LSU | E. J. Ourso College of Business
Department of Economics

DEPARTMENT OF ECONOMICS WORKING PAPER SERIES

Traffic and Crime

Louis-Philippe Beland
Louisiana State University

Daniel A. Brent
Louisiana State University

Working Paper 2017-02
http://faculty.bus.lsu.edu/papers/pap17_02.pdf

Department of Economics
Louisiana State University
Baton Rouge, LA 70803-6306
http://www.bus.lsu.edu/economics/

Traffic and Crime*

Louis-Philippe Beland
Louisiana State University

Daniel Brent
Louisiana State University

January, 2017

Abstract

We study the link between crime and emotional cues associated with unexpected traffic. Our empirical analysis combines police incident reports with observations of local traffic data in Los Angeles from 2011 to 2015. This rich dataset allows us to link traffic with criminal activity at a fine spatial and temporal dimension. Our identification relies on deviations from normal traffic to isolate the impact of abnormally bad traffic on crime. We find that traffic above the 95th percentile increases the incidence of domestic violence, a crime shown to be affected by emotional cues, but not other crimes. The results represent a lower bound of the psychological costs of traffic; an externality that is not typically quantified in contrast to pollution, health impacts and lost time that have been established in the literature.

JEL Classification: R28, D03, J12
Keywords: Traffic, Crime, Externalities, Emotional cues

*Beland: Department of Economics, Louisiana State University, lbeland@lsu.edu. Brent: Department of Economics, Louisiana State University, dbrent@lsu.edu. We would like to thank Chelsea Ursaner, open data coordinator at the Office of Los Angeles Mayor for her precious help with the crime data.

1 Introduction

Traffic congestion is a severe problem in many cities that imposes substantial costs on the economy due to lost time, pollution, and increased gasoline expenditure. In metropolitan areas, road congestion led consumers to purchase 2.9 *additional* billion gallons of fuel and spend 5.5 billion hours sitting in traffic (Schrank et al., 2012). According to the Texas A&M Transportation Institute, an average commuter wastes 42 hours a year stuck in traffic - more than an entire week of full time work.[1] Given that most roads in the U.S. are unpriced, the externalities associated with traffic represent an enormous welfare cost to urban residents.

Sitting in traffic is an extremely unpleasant use of time for most people, and in certain circumstances unexpected traffic can be incredibly disruptive.[2] 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).[3] Using subjective well being data, recent research by Anderson et al. (Forthcoming) shows that the estimated costs of congestion greatly exceed typical estimates that account for lost time and reliability. This discrepancy is consistent with large psychological costs of traffic congestion, although this is not tested directly.[4]

In this paper, we extend the literature on the costs of traffic congestion by estimating the psychological costs of traffic. In particular, we focus on the effect of traffic on domestic violence, which has been shown to be sensitive to emotional cues from local football teams' unexpected losses (Card and Dahl, 2011). We estimate the impact of emotional cues due to unexpected high traffic on the incidence of domestic violence in Los Angeles County. Los Angeles is a candidate for the worst traffic in the U.S.; six of the country's 10 most congested stretches of highway are in metro Los Angeles.[5] Our primary contribution is to quantify a

[1] See the Annual Urban Mobility Scorecard report from Texas A&M Transportation Institute available at: http://mobility.tamu.edu/ums/.

[2] Traffic can cause a late arrival to work or missing a business meeting, flight, or court appearance.

[3] For estimates of the value of time and reliability see among others Small et al. (2005).

[4] While Anderson et al. (Forthcoming) account for the aggregate costs of traffic on subjective well being, they do not isolate the psychological costs of traffic. Additionally, previous research finding an effect of traffic on psychological outcomes is based on survey data that uses reflective traffic conditions and self reported health.

[5] See the INRIX 2015 Traffic Scoreboard, available at: http://inrix.com/scorecard/.

specific outcome of the emotional costs of traffic congestion using observational data. We also build on the literature of the economic consequences of emotional cues. Most people who are stuck in traffic will not be induced to commit crimes, but still bear a psychological burden from traffic; therefore we consider our estimates a lower bound on the psychological cost of traffic.

