffic. We document an additional externality of traffic congestion and highlight the negative effect of traffic on one of the many public goods that rely on well-functioning road infrastructure.

JEL Classification: R28, D03, J12
Keywords: Traffic, Public Goods, Externalities, Emergency Response Times

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1 Introduction

According to the National Emergency Number Association, over 240 million 911 calls are placed every year in the United-States.[1] Rapidly responding to emergency calls requires both an efficient network of first responders and dispatchers as well as an effective road infrastructure system. The literature shows that response times are critical for a number of health outcomes including hospitalization, rehabilitation and survival following an accident, stroke or heart attack (Wilde, 2013; Emberson et al., 2014; Jena et al., 2017). Police response times have also been shown to affect crime clearance rates (Blanes i Vidal and Kirchmaier (2015)). Although first responders are typically expeditious, one factor beyond their control that affects response times is traffic. This is a particularly pressing concern giving increasing trends of urbanization that have led to commensurate increases in traffic congestion.

In this paper, we examine the relationship between traffic and emergency response times by fire departments. In addition to responding to fires, we also have data on fire departments providing emergency medical services (EMS) and responding to other non-fire emergencies. We match traffic data at a fine spatial and temporal scale to incident report data from fire departments. The fire data consist of over 2.7 million incidents from 2008-2015 across California collected by the National Fire Incident Reporting System (NFIRS). The traffic data, collected from the California Department of Transportation, consists of roughly 21 billion observations from 25,000 stations at a five-minute interval resolution. The fine scale traffic data allows us to merge traffic conditions immediately preceding the emergency event by zip code, date, and the time of day. We assign zip code level traffic conditions for every call to the fire department immediately prior to the fire department receiving the alarm. Our identifying assumption is that traffic in a given zip code, in a given month, on a given day of the week, within a given hour is uncorrelated with unobservables affecting emergency response times. This is plausibly exogenous since we use the traffic before the fire/accident occurs. Our final dataset, consists of 1.3 million incidents merged with zip code level traffic conditions.

We make three main contributions to the literature. First, we investigate a new external-

[1] For more details, see https://www.nena.org/?page=911Statistics

ity of traffic by showing how traffic congestion affects an important public good, the ability of first responders to arrive on scene of emergencies. Second, we show how a variety of policies affect both response times and the marginal effect of traffic on response times. Third, we estimate the economic damage imposed by slower response times due to traffic congestion. The results improve the understanding of the societal costs of traffic as well as the challenges facing first responders.

Our results show that traffic slows down fire trucks arriving at the scene of an emergency. This applies both for fire departments responding to fires and providing emergency medical services. Increasing the response time of first responders represents a newly documented externality to traffic, in additions to lost time, pollution, house prices, health, happiness and crime (e.g. Kahneman et al. (2004); Currie and Walker (2011); Knittel et al. (2016); Ossokina and Verweij (2015); Anderson et al. (2016) and Beland and Brent (2018)). The effects are highly nonlinear; increases in response time are primarily due to traffic in the right tail of the traffic distribution. We find suggestive evidence that fire departments in high traffic times and during peak congestion periods are able to adapt to high traffic, and that unexpected traffic has a larger effect on response times.

Additionally, we investigate road congestion policies (high-occupancy vehicle lanes (HOV), toll roads, public transportation), as well as municipal expenditures that can mitigate this problem. Allocating more money to fire departments decreases response times but does not reduce the marginal effect of traffic on response times. None of the other policies have any effect on response times, and only spending on public transit mitigates the impact of traffic on response times. Lastly we show that traffic congestion increases the monetary damages of fires.

In aggregate, the increased monetary damages from fires and emergency medical services due to traffic are approximately \$130-\$360 million per year in California. These costs do not account for increased response times for ambulances or police, and therefore should be considered a lower bound for the costs of traffic on emergency response services. Additionally, we do not capture adapting expenditures by fire departments to cope with traffic congestion. Our results are robust to multiple specifications and robustness tests including metro-by-date fixed effects, different definitions of our traffic variable, and relaxing the temporal assumptions for assigning traffic to an emergency. The results are consistent across each of the major metropolitan areas in California.

Our results highlight the importance of well-functioning road infrastructure in the efficient provision of a public good. Since rapid response by first responders is critical, simply using the value of time and reliability and health effects from pollution will underestimate the costs of traffic congestion. As urbanization shifts higher shares of the population to cities, it is important to understand the value of a well functioning road network.

The rest of the paper is organized as follows: Section 2 discusses the related literature; Section 3 provides a description of the data and presents descriptive statistics; Section 4 presents the empirical strategy; Section 5 is devoted to the main results, heterogeneity of the impacts and a series of robustness checks; and Section 6 concludes with policy implications.

2 Related literature

Our paper is related to the literature on externalities associated with traffic congestion, the importance of emergency response times, and road congestion policies. This article first fits into a broad literature investigating negative externalities to traffic. One of the largest externalities is the value of time and fuel expenditures associated with congestion, which is estimated to cost U.S. commuters $121 billion in 2011 (Schrank et al. (2012)). The literature has also quantified several other externalities of traffic, including pollution, health and housing prices. Currie and Walker (2011) show that traffic reductions due to the introduction of electronic toll collection, (E-ZPass) reduce vehicle emissions near highway toll plazas, which subsequently reduces prematurity and low birth weight among mothers near a toll plaza. Pollution from traffic also negatively affects children's contemporaneous health (Knittel et al., 2016) and has a long run effect on mortality within the elderly population (Anderson, 2015). Ossokina and Verweij (2015) exploit a quasi-experiment that reduces traffic congestion on certain streets in the Netherlands and find that the decrease in traffic leads to an increase in housing prices. While the primary costs of traffic are mostly due to lost time and reliability, there is research using survey data linking traffic to negative mental health outcomes, including stress and aggression (Parkinson, 2001; Hennessy and

Wiesenthal, 1999; Gee and Takeuchi, 2004; Gottholmseder et al., 2009; Roberts et al., 2011; Künn-Nelen, 2016; Anderson et al., 2016). Moreover, Beland and Brent (2018) find that extreme traffic events lead to an increase in domestic violence in Los Angeles. There are several papers that investigate the role of traffic congestion in private decisions related to driving behavior (Burger and Kaffine, 2009; Couture et al., Forthcoming).

This paper is also related to the literature on the importance of emergency response times. There are several medical papers that examine the effect of response times on health outcomes. The general consensus is that slower response times increase mortality for cardiac arrest, but not for general trauma (Larsen et al., 1993; Pell et al., 2001; Newgard et al., 2010). However, recent papers show that the lack of an association between response times and general trauma mortality may be due to endogeneity: first responders devote more resources (e.g. faster response times) to more severe trauma events that have higher mortality rates.

Wilde (2013) uses distance from the hospital as an instrument to investigate the impact of response time on mortality and hospital utilization. The instrumental variable approach shows that increased emergency response times significantly increase mortality and the likelihood of being admitted to the hospital, while the OLS approach finds no effect. Jena et al. (2017) exploits marathons as a natural experiment that increases response times to investigate the effect on cardiac arrest outcomes. They find that patients who were admitted to marathon-affected hospitals with acute myocardial infarction or cardiac arrest on marathon dates had longer ambulance transport times before noon (4.4 minutes longer) and higher 30-day mortality than patients who were hospitalized on other days. The effect of response times is not limited to medical outcomes, as Blanes i Vidal and Kirchmaier (2015) show that police response times affect crime clearance rates. They find suggestive evidence in support of two mechanisms: an increase in response time increases the likelihood of an immediate arrest and the likelihood that a suspect will be named by a victim or witness. We contribute to the literature by highlighting how traffic is an important input to emergency response times for fire departments using data at a fine spatial and temporal scale.

Our paper is also related to the literature on road congestion policies that aim to reduce traffic externalities. According to Duranton and Turner (2011), building new capacity is unlikely to reduce congestion in the long-run since the elasticity of travel demand with respect to capacity is roughly equal to one. Other research analyze policies such as dynamic tolling (De Borger and Proost, 2013; Gross and Brent, 2018), road pricing (Gibson and Carnovale, 2015), HOV and HOT lanes (Konishi and Mun, 2010; Bento et al., 2014, 2013) and public transportation (Anderson, 2014; Adler and van Ommeren, 2016; Bauernschuster et al., 2017; Gendron-Carrier et al., 2018). This literature finds that these policies affect driving behaviors, decrease travel time, reduce congestion, and curtail pollution. We contribute by investigating if theses policies affect the work of first responders.

In sum, we contribute to these literatures in several ways. We first contribute by showing that traffic is an important issue for emergency response times by fire departments. This constitutes an additional externality to traffic and highlights the interaction of two public goods: emergency response services and road infrastructure. We also contribute by investigating policies (HOV lanes, toll roads, public transportation, and spending) that can potentially decrease response time and mitigate the negative impact of traffic on first responders.

3 Data & Descriptive statistics

3.1 Data sources, Dataset creations & descriptive statistics

The fire department incident data are collated from fire departments by the National Fire Incident Reporting System (NFIRS). NFIRS represents a uniform reporting standard for fire departments and emergency medical services (EMS), and represents the world's largest national database on fire incident reporting. The Federal Emergency Management Agency (FEMA) administers the NFIRS database. This database contains roughly 40 million incidents nationwide from 2008-2015. We focus on California due to the availability of high resolution traffic data; there are approximately 2.7 million incidents from 2008-2015 in California. There are eleven modules that contain detailed data on different elements of fire incidents. We use the basic module that includes data on the time the alarm was raised and the time the fire department arrived on scene at the emergency. We focus on three types of calls: fire, emergency medical service, and other hazards. We exclude other types of incidents that do not require rapid arrival on the scene such as being locked out of a residence or animal control. Fire departments also report the dollar value of property and contents damaged due to the fire. We exclude all incidents coded as wildfires because these incidents likely have different dynamics for response times and monetary damages relative to most fires occurring in urban areas.

The traffic data are obtained from the California Department of Transportation through the Caltrans Performance Measurement System (PeMS).[2] We access annual Station 5-minute datasets from 2008 to 2015 for approximately 25,000 monitoring stations over California. There are over 840,000 five minute intervals for each of the 25,000 stations representing approximately 21 billion observations of traffic data. Since the fire incident data are geocoded at the zip code level, we aggregate the traffic data to the zip code level. For each five minute interval within each zip code, we generate the average deviations from free-flow speeds (traffic from midnight to 3 am) weighted by station occupancy. Our traffic delay variable is therefore the occupancy-weighted average deviation from free-flow speeds in miles per hour (mph) in a five minute interval across all monitoring stations in a given zip code. The average delay across all times and zip codes is 4.7 mph, 6.8 mph during the morning commute, and 10 mph during the evening commute. In the regressions, we standardize the average delay variables to have mean zero and standard deviation one.

Monitoring stations only exist in a subset of zip codes so our final traffic dataset is comprised of a balanced panel of 725 zip codes by 840,000 five-minute intervals over eight years, leading to a balanced panel of almost 50 million observations. The monitoring stations are primarily on major roads in urban areas, although some non-urban areas are included. While the sample is not necessarily representative in this respect, we do capture the urban areas where traffic is most likely to be a major challenge for fire departments. Figure 1 presents a map of the study location and the roads considered.[3]

In order to merge the traffic data to the fire incident data, we assign the most recent five-minute traffic data *prior* to the alarm being raised. This ensures that the incident did not cause the traffic. We have the exact minute that the alarm was raised, but five-minute

[2] The data can be accessed via http://pems.dot.ca.gov/ A free account needs to be established.

[3] We contacted the fire departments to find out if traffic represented a challenge and whether they used the roads contained in the PemS data. Both the Los Angeles and San Francisco fire departments responded that traffic represented a challenge, that they use freeways, and that spillover traffic from freeways impacted response times. These correspondence are available upon request.

intervals for the traffic data. Therefore, the traffic interval will begin 6-10 minutes prior to the alarm being raised.[4] We also explore other temporal assignments of traffic including up to 60 minutes of traffic and a 10 minute buffer prior to the alarm time. Additionally, we generate traffic delays using other specifications of traffic such as the deviations in terms of travel times and not weighting by station occupancy.

We merge several additional data sets in order to investigate potential policies to mitigate the negative impact of traffic on first responders response time. In order to assess the effect of transportation policies, we use geocoded locations of high-occupancy vehicle lanes (HOV), high-occupancy toll lanes (HOT), and rail stations from the California Department of Transportation. We also incorporate data on annual municipal expenditure on a variety of categories obtained from the California State Controller.[5] From the Controller data, we generate variables for total per capita municipal expenditure as well as per capita expenditure on fire departments, EMS, police, roads, and public transport. In order to ensure that the spending occurs prior to the fire incidents, we merge expenditures from the most recent year prior to the incident. Lastly, we also use the 2010-2014 American Community Survey (ACS) from the Census Bureau to obtain aggregate zip code level characteristics to analyze heterogeneity by demographics. The final dataset contains 1.3 million observations of fire incidents merged with traffic conditions.[6]

Figure 2 shows a histogram of the time it takes for the fire department to arrive on the scene after they receive the alarm (in minutes). The vertical line shows that the average response time is slightly below 8 minutes, and after removing very high outliers the average response time is 6.5 minutes. Figure 3 displays the average deviation in MPH across all zip codes by time of day. Consistent with most urban areas, Figure 3 shows notable peak traffic in the morning and afternoon.

Traffic in California is a severe issue in several major cites. For example, Los Angeles is a candidate for the worst traffic in the United-States and in the world; six of the country's 10 most congested stretches of highway are in the Los Angeles metropolitan area. Drivers in Los

[4] For example, if the alarm was raised between 1:31-1:35 we will use traffic from 1:25-1:30.

[5] The data are available online at `https://bythenumbers.sco.ca.gov/`.

[6] We remove outliers that may skew the results by dropping incidents with response time exceeding the 99.75th percentile, which is 45 minutes.

Angeles spent 102 hours battling traffic congestion during peak hours in 2017.[7] According to Sorensen (2009), congestion is due to the high population density and the fact that parking is cheap and abundant. San Francisco is also among the top ten of worse cities for traffic conditions in the United-States and ranks third behind Los Angeles and New York. The typical driver in the San Francisco area faces an average of 79 hours of congestion. The situation is also problematic in other cities in California such as San Diego (48 hours of congestion and ranked 13th worse cities in the U.S.) and Sacramento (25 hours of congestion). We replicate Figure 3 for each major metropolitan area as well as zip codes not in a major metro area in Figure 4. The Bay Area (which includes San Francisco, Oakland, Berkeley, and San Jose) and Los Angeles have the worse traffic followed by San Diego and Sacramento. Zip codes outside of major metro areas (Other) do not experience severe delays.

4 Methodology

To quantify the impact of traffic on response time and damages, we estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 LagDelay_{it-1} + \beta_Z + \beta_{MY} + \beta_D + \beta_H + \tau + \tau^2 + \epsilon_{it} \tag{1}$$

where Y_{it} is the outcome of interest in zip code i on day t. Our main outcomes of interest are responses time (in minutes) and the natural log of the dollar value of damages from fires. Response time is the time elapsed from when the alarm is sounded until the fire department arrived on the scene in minutes. All zero values and high outliers above the 99.75th percentile (45 minutes) are dropped. Loss (or damage) is the natural log of the monetary value of damaged property and contents from a fire. $LagDelay_{it-1}$ is the standardized deviation from free-flow in miles per hours during the five minutes immediately preceding the fire alarm. We use zip code level fixed effects (β_Z) to control for static spatial unobserved effects. To control for time-varying unobservables, we include year-by-month (β_{MY}), day-of-week (β_D), and hour of day (β_H) fixed effects. Our identifying assumption is that the lagged deviations from average traffic in a given zip code, in a given month, on a given day of the week, at

[7] See the INRIX Traffic Scoreboard, available at: http://inrix.com/scorecard/.

a given hour is uncorrelated with response times except through the mechanism of traffic. We posit that traffic congestion is plausibly exogenous because we use the traffic *before* the fire/incident occurs. Robust standard errors are clustered at the zip code level. To better understand the relationship between traffic and response time, we investigate heterogeneous impact along several dimensions: time of day, individual cities and zip code characteristics including average traffic. We also look at several alternative traffic specifications, including different traffic conditions before the alarm is received and alternative definition of traffic delays. Finally, we analyze policies that can potentially mitigate the results and investigate how these policies affect response time and damages from fires.

5 Results

5.1 Main Results

Table 1 presents the primary results of the impact of traffic on response time. The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm. Column (1) presents results for all observations (fires, all emergency medical services (EMS), and all emergency calls) and shows that traffic leads to a significant increase in response time. Columns (2) and (3) present results for fires and EMS calls, respectively and show that traffic increases response times for fires and EMS calls. The sample for the regression presented in column (4) represents all incidents where rapid response times are critical and is our primary specification for all future regressions except where noted. Column (4) presents results for all emergency calls which include fires, EMS calls, and incidents where the fire department is dispatched to address incidents involving overpressure rupture, explosion, overheating or hazardous conditions without fires. Once again, traffic significantly increase response time.

Since the Lag Delay is standardized, the interpretation of the coefficient is the change in response times (in minutes) for a one standard deviation increase in traffic congestion. A one standard deviation increase in traffic delay ($\approx$ 8 mph) is roughly equivalent to the average delay during the morning peak congestion period. Our preferred specification in column (4) shows that the increase in response time is 0.055 minutes, equating to a roughly 1% increase in response times.[8]

5.2 Heterogeneous Effects

We examine heterogeneous impacts for different times of day, locations, and traffic conditions. As shown in Figure 3, traffic congestion varies significantly over the course of the day, so we run regressions for the different times of the day. Table 2 reports regression results for the effect of traffic on response times during Peak, Off-Peak, AM Peak and PM Peak periods. Peak refers to alarms initiated in the peak morning (6:00-7:59 AM) and evening (4:00-6:59 PM) commutes, while Off-Peak refers to all other times. Column (1) and (2) focus on alarms initiated in Peak and Off-Peak hours, respectively. Columns (3) and (4) focus exclusively on morning and evening peak periods. Traffic increases response times during all times of the day with the largest effects in the Off-Peak and morning peak periods.

To examine whether zip codes with different traffic profiles experience different marginal effects, we also run regressions for different subsets of the sample based on zip code level traffic conditions. Table 3 reports regression results that divide the sample by zip codes' mean and standard deviation of traffic. Columns (1) and (2) present regressions that restrict the sample to zip codes with average delays above and below the sample median, respectively. Column (3) and (4) present regressions that restrict the sample to zip codes with standard deviation of delays above and below the sample median. Table 3 shows that in all four samples, traffic significantly increases response time, and the effect is significantly more pronounced in low traffic zip codes and low standard deviation zip codes. This suggest habituation and adaptation by first responders in high traffic and high standard variation zip codes that allow them to better cope with traffic congestion.[9]

We next explore the role of expected vs unexpected traffic. In Table 4, we estimate moving average models to predict traffic and then use both the predicted value and the residual as regressors, which we refer to as Expected and Unexpected, respectively. The moving average regressions include all fixed effects as our base specification along with recent traffic.

[8] While the average effect is small there are incidents that face traffic speeds that deviate from free flow by more than 15 MPH, and we investigate the heterogeneity of the effect below. We also present below the impact of traffic on damages and find an economically significant impact of traffic on damages.

[9] It should be noted that most zip codes with high traffic also have a high standard deviation of traffic.