Our empirical analysis combines police incident reports with observations of local traffic data in Los Angeles from 2011 to 2015. This rich dataset allows us to link traffic with criminal activity at a fine spatial and temporal dimension. Our empirical strategy relies on unexpected traffic shocks to estimate the effect of traffic on domestic violence. We find that extreme traffic (above the 95th percentile) significantly increases the incidence of domestic violence by approximately 6%. Since our primary outcome of interest, domestic violence, typically occurs in the home, we are confident that the offender faced the traffic that is typical of the commute at the location of the crime. We control for static unobserved effects across space with fixed effects, and time-varying measures of traffic in the most recent week and month to control for changes in traffic expectations. Our results are consistent with a model of emotional cues, and are robust to several specifications and falsification tests. There is no effect of traffic on lagged crime, no effect of evening traffic on morning crimes, and no effect of traffic on other categories of crime such as property crime and homicides. Increased domestic violence is concentrated in low-income and high-crime areas. The effects are also economically important. Using published estimates of the costs of different crimes indicates that extreme traffic is responsible for approximately $5-10 million in annual damages due to increased incidence of domestic violence.[6]

The rest of the paper is organized as follows: Section 2 discusses the related literature; Section 3 provides a description of the data and present 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.

[6]Direct and indirect cost to assaults are valued at $107,020 in 2008 dollars according to McCollister et al. (2010). While these additional costs are small relative to the cost of lost time and pollution, we consider them to be extreme lower bounds. Domestic violence is severely underreported and most drivers who experience acute congestion will not commit crimes but still suffer some welfare loss due stress.

2 Literature review

Our paper is related to the literature on externalities associated with traffic congestion, emotional cues and determinants of crime. Several papers find a negative impact of traffic on psychological health, anger and stress. Gee and Takeuchi (2004) is one of the first papers to establish a link between self-reported traffic stress with perceived physical and psychological health conditions. Gottholmseder et al. (2009) improve on the statistical methodology and find a relationship between commuting features, including travel predictability, and self-reported stress. More recent work by Künn-Nelen (2016) shows that while self-reported commuting times have an impact on self-reported health outcomes and doctor visits, there is little effect of commuting time on objective health outcomes. Both Roberts et al. (2011) and Künn-Nelen (2016) find that effect of commuting on health predominantly manifests itself in women as opposed to men. Research by Anderson et al. (Forthcoming), using subjective well being data in China, shows that the estimated costs of congestion greatly exceed typical estimates that account for lost time and reliability. In the psychology literature, traffic is found to lead to increased anger and aggression (Parkinson, 2001; Hennessy and Wiesenthal, 1999).

We build on this literature in several ways. First, we link observed traffic data with an observed stress-related outcome. Most of the traffic data in the existing literature relies on survey data that only captures a self-reported snapshot of traffic conditions. This mutes most of the time series variation in actual traffic conditions. Our traffic data are built on a rich panel of hourly data from different roads and directions that enables us to provide a representative depiction of actual traffic conditions. Similarly, most of the positive health effects are also based on self reported outcome data. Conversely, our measure of the psychological costs of traffic data relies on observed crimes from police incident reports. Therefore, we significantly advance the literature on the psychological costs of traffic congestion.

This article also fits into a broad literature investigating negative externalities to traffic. The largest traffic externality is likely the value of time and fuel expenditures associated with congestion. Schrank et al. (2012) estimates these two categories cost U.S. commuters $121 billion in 2011. However, the economics literature has also quantified several other externalities of traffic. Ossokina and Verweij (2015) exploits a quasi-experiment that reduce traffic congestion on certain streets in the Netherlands and find that the decrease in traffic leads to an increase in housing price. 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. In addition to negatively affecting infant health, by exploiting quasi-random variation in wind direction Anderson (2015) shows that traffic has a long run effect of increasing mortality within the elderly population. Quantifying the total economic cost of traffic congestion is important when deciding how to optimally manage congestion. For example, Gibson and Carnovale (2015) shows that tolling not only reduces traffic but also leads to lower levels of air pollution. Another strand of the literature focus on policies to reduce externalities to traffic such as congestion pricing through dynamic tolling (e.g. De Borger and Proost (2013); Gross and Brent (2016)).