The columns show different specifications for predicting our primary independent variable: zip code level traffic prior to a fire alarm. Columns (1) and (2) present moving average models using the traffic observations for the most recent week and month, respectively, using the traffic during the exact same hour of the day. Columns (3) and (4) present a similar specification for traffic in the last week or month but expand the temporal period used to predict traffic to all hours during the same peak period (AM, PM, or Off-Peak).[10] Table 4 shows that there is an impact for both predicted and unpredicted traffic when the prediction is sufficiently accurate. As the prediction becomes less accurate, unexpected traffic becomes more important.[11]

Next, we investigate heterogeneity in response time across metropolitan areas in Table 5. Column (1) presents the results for the Los Angeles (LA) metro area, column (2) for the Bay Area (SF), column (3) for the San Diego (SD) metro area, column (4) for the Sacramento (SAC) metro area, and column (5) for all observations not within one of the four aforementioned metro areas.[12] Table 5 shows that traffic causes an increase in response time in Los Angeles, San Francisco, San Diego and Sacramento but not in the non-urban locations (the coefficient is positive but not significant). This indicates that, unsurprisingly, traffic only slows down fire departments in highly urbanized areas. Another interesting finding is that the effect is remarkably consistent across metro areas, ranging from 0.051 to 0.066 minutes for a one standard deviation increase in delays.

Table 6 investigates the response time by zip code characteristics. Columns (1) and (2) present the results for high and low income areas, respectively. Columns (3) and (4) present results for high non-white areas and low non-white areas, respectively. High income refers to zip codes above the sample median for median household income and high non-white refer to zip codes that are above the sample median for the percentage of people that are not white. Column (5) presents the base impact and interaction terms for high income and low-non

[10] First Stage shows the coefficient on the moving average variable in the first stage regression - a perfect prediction will have a value of one. Both the residuals and predicted values are standardized.

[11] One reason why we show multiple specifications of the moving average model is that we do not know how accurately fire departments can predict traffic. If fire departments make accurate traffic predictions, then they will know when traffic causes increased response times.

[12] We use general metropolitan areas as opposed to municipal boundaries. This means that all metro areas include multiple fire departments.

white areas. Table 6 shows that traffic increase significantly the response time in all areas and the difference between areas are not statistically significant.

Next, we examine nonlinearities in traffic congestion. This is similar to examining peak traffic congestion and high traffic zip codes, but we also include time series variation in traffic condition. This specifications more precisely identifies incidents where the fire department faces very severe traffic. We specify the regression using decile indicators variables for lagged traffic delay, where the fifth decile is omitted to avoid perfect multicollinearity.[13] Therefore, the coefficients can be interpreted as the change in response times relative to the median traffic within a certain decile. Figure 5 plots the coefficients and 95% confidence intervals for traffic decile indicators and shows that the impact on response times is concentrated in the three highest deciles (8-10). Traffic below the median does improve response times.[14] Traffic in the 10th decile increases response times by 3%. This is consistent with other research that finds that traffic variability and right tail events, in addition to average congestion, generate significant costs (Beland and Brent, 2018; Gross and Brent, 2018).

Figure 6 presents regression results for the decile indicators after separating the sample into High and Low traffic areas. The High Traffic and Low Traffic regressions limit the sample to zip codes with average delays above and below the median average delay. Figure 6 shows similar results to Figure 5, and the effect of traffic on response time is higher in zip codes with low traffic. This is consistent with the explanation that unexpected traffic leads to larger increases in response times. Fire departments in high traffic areas may expect extreme traffic events and invest in resources to cope with those events. Figure 7 shows the regression results for decile indicators sample after isolating the sample, and generating the deciles, for each metropolitan area. Once again, in all four major metropolitan areas, traffic in the right tail generates most of the increase in response times and non-urban areas do not experience any significant effects.

[13]The regression includes zip code, year-by-month, day-of-week, and hour-of-day fixed effects.

[14]Figure A.1 plots the coefficient for indicators variables for deciles of traffic congestion within each zip code. Results are qualitatively the same as Figure 5

5.3 Robustness

In order to test whether alternative confounding effects are driving the results, we investigate the robustness of the results to different levels of fixed effects, clustering, and specifications of the traffic variable. Our first set of robustness results, presented in Table 7 shows a variety of different sets of fixed effects and clusters for the standard errors. Column (1) replicates the base effect, column (2) replaces year-by-month fixed effects with date fixed effects, column (3) replaces year-by-month fixed effects with metro-by-year-by-month fixed effects, column (4) uses metro-by-date fixed effects, and column (5) interacts all fixed effects (year-by-month, hour-of-day, and day-of-week) with metro fixed effects. Columns (6) and (7) replicate the specification in column (5) but employ two way clustering for zip code and year-by-month and zip code and hour-of-day, respectively. Table 7 shows that the results are robust to all the alternative specifications and the coefficients are very similar across all columns.

There are more zip codes than fire departments so we prefer using zip code fixed effects in our main specifications. However, some zip codes are served by more than one fire department and there may be unobserved fire department specific effects. Therefore, we also replicate these specifications using both zip code and fire department fixed effects as well as including fire departments as an additional cluster in the standard errors. The results are essentially unchanged and are reported in Table A.1 in the Appendix.

Our primary traffic congestion variable is the deviation from free flow in terms of speed (in mph). As described in section 3, we also generate deviations from zip code free-flow travel times. This variable is specified as the standardized deviation from free flow travel times in the five minutes preceding the alarm by free-flow travel times. Table 8 replicates Table 7 using travel time deviations instead of speed deviations. Table 8 shows once again that traffic increases response times in all the different specifications, and the magnitudes are very similar.

Lastly, we investigate different temporal specifications of the traffic variable. Our primary specification uses traffic in the previous five minutes using a five minutes lag from when the alarm was raised. Table 9 presents different traffic specifications to estimate the impact of traffic on response time. The first five columns use a five minute lag before the alarm but expand the historical window of traffic used to generate the congestion variable. The last three columns use a ten minute lag before the alarm was raised and various times to generate the traffic conditions.[15] In all specifications, the results are similar. Table 9 shows that traffic increases response times by first responders and that the results are robust to different ways of calculating traffic congestion.

5.4 Policy Investigation

In order to understand how municipalities are coping with the effect of traffic on first responders, we investigate potential road congestion policies (HOV lanes, toll roads, public transportation, and spending) that could potentially mitigate the negative impact of traffic on response time. In order to explore how carpool lanes, tolling, and rail public transport mitigate the effect of traffic on response times, we create indicator variables for zip codes that have HOV lanes and toll roads and interact those variables with traffic. Table 10 presents the results of these regressions. Column (1) presents the impact of HOV lanes, column (2) studies the impact of toll lanes, and columns (3) and (4) present the impact of the zip code being served by the rail system and metro stations, respectively.[16] Column (5) interacts all four policies with traffic. Table 10 shows than none of the interaction terms for those policies are statistically significant and the main effect of traffic on response time is again statistically significant and similar to Table 1. In sum, these policies do not appear to decrease the negative impact of traffic on response times. These policies may decrease congestion, but they do not mitigate the marginal effect of congestion on response times.

Table 11 presents the impact of lagged city expenditure on response time.[17] We consider the following expenditure categories: total, road, transit, fire department and EMS spending. We include both the base effect and the interaction of spending with traffic. Spending variables are defined as hundreds of dollars per capita. Table 11 shows that spending an additional \$100 per person per year on fire departments reduces response times by 1.5 minutes,

[15] If an alarm was raised at 11:50 the base specification (5 min with 5 min lag) uses traffic from 11:40-11:45). The 30 min with 5 min lag will use traffic from 11:15-11:45, and the 30 min with 10 min lag uses traffic from 11:10-11:40.

[16] Metro stations are a subset of rail stations that focus on local transportation. By contrast, rail stations also include longer distance (inter-city) rail lines.

[17] Unlike our broad definition for metropolitan area, city expenditure is defined at the municipal level and there are multiple municipalities in each metro area. Therefore, the expenditure data has a finer spatial resolution than the four broad cities.

and the result is statistically significant. This is a large increase in spending as the average municipality spends only $167 per person per year, so $100 represents a 60% increase in spending. Examining the interaction effects shows that spending on fire departments does not decrease the effect of traffic on response times, although spending on public transit does.[18]

In order to assess the economic impact of traffic congestion on increased response times, we analyze the effect of traffic on damages from fires. Table 12 presents the regression results of traffic on damages where the dependent variable is the natural log of the dollar value of damages. These regressions only utilize fires as opposed to other emergencies.[19] The first three columns use the full sample while the last three remove high damages outliers, defined as fires generating over $1 million of damage. Column (1) presents our base specifications, column (2) present the impact by quintiles and column (3) presents our base specification with additional controls for spending category.[20] Column (1) shows that a one standard deviation in delays increases damages by roughly 3%. Column (2) shows that the negative impact of delays on damages is concentrated among the 5th quintile of delays (larger delays). Incorporating spending data in Column (3) shows that spending on transit and fire department has negative and significant impact on the monetary impact of damages. Column (4)-(6) replicates column (1)-(3) but remove high damages outliers and the results are qualitatively the same.

Estimates for Aggregate Costs

From the damage estimates, we generate back of the envelope calculations for the aggregate economic effect of traffic on emergency response services. First, we examine the effect of traffic on the the dollar value of damages from fires. This does not include any injuries or deaths, nor does it include the effect of reduced response times on other types of emergencies. A one standard deviation increase in traffic, roughly equivalent to the average traffic con-

[18]Total spending increases response times, but that may be representing a demand or population effect. Total spending increases the marginal effect of traffic, though the effect is very small.

[19]These regressions drop all observations where the damage was zero but the value of property is missing. These observations may represent fires where the reporting department did not fully complete the damage section of the form.

[20]We use quintiles instead of deciles due to the smaller sample size in the fire regressions. The third quintile is omitted so the interpretation of the dummies is the effect relative to median traffic.

gestion during peak periods, generates an additional $12 million dollar in fire damages per year.[21] Extrapolating to all fires in California, including fires not in our dataset, generates damages of roughly $33 million of increased fire damages per year.[22]

In order to assess the costs from non-fire emergencies, we also evaluate the impact of increased response times due to traffic on EMS mortality rates. Wilde (2013) estimates that a one minute increase in EMS response times leads to a 1% increase in 90-day mortality rates. Using the 1% marginal mortality effect combined with our estimates of traffic on response times shows that a one standard deviation increase in traffic is responsible for an additional 23 deaths per year, assuming a base mortality rate of 6% found in Wilde (2013). Extrapolating to all EMS services provided by fire departments in California generates 64 additional annual deaths due to a one standard deviation increase in traffic. Using the U.S. Department of Transportation's Value of a Statistical Life of $9.6 million, a one standard deviation increase in traffic leads to $220-$614 million of damages due to increased mortality from EMS services.[23] If we combine the fire and EMS costs and scale them by average traffic (average traffic is 56% of the standard deviation of traffic) the current annual damages from average traffic due to slower emergency response times in California is roughly $130-$360 million dollars. These are clearly rough approximations that require significant extrapolation and should primarily used to provide the general range of economic damages due to traffic slowing down first responders. These damages do not account for costs associated with police or paramedics when fire departments are not on the scene, although they are likely to face increased response times due to traffic congestion.

6 Conclusion

This paper examines the relationship between traffic and emergency response times. We match traffic data at a fine spatial and temporal scale to incident report data from fire

[21]This is calculated by multiplying the marginal effect of damages (3% times the mean damage, which is $35,879) by the number of fires per year and scaling the effect by average traffic.

[22]The extrapolation uses all fires with damages in the NFIRS data and scales divides by 0.75 to account that only 75% of fire incidents are reported to NFIRS. Similar to our regressions, these estimates exclude all wildfires.

[23]Documentation of revised value of statistical life estimates for the Department of Transportation are provided at: https://www.transportation.gov/sites/dot.gov/files/docs/2016%20Revised%20Value%20of%20a%20Statistical%20Life%20Guidance.pdf. This is consistent with the upper range estimated by Kniesner et al. (2012).

departments, using fire department data collected by the NFIRS and traffic data from the California Department of Transportation for 2008 to 2015. Our results show that traffic delays fire trucks arriving at the scene of fires, EMS, and other emergencies. Traffic also increases the average monetary damage from a fire. Our results document an additional externality of traffic congestion and highlight the importance of a well-functioning road network. We then investigate potential common congestion policies that might mitigate this problem. HOV lanes, toll roads, public transportation, and spending do not decrease the marginal effect of traffic on response times. Allocating more money to the fire departments decreases response times but does not mitigates the negative effect of traffic. Spending on public transit is the only expenditure that mitigates the effect of traffic on response times, but the marginal effect of one dollar per person is small.

In aggregate, the increased monetary damages from fires and emergency medical services due to traffic is approximately $130-$360 million per year in California. These costs do not account for increased response times for ambulances or police, and therefore should be considered a lower bound for the costs of traffic on emergency response services. The results document an additional benefit for reducing traffic and also highlight the benefit of increased spending on fire department. We do not account for costs of adaptive investments that fire departments undertake to cope with traffic congestion. New stations or trucks might need to be purchased in order to maintain adequate response times, further increasing the costs of traffic congestion on first responders. Lastly, the results highlight the importance of understanding linkages between public goods. A fire department relies on well functioning roads to perform their duties, and many other public goods that rely on alternative public goods. Understanding these linkages is important for properly allocating scarce public resources.

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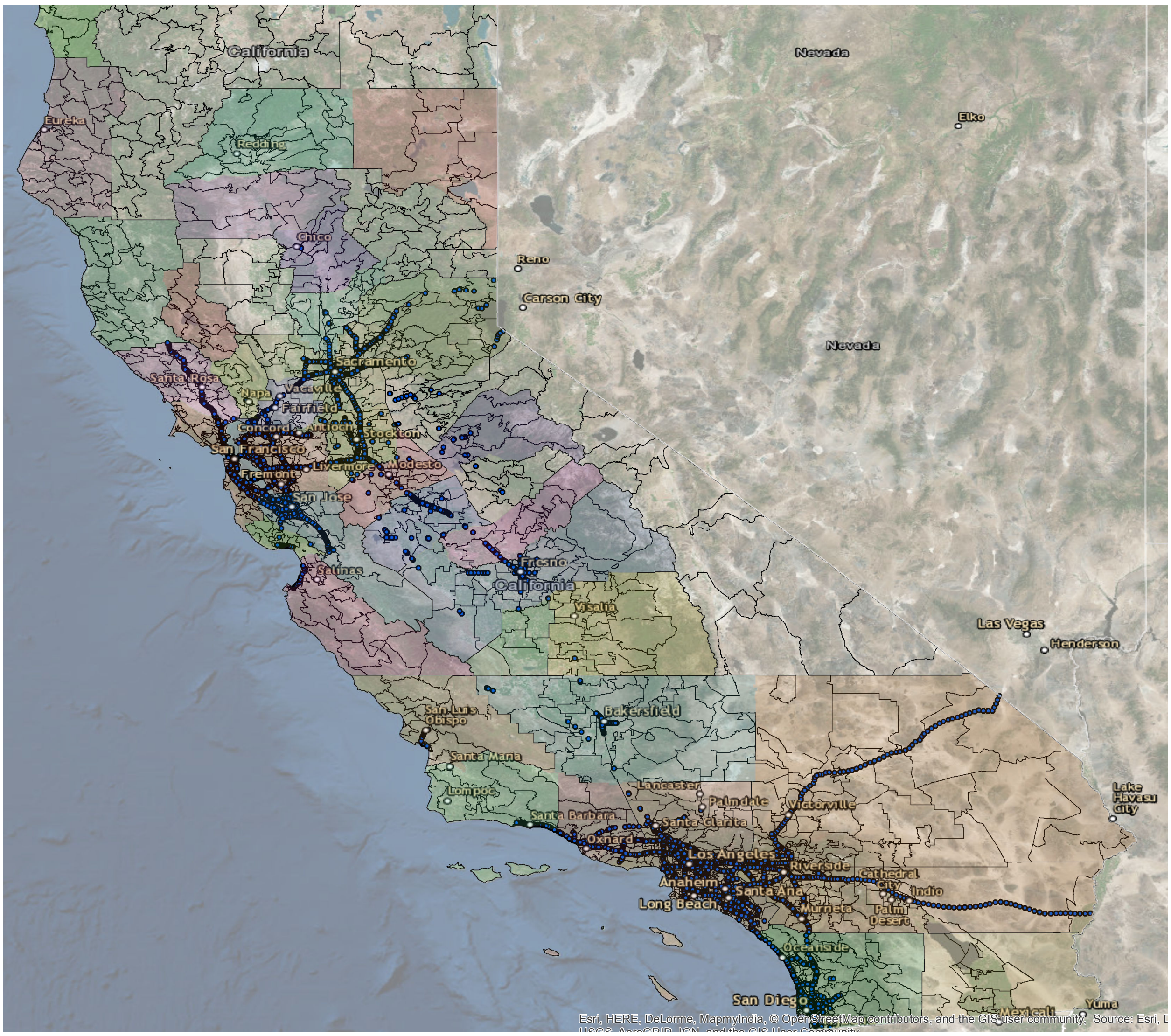
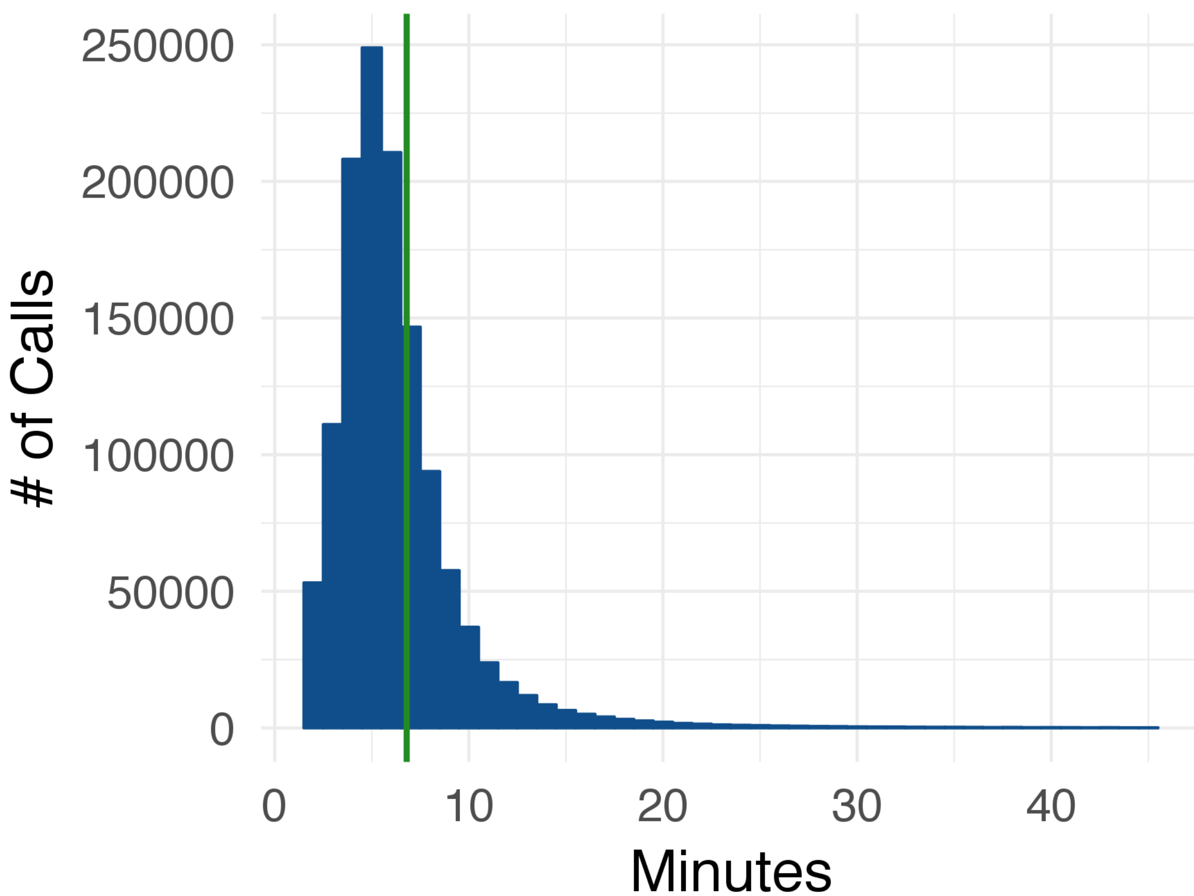
Figure 1: Study Location