Our paper is also related to the literature on unexpected emotional cues and their impact on economic outcomes. The closest paper in this literature is Card and Dahl (2011) who study the link between family violence and the emotional cues associated with wins and losses by professional football teams. They use police reports of violent incidents on Sundays during the professional football season in the United States. They find that upset losses (defeats when the home team was predicted to win by four or more points) lead to a 10% increase in the rate of at-home violence by men against their wives and girlfriends and the impact is larger for important games. While Card and Dahl (2011) establish an important finding, there are potentially less policy levers to address unexpected football losses compared to managing traffic congestion. Additionally, there are a limited number of football games whereas traffic is a daily concern for many urban residents.

There are several related studies on emotional cues and economic outcomes. Eren and Mocan (2016) find that criminal sentences set by Louisiana judges for juvenile crimes are harsher following an unexpected loss by the local university's football team. Duncan et al. (2016) shows that emotional cues due to Super Bowl exposure is associated with a small, but precisely estimated, increase in the probability of low birth weight. There is a related literature documenting the changes in stress and behavior following a dramatic event. For example, the emotions associated with tragic events have been shown to affect birth outcomes and student performance.[7]

Our research is also part of a strand of the literature that studies the determinants of crime. Crime has been shown to be affected by many different factors. For example, Schneider et al. (2016) find that domestic violence is affected by negative labor market conditions. Cui and Walsh (2015) find that following a vacant home foreclosure there is an increase in violent crime and a smaller increase in property crime. Heaton (2012) finds that legalization of Sunday packaged liquor sales affect crime. Ranson (2014) finds that weather and climate change affect crime; temperature has a strong positive effect on criminal behavior, with little evidence of lagged impacts. Herrnstadt and Muehlegger (2015) estimate the causal effect of pollution on criminal activity in Chicago by comparing crime on opposite sides of major interstates on days when the wind blows orthogonally to the direction of the interstate and find that violent crime is 2.2 percent higher on the downwind side. We document an additional determinant of crime: the stress caused by unexpected high traffic.

3 Data, descriptive statistics and traffic conditions

3.1 Data sources

Data on crime in Los Angeles come from police incident reports from two sources: the Los Angeles Police Department (LAPD) and the Los Angeles Sheriff Department (LASD). The LAPD police reports represent all crimes that take place in the City of Los Angeles and were accessed via the Los Angeles Open Data website.[8] The LAPD data are available from 2011 to 2015 and contain information on the date, time, location and type of crime. The LASD police report data are obtained through Los Angeles County GIS Data Portal, and contain data for all crimes in the LASD jurisdiction.[9] The LASD serves 40 incorporated cities and all unincorporated areas of Los Angeles County. These two datasets represent the

[7]For birth outcomes see Eskenazi et al. (2007) following the September 11th terrorist attacks, and Currie and Rossin-Slater (2013) following Hurricane Katrina. For student performance, see Beland and Kim (2016) after a shooting in a high school and Imberman et al. (2012) after a hurricane.

[8]Data are available at https://data.lacity.org/ by searching for "LAPD Crime and Collision Raw Data".

[9]The LASD data are available from 2005, but we only use 2011-2015 to match with the LAPD data. The LASD crime data are accessed at: http://egis3.lacounty.gov/dataportal/2012/03/05/crime-data-la-county-sheriff/.

vast majority of crime in Los Angeles County.[10] We consider the following crimes: assault, domestic violence, property crime, homicides and all crimes.