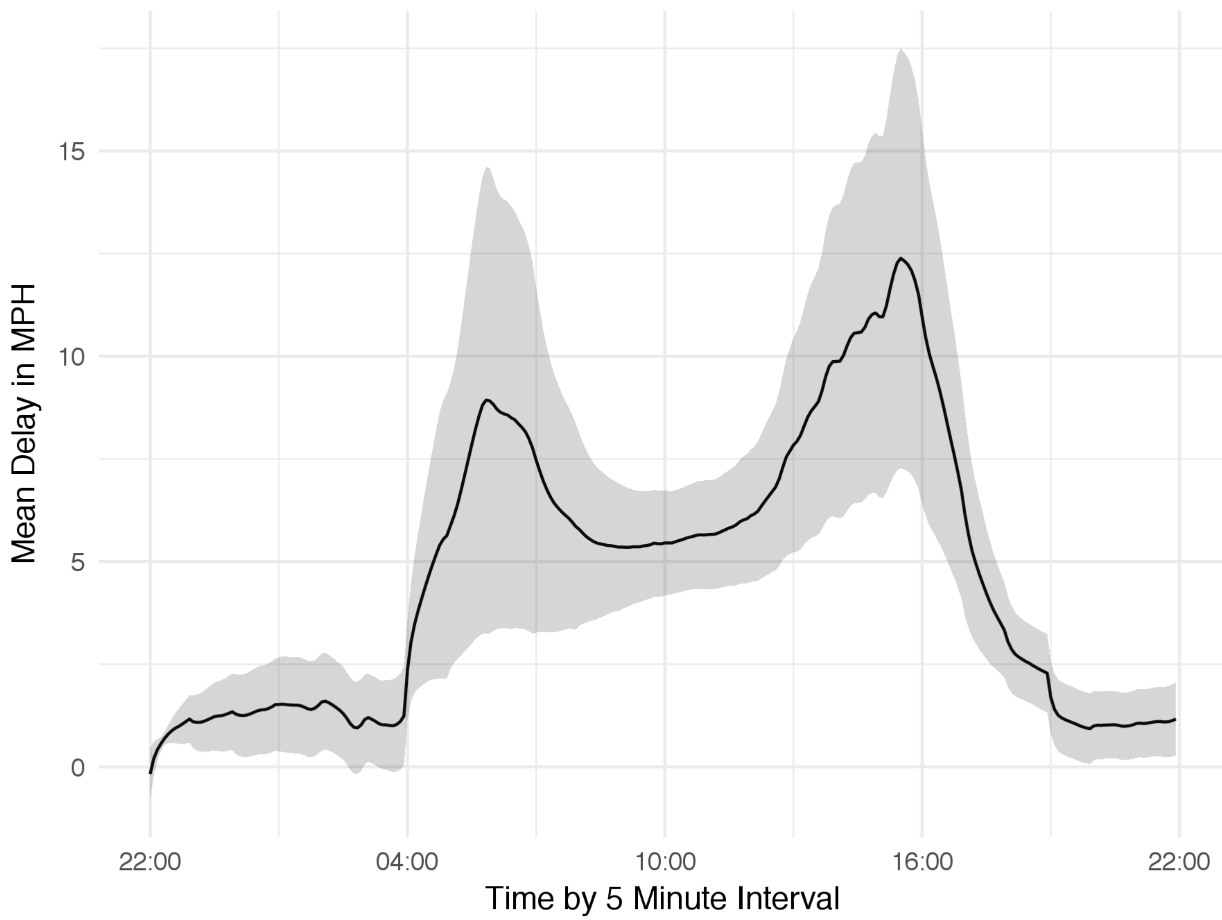
Notes: The figure plots the study location.

Figure 2: Response Time



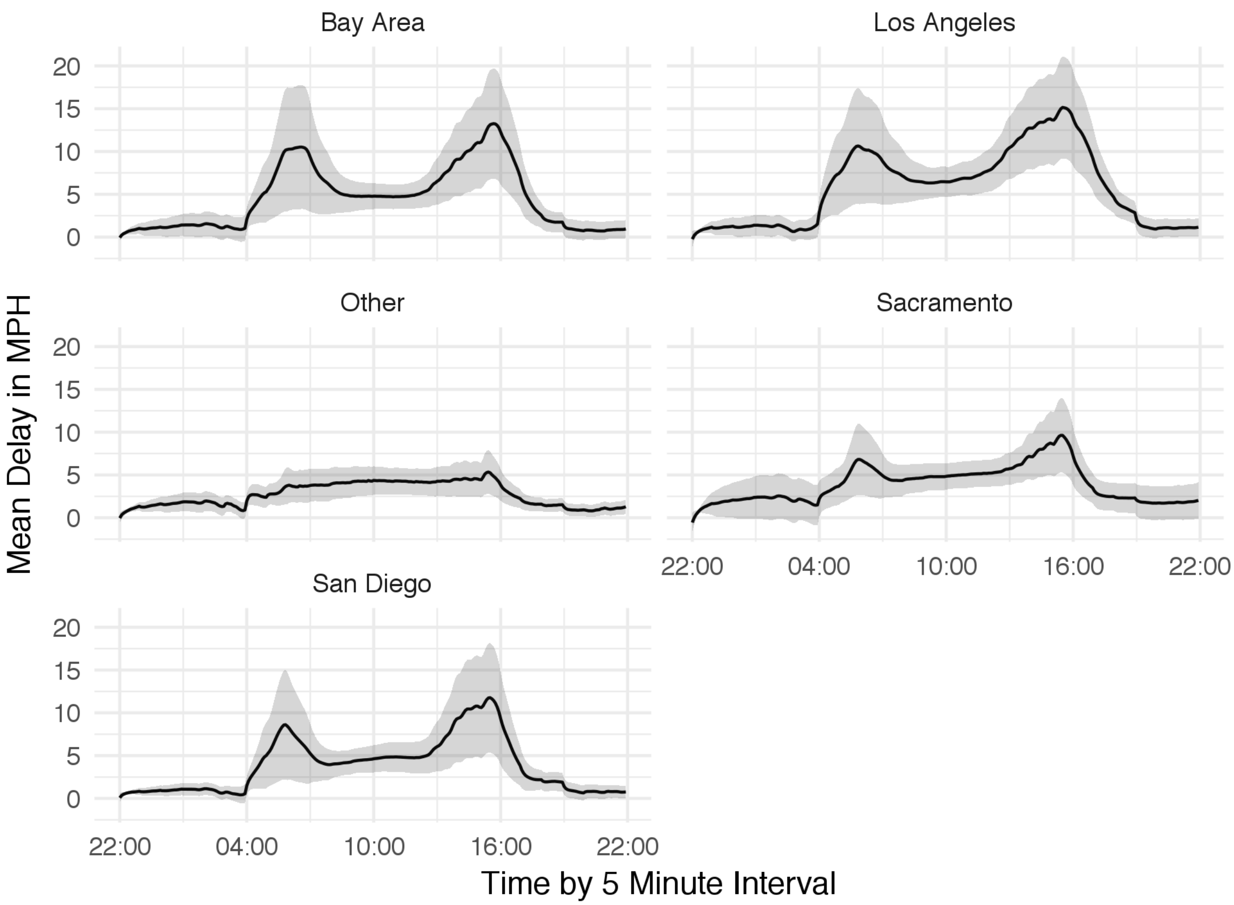
Notes: The figure plots the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time) on the horizontal axis. Data are from the NFIRS from 2008-2014.

Figure 3: Traffic Delay by Time of Day



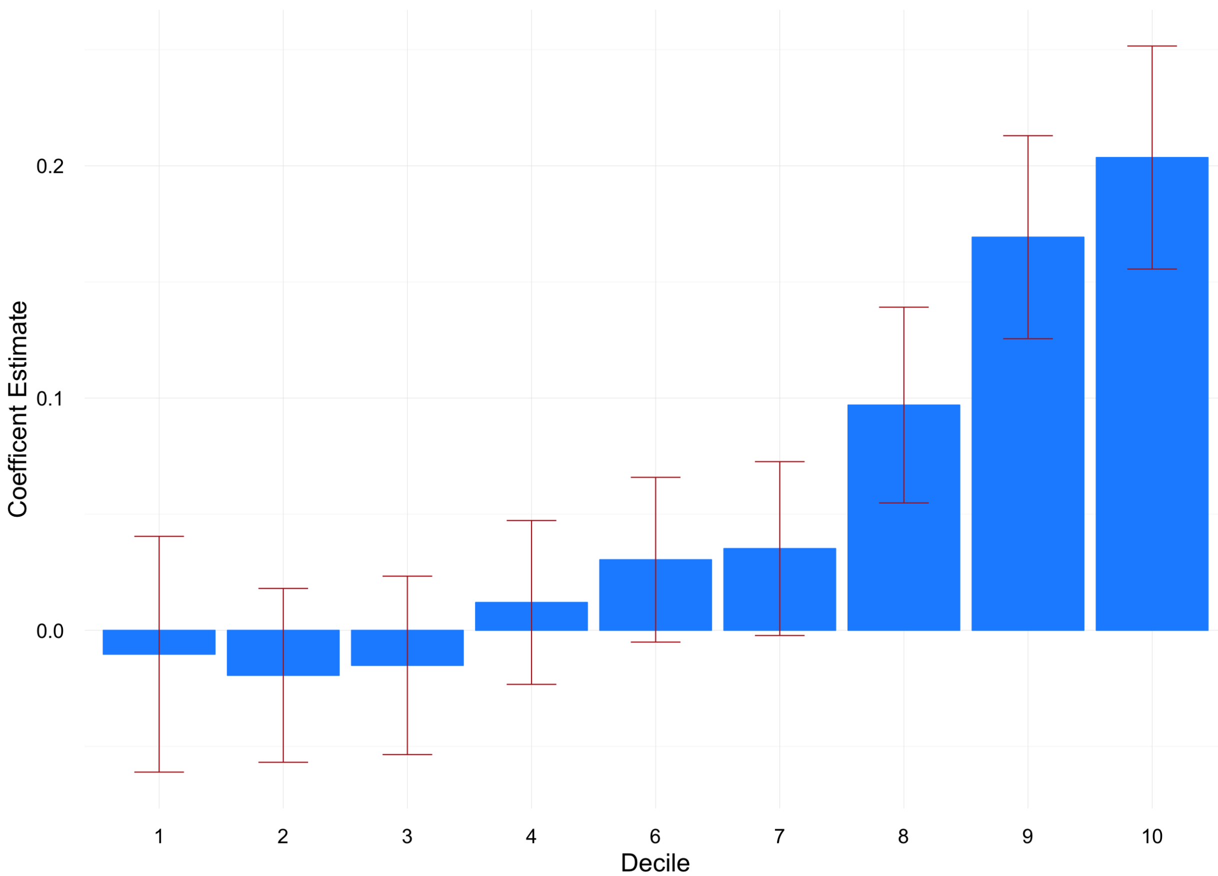
Notes: The figure plots the delay in miles per hour (MPH) by time of day. Data are from the California Department of Transportation Performance Measurement System (PeMS) from 2008-2014.

Figure 4: Traffic Delay by Time of Day Across Metro Areas



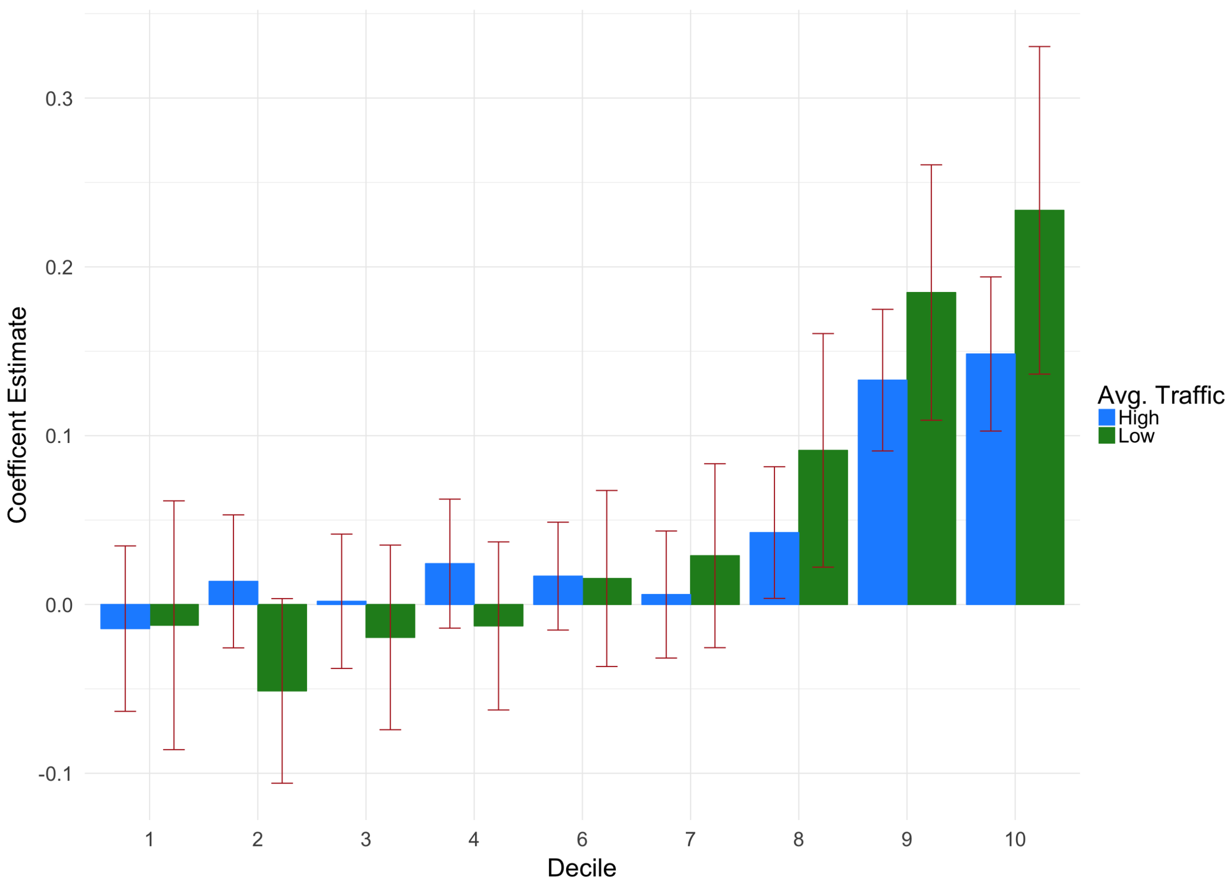
Notes: The figure plots the delay by time of day for each core based statistical area (CBSA). Data are from the California Department of Transportation Performance Measurement System (PeMS).

Figure 5: Effect of Deciles of Traffic on Response Time



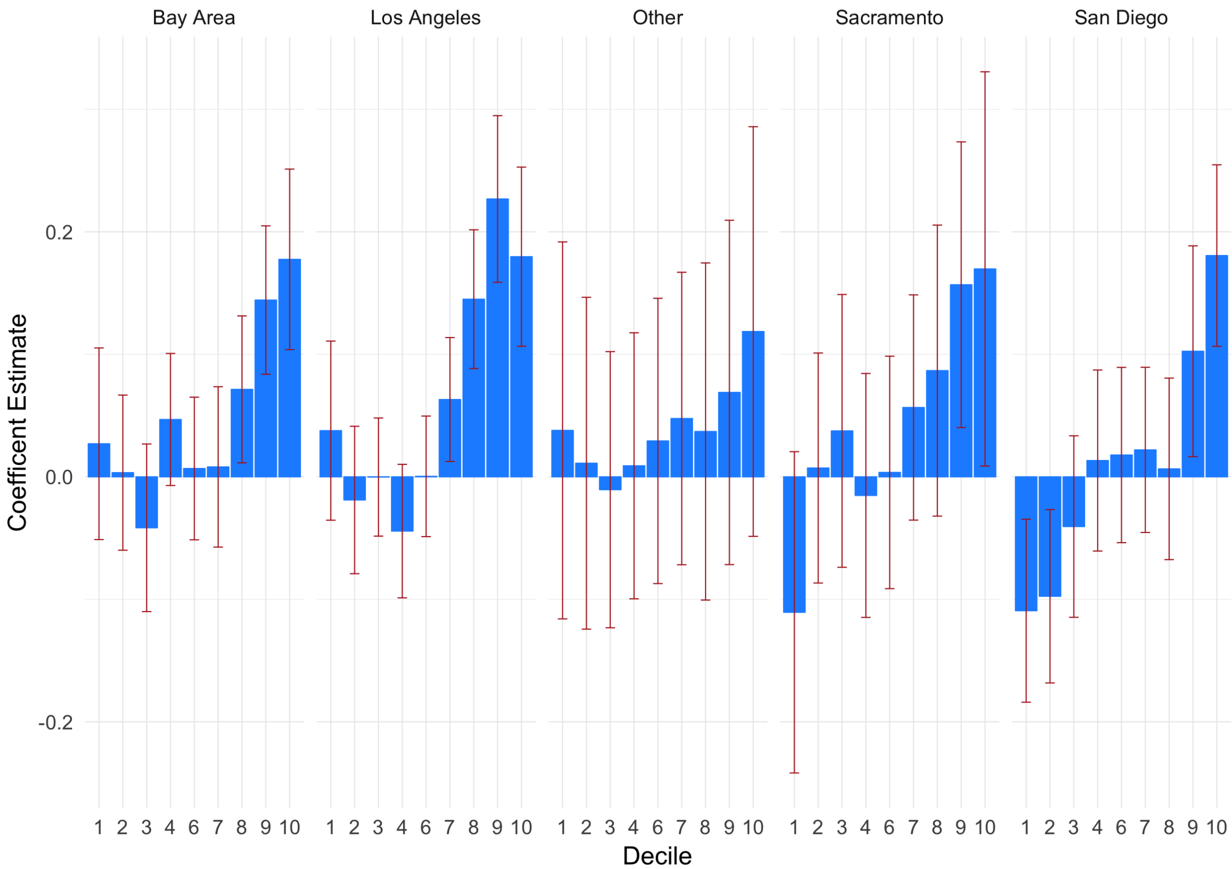
Notes: The figure plots the coefficient for indicators variables for deciles of traffic congestion from a regression where the dependent variable is response time (in minutes). The fifth decile is omitted to prevent perfect multicollinearity. The regression includes zip code, year-by-month, day-of-week, and hour-of-day fixed effects. The 95% error bars are generated from robust standard errors clustered at the zip code level.