We control for weather in the city that could affect both crime and traffic. We collect daily data on rain, maximum temperature and wind speed in Los Angeles from the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information.[11]

The traffic data for Los Angeles are obtained from the California Department of Transportation through the Caltrans Performance Measurement System (PeMS).[12] We access annual Station Hour datasets from 2011 to 2015 from the PeMS data clearinghouse for California District 7, restricting the stations to Los Angeles County. These datasets contain over 22 million observations of hourly speeds from 543 unique stations in Los Angeles County for the two major interstates in our analysis. We focus on two major roads, I-10 and I-5, that represent the primary north-south and east-west routes to downtown Los Angeles. We also gather data on the location of metro stations from Los Angeles Open Data website and average zip code-level income data from the U.S. Census American Community Survey.[13]

3.2 Dataset creations & descriptive statistics

To measure the impact of traffic on crime, we assign each zip code to the closest major highway that connects to the downtown area. We focus on two major roads, I-10 and I-5, that represent the primary north-south and east-west routes to downtown Los Angeles. While these are not the only means of transportation in the Los Angeles Metro area they are likely to be correlated with traffic on other nearby routes of the same direction. Our main measure of high traffic is when the cumulative travel time is above the 95th percentile for a given zip code in a given day. This is built by combining traffic from the morning and evening travel times based on a typical pattern of driving toward downtown in the morning and away from downtown in the evening. We explore the robustness of our results

[10]The maps for the LAPD and LASD jurisdiction are available from the Los Angeles Times: http://maps.latimes.com/lapd/ and http://maps.latimes.com/sheriff/.

[11]Weather data are available at: https://www.ncdc.noaa.gov/cdo-web/datasets.

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

[13]Data are available at https://data.lacity.org/A-Livable-and-Sustainable-City/Los-Angeles-County-Metro-Rail-Station-Portal-Locat/s2k2-nqiy.

to alternate measures of traffic such as the maximum daily travel time for a given zip code. In order to assign each zip code to the nearest road, we calculate the driving distance from the zip code centroid to the nearest on-ramp for both I-10 and I-5, two of the major roads in Los Angeles. This calculation was conducted in ArcGIS using the Network Analyst tool and the road network for Los Angeles County obtained from the Los Angeles County GIS Data Portal. Once we have driving distances from each zip code to both I-10 and I-5, we assign the closest road to the zip code. Since some zip codes are roughly equidistant to I-10 and I-5, as a robustness check we relax the closest route assumption by dropping zip codes whose difference in driving distances between the two routes are small. Figure 1 presents the mapping of zip codes to roads. We use a static measure of driving distance to assign a zip code a time series of traffic from either I-10 or I-5.

Figure 2 presents the traffic congestion by route, direction and time of day. It shows that the I-10 West is heavy in the morning (between 6:00 and 9:00) with travel time reaching 70 minutes and I-10 East is congested in the afternoon with travel time reaching about 80 minutes (between 15:00 and 18:00). The I-5 North and I-5 South are congested both in the morning and in the afternoon. Table A.1 presents key descriptive statistics (mean, standard deviation, minimun and maximum) for daily average traffic in AM and PM for zip codes in our data set. It shows a mean travel time of 70 minutes in the morning and 77 minutes in the evening. To proxy for the daily commute, we aggregate the typical daily morning and evening commutes based on the location of the zip code relative to downtown. For example, a zip code east of downtown will be assigned to I-10 and the cumulative traffic will be the aggregation of the westbound morning traffic and the eastbound evening traffic.[14] We also analyze the effects of morning and evening traffic separately. The final traffic dataset is a panel of daily traffic observations for each zip code.

The crime data provide a fine spatial and temporal resolution, and in order to match the crime data to the traffic data, we aggregate all crimes within a zip code over the course of the day in each of the categories to obtain our dependent variables.[15] All crimes that

[14]The morning period is defined as 6:00-9:00 AM and the evening period is defined as 3:00-7:00 PM.

[15]The crime data are available at finer spatial resolutions than zip codes, but when aggregating up subcategories, such as domestic violence, there is little daily variation in the crime data due to a mass of zeros.

occur before 5 AM are assigned to the previous day and are coded as nighttime crimes. This allows crimes committed prior to 5 AM to be affected by traffic in the previous day. For example, we assume that a crime committed at 1:00 AM can be influenced by getting stuck in traffic on the way home from work. Figure 3 presents a map of average daily domestic violence incident by zip code in Los Angeles. The maximum daily average domestic violence incidents is 1.8 and many regions have an average of 0.4 and below. Figures B.1, B.2 and B.3, in appendix, present similar figures for all crimes, property crimes and assault in Los Angeles. The figures show that some zip codes have large average daily crime incidents (reaching above 20 daily crimes for some areas). Table A.2 presents key descriptive statistics (mean, standard deviation, minimun and maximum) for daily average crimes by zip code for total crime and evening crime. It shows, for example, that mean total crime by zip code in a given day is 3.7 while the average incidence of domestic violence 0.16.

3.3 Traffic in Los Angeles

Traffic in Los Angeles is a severe problem. According to a Texas A&M transportation Institute report, drivers in Los Angeles spend on average 80 hours or 3.5 days a year in gridlock.[16] Los Angeles has the biggest difference between normal travel times and rush hour travel times in the United-States. Rush hour can be 43 percent slower than non-peak hours. According to Sorensen (2009), congestion is due to the very high population density of Los Angeles metropolitan region, and the fact that parking is cheap and abundant. Most drivers do not pay the full economic and social costs of driving. A recent Los Angeles Times poll shows that traffic is the top of concern for Los Angeles resident, topping personal safety, personal finances and housing costs.[17]

4 Methodology

To estimate the impact of traffic on domestic violence, we rely on deviations from normal traffic to isolate the impact of abnormally bad traffic on crime. Following Card and Dahl

[16] See the Annual Urban Mobility Scorecard report from Texas A&M Transportation Institute available at: http://mobility.tamu.edu/ums/

[17] see http://www.latimes.com/local/lanow/la-me-ln-traffic-still-tops-crime-economy-as-top-l-a-concern-poll-finds-20151007-story.html

(2011), we estimate the following Poisson count model:

$$\begin{aligned} Crime_{it} = \beta_0 + \beta_1 HighTraffic_{it} + \beta_2 E[Traveltime] + \\ \beta_3[Weather] + \beta_{MY} + \beta_D + \beta_Z + \tau + \tau^2 + \epsilon_{it} \end{aligned} \tag{1}$$

where $Crime_{it}$ is the number of domestic violence incidents in zip code i on day t. Our main analysis focus on domestic violence but also look at other types of crime (property, assault, homicide and all crimes). Zip codes are assigned to the closest road going toward downtown in the morning and from downtown in the afternoon. $HighTraffic_{it}$ measures unexpected high traffic. We measure high traffic as the above 95% cumulative travel time for a given zip code and day of the week. E[Traveltime] is a measure of expected travel time for a given zip code. It contains information on the average traffic for the last week and month for a given zip code. Our coefficient of interest, β_1, measures the impact of abnormally high traffic on our outcomes. [Weather] is a vector of weather covariates: rain, maximum temperature and wind. We use zip code level fixed effects (β_Z) to control for static spatial unobserved effect, and also include fixed effects for the year-by-month (β_{MY}) and day-of-week (β_D) fixed effects. We cluster the standard errors at the zip code level.

To better understand the relationship between traffic and crime, we also estimate the effect using different thresholds for extreme traffic. We also consider the possibility that traffic has heterogeneous effects on crime. First, we investigate how the timing of traffic (morning vs. evening traffic) impacts crime, and the persistence of traffic shocks on domestic violence. Next, we examine the cross sectional heterogeneity by dividing the sample based on three zip code level characteristics: income, average crime, and distance to downtown