Figure 6: Effect of Deciles of Traffic on Response Time by Traffic Conditions



Notes: The figure plots the coefficient for indicators variables for deciles of traffic congestion from regressions where the dependent variable is response time (in minutes). The results are from two regressions, the High Traffic and Low Traffic regressions limit the sample to zip codes with average delays above and below the median average delay. The fifth decile is omitted to prevent perfect multicollinearity. The regressions includes zip code, year-by-month, day-of-week, and hour-of-day fixed effects. The 95% error bars are generated from robust standard errors clustered at the zip code level.

Figure 7: Effect of Deciles of Traffic on Response Time by Metro Area



Notes: The figure plots the coefficient for indicators variables for deciles of traffic congestion from regressions where the dependent variable is response time (in minutes). The results are from separate regressions for each core based statistical area (CBSA), and the deciles are calculated within each CBSA. Other refers to all zip codes not in one of the major CBSAs listed. The fifth decile is omitted to prevent perfect multicollinearity. The regressions includes zip code, year-by-month, day-of-week, and hour-of-day fixed effects. The 95% error bars are generated from robust standard errors clustered at the zip code level.

Table 1: The Effect of Traffic on Response Time

	(1) All Observations	(2) Fires	(3) EMS	(4) Emergency Calls
Lag Delay	0.0569***	0.0274**	0.0511***	0.0553***
	(0.00659)	(0.0125)	(0.00638)	(0.00662)
Zip Code FEs	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes
Observations	1,227,827	239,835	668,746	1,044,356
Zip Codes	721	709	608	719

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns denote subsets of the data for incidents representing fires, all emergency medical services (EMS), and all emergency calls. Emergency calls includes fires, EMS calls as well as incidents where the fire department is dispatched to address incidents involving overpressure rupture, explosion, overheating or hazardous conditions without fires. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Heterogeneity in Traffic on Response Time by Time of Day

	(1) Peak	(2) Off-Peak	(3) AM Peak	(4) PM Peak
Lag Delay	0.0416***	0.0748***	0.0739***	0.0320***
	(0.00747)	(0.0101)	(0.0134)	(0.00825)
Zip Code FEs	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes
Observations	344,053	700,280	100,981	243,049
Zip Codes	696	713	651	691

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns examine different subsets of the sample by time of day. Peak focuses on alarms initiated in the peak congestion (6:00-7:59AM and 4:00-6:59PM), while Off-Peak is all other times The AM and PM Peak columns restrict the sample to morning (6:00-7:59AM) and evening (4:00-6:59PM) respectively. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Heterogeneity in Traffic on Response Time by Traffic Conditions

	(1) High Traffic	(2) Low Traffic	(3) High Std. Dev.	(4) Low Std. Dev.
Lag Delay	0.0328***	0.0936***	0.0352***	0.109***
	(0.00668)	(0.0161)	(0.00638)	(0.0177)
Zip Code FEs	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes
Observations	529,230	515,126	535,806	508,550
Zip Codes	381	338	384	335

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns examine different subsets based on zip code level traffic conditions. The High and Low Traffic columns restrict the sample to zip codes with average delays above and below the sample median. The High and Low Std. Dev. columns restrict the sample to zip codes with standard deviation of delays above and below the sample median. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Heterogeneity in Traffic on Response Time by Traffic Expectations

	Hour		Peak	
	(1)	(2)	(3)	(4)
	Week	Month	Weak	Month
Expected	0.0350***	0.0374***	0.00971	0.0137*
	(0.00931)	(0.0104)	(0.00774)	(0.00764)
Unexpected	0.0371***	0.0368***	0.0446***	0.0424***
	(0.00421)	(0.00413)	(0.00467)	(0.00467)
First Stage	.78	.84	.67	.52
Zip Code FEs	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes
Observations	1,017,957	1,015,428	1,018,343	1,016,980
Zip Codes	719	716	719	718

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Residual and Prediction refer to the residuals and predicted values from a moving average regression with all fixed effects and recent delays. The columns show different specifications for the month average; either the previous week or month and using the same our or same peak period (AM, PM or Off-Peak). First Stage shows the coefficient on the moving average variable in the first stage regression - a perfect prediction will have a value of one. Both the residuals and predicted values are standardized. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Heterogeneity in Traffic on Response Time: Different Metro Areas

	(1)	(2)	(3)	(4)	(5)
	LA	SF	SD	SAC	Other
Lag Delay	0.0527***	0.0509***	0.0526***	0.0662**	0.0186
	(0.0115)	(0.00834)	(0.0136)	(0.0280)	(0.0331)
Metro	LA	SF	SD	SAC	Other
Zip Code FEs	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes	Yes
Observations	355,963	203,146	174,353	127,180	183,714
Zip Codes	312	148	64	62	133

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns show regressions for each metro area separately. Other contains all zip codes not in one of the four major cities shown. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Heterogeneity in Traffic on Response Time by Demographics

	(1) Hi Income	(2) Low Income	(3) High Non-White	(4) Low Non-White	(5) Interactions
Lag Delay	0.0612***	0.0498***	0.0401***	0.0661***	0.0550***
	(0.00843)	(0.0106)	(0.00807)	(0.0106)	(0.0143)
Lag Delay*Hi Income					-0.00388
					(0.0129)
Lag Delay*Hi Non-White					0.00436
					(0.0129)
Zip Code FEs	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes	Yes
Observations	538,193	506,163	526,152	518,204	1,044,356
Zip Codes	428	291	357	362	719

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns examine different subsets based on zip code level demographics. The High and Low Income/Non-White columns restrict the sample to zip codes with above and below the sample medians. Column (5) interacts traffic delays with indicators for above the sample median income and proportion non-white. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Robustness to Different Specifications

	(1) Base	(2) Date	(3) Metro*YM	(4) Metro*Date	(5) Metro*All	(6) Metro*All	(7) Metro*All
Lag Delay	0.0553***	0.0497***	0.0520***	0.0465***	0.0506***	0.0506***	0.0506***
	(0.00662)	(0.00647)	(0.00654)	(0.00632)	(0.00649)	(0.00761)	(0.00743)
Zip Code FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	No	No	No	No	No	No
Day-of-week FEs	Yes	Yes	Yes	Yes	No	No	No
Hour-of-day FEs	Yes	Yes	Yes	Yes	No	No	No
Date FEs	No	Yes	No	No	No	No	No
Metro*Date FEs	No	No	No	Yes	No	No	No
Metro*Year*Month FEs	No	No	Yes	No	Yes	Yes	Yes
Metro*Day-of-week FEs	No	No	No	No	Yes	Yes	Yes
Metro*Hour-of-day	No	No	No	No	Yes	Yes	Yes
SE Cluster	Zip	Zip	Zip	Zip	Zip	Zip & Month	Zip & Hour
Observations	1,044,356	1,044,350	1,044,356	1,044,247	1,044,356	1,044,356	1,044,356
Zip Codes	719	719	719	719	719	96	24

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns examine different levels of fixed effects and two way clustering of the standard errors. Robust standard errors clustered at the level described in the bottom panel are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Robustness to Different Specifications - Travel Times

	(1) Base	(2) Date	(3) Metro*YM	(4) Metro*Date	(5) Metro*All	(6) Metro*All	(7) Metro*All
Travel Times	0.0421***	0.0398***	0.0397***	0.0376***	0.0404***	0.0404***	0.0404***
	(0.00608)	(0.00598)	(0.00598)	(0.00575)	(0.00564)	(0.00560)	(0.00623)
Zip Code FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	No	No	No	No	No	No
Day-of-week FEs	Yes	Yes	Yes	Yes	No	No	No
Hour-of-day FEs	Yes	Yes	Yes	Yes	No	No	No
Date FEs	No	Yes	No	No	No	No	No
Metro*Date FEs	No	No	No	Yes	No	No	No
Metro*Year*Month FEs	No	No	Yes	No	Yes	Yes	Yes
Metro*Day-of-week FEs	No	No	No	No	Yes	Yes	Yes
Metro*Hour-of-day	No	No	No	No	Yes	Yes	Yes
SE Cluster	Zip	Zip	Zip	Zip	Zip	Zip & Month	Zip & Hour
Observations	1,019,389	1,019,383	1,019,389	1,019,283	1,019,389	1,019,389	1,019,389
Zip Codes	716	716	716	716	716	96	24

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Travel Times is the percentage increase in zip code level travel times prior to the alarm. The columns examine different levels of fixed effects and two way clustering of the standard errors. Robust standard errors clustered at the level described in the bottom panel are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Robustness to Different Traffic Variables

	5min Lag					10min Lag		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	5min	10min	20min	30min	60min	5min	30min	60min
Lag Delay	0.0553***	0.0550***		0.0545***	0.0537***	0.0526***	0.0526***	0.0526***
	(0.00662)	(0.00666)		(0.00684)	(0.00694)	(0.00690)	(0.00690)	(0.00690)
Zip Code FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,044,356	1,044,361	1,050,924	1,044,376	1,044,405	1,041,840	1,041,840	1,041,840
Zip Codes	719	719	737	719	719	719	719	719

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns examine different ways to create the traffic conditions prior to the alarm. Robust standard errors clustered at the level described in the bottom panel are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Interactions with Tolling and Public Transport

	(1) HOV	(2) Toll	(3) Rail	(4) Metro	(5) All
Lag Delay	0.00657***	0.00712***	0.00706***	0.00672***	0.00695***
	(0.00113)	(0.000900)	(0.00103)	(0.000939)	(0.00139)
Lag Delay*HOV	0.000843				0.000515
	(0.00153)				(0.00166)
Lag Delay*Toll		-0.000570			-0.00112
		(0.00192)			(0.00207)
Lag Delay*Rail			-0.000297		-0.00188
			(0.00153)		(0.00215)
Lag Delay*Metro				0.00123	0.00296
				(0.00177)	(0.00248)
Zip Codes FEs	Yes	Yes	Yes	Yes	Yes
Month-Year FEs	Yes	Yes	Yes	Yes	Yes
Day of Week FEs	Yes	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes	Yes
Observations	1,044,362	1,044,362	1,044,362	1,044,362	956,655
Zip Codes	725	725	725	725	614

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns interact traffic delays with various indicator variables that affect transportation. HOV is equal to one if the zip code as high occupancy vehicle lanes, Toll is equal to one if the zip code has toll roads, Rail is equal to one if there are rail stations in the zip code, and Metro is equal to one if there is a municipal metro station in the zip code. Robust standard errors clustered at the level described in the bottom panel are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Interactions with Lagged Municipal Expenditures

	(1) Base	(2) Interaction
Lag Delay	0.00701***	0.00489***
	(0.000843)	(0.00171)
Total Spending$_{T-1}$	0.221***	0.209***
	(0.0474)	(0.0474)
Road Spending$_{T-1}$	-0.0656	-0.0453
	(0.175)	(0.182)
Transit Spending$_{T-1}$	-0.196	-0.108
	(0.358)	(0.362)
Fire Spending$_{T-1}$	-1.521***	-1.493**
	(0.580)	(0.588)
EMS Spending$_{T-1}$	-0.692	-0.655
	(1.746)	(1.811)
Lag Delay*Total$_{T-1}$		0.00180***
		(0.000672)
Lag Delay*Road$_{T-1}$		-0.00357
		(0.00459)
Lag Delay*Transit$_{T-1}$		-0.0122**
		(0.00490)
Lag Delay*Fire$_{T-1}$		-0.00428
		(0.00901)
Lag Delay*EMS$_{T-1}$		-0.00750
		(0.0224)
Zip Codes FEs	Yes	Yes
Month-Year FEs	Yes	Yes
Day of Week FEs	Yes	Yes
Hour-of-day FEs	Yes	Yes
Observations	953,637	953,637
Zip Codes	614	614

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The regressions include city level per-capita spending on various municipal expenses in the previous year in hundreds of dollars. Column (2) includes spending and the interactions of spending with traffic delays. Robust standard errors clustered at the level described in the bottom panel are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: The Effect of Traffic on Damages

	Full Sample			Remove High Damage Outliers		
	(1) Base	(2) Quintiles	(3) Spending	(4) Base	(5) Quintiles	(6) Spending
Lag Delay	0.0295**		0.0251*	0.0301**		0.0272*
	(0.0147)		(0.0148)	(0.0147)		(0.0165)
Lag Delay Q1		0.0499			0.0420	
		(0.0317)			(0.0316)	
Lag Delay Q2		-0.0169			-0.0129	
		(0.0309)			(0.0309)	
Lag Delay Q4		0.0105			0.0134	
		(0.0296)			(0.0292)	
Lag Delay Q5		0.0778**			0.0782**	
		(0.0383)			(0.0379)	
Total Spending$_{T-1}$			0.00484			-0.000112
			(0.00376)			(0.00289)
Road Spending$_{T-1}$			-0.0171			-0.0270
			(0.0212)			(0.0228)
Transit Spending$_{T-1}$			-0.306***			-0.296***
			(0.0471)			(0.0491)
Fire Spending$_{T-1}$			-0.127**			-0.0726**
			(0.0513)			(0.0353)
EMS Spending$_{T-1}$			-0.0969			-0.0472
			(0.131)			(0.0944)
Zip Code FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Hour-of-day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,040	83,705	72,549	80,734	83,392	72,286
Zip Codes	635	654	614	635	654	645

Notes: The dependent variable is the natural log of the dollar value of damages from a fire. Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. Lag Delay Q1-Q5 are dummy variables for quintiles of traffic congestion, with the third quintile omitted. The regressions in columns (3) and (4) include city level per-capita spending on various municipal expenses in the previous year in hundreds of dollars. Robust standard errors clustered at the zip code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

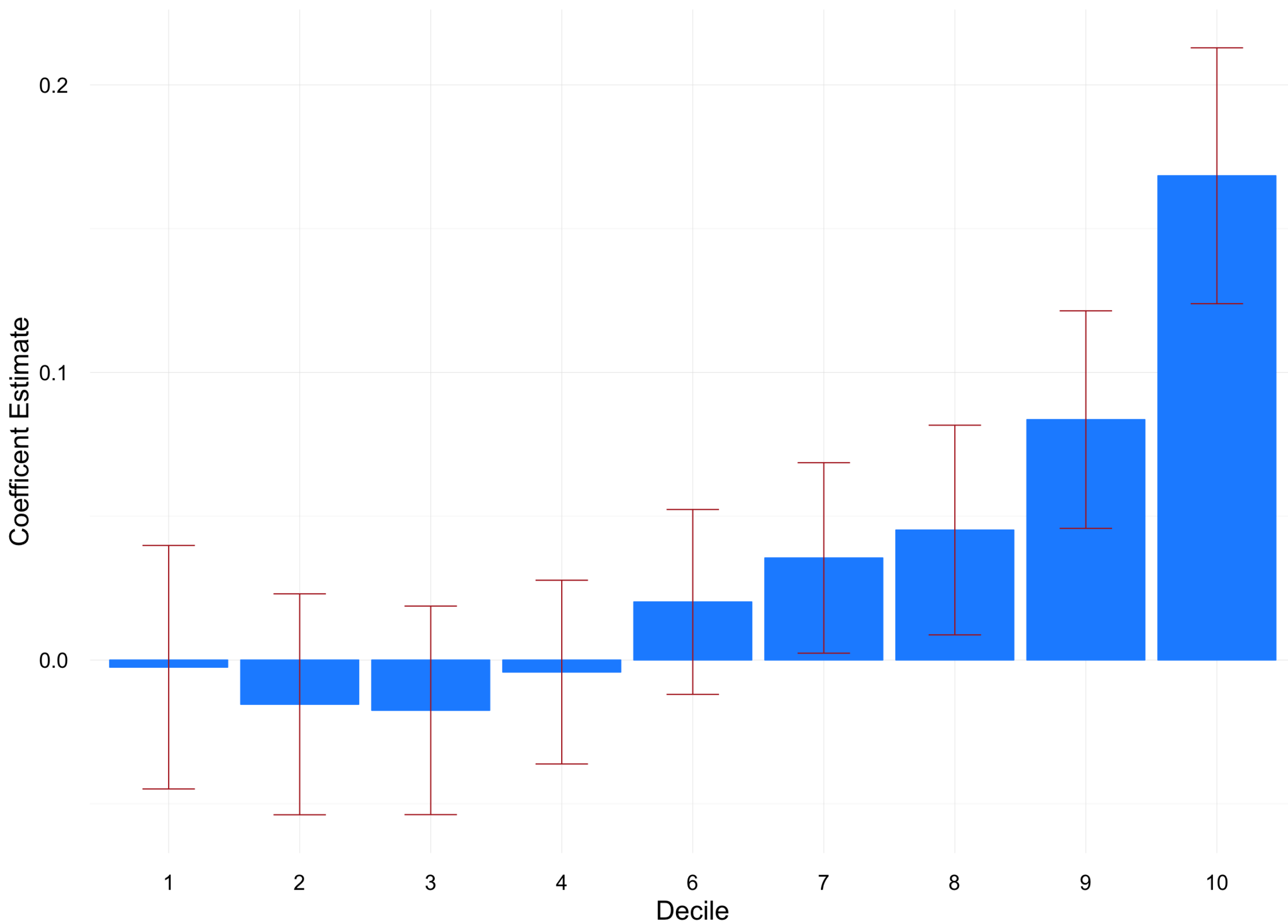
Appendix

Table A.1: Robustness to Different Specifications with Fire Department Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Base	Date	Metro*YM	Metro*Date	Metro*All	Metro*All	Metro*All
Lag Delay	0.0557***	0.0505***	0.0533***	0.0476***	0.0506***	0.0506***	0.0506***
	(0.00770)	(0.00770)	(0.00719)	(0.00706)	(0.00745)	(0.00820)	(0.00807)
Zip Code & FD FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FEs	Yes	No	No	No	No	No	No
Day-of-week FEs	Yes	Yes	Yes	Yes	No	No	No
Hour-of-day FEs	Yes	Yes	Yes	Yes	No	No	No
Date FEs	No	Yes	No	No	No	No	No
Metro*Date FEs	No	No	No	Yes	No	No	No
Metro*Year*Month FEs	No	No	Yes	No	Yes	Yes	Yes
Metro*Day-of-week FEs	No	No	No	No	Yes	Yes	Yes
Metro*Hour-of-day	No	No	No	No	Yes	Yes	Yes
SE Cluster	Zip & FD	Zip & FD	Zip & FD	Zip & FD	Zip & FD	Zip & FD & Month	Zip & FD & Hour
Observations	1,022,980	1,022,974	1,022,980	1,022,872	1,022,980	1,022,980	1,022,980
Zip Codes	400	400	400	400	400	96	24

Notes: The dependent variable is the number of minutes it takes for the fire department to arrive on the scene after they receive the alarm (Response Time). Lag Delay is the standardized ($\mu = 0$ and $\sigma = 1$) deviation from free flow in miles per hour. The columns examine different levels of fixed effects and two way clustering of the standard errors. Robust standard errors clustered at the level described in the bottom panel are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Effect of Zip Code Deciles of Traffic on Response Time



Notes: The figure plots the coefficient for indicators variables for deciles of traffic congestion within each zip code from a regression where the dependent variable is response time (in minutes). The fifth decile is omitted to prevent perfect multicollinearity. The regression includes zip code, year-by-month, day-of-week, and hour-of-day fixed effects. The 95% error bars are generated from robust standard errors clustered at the zip code level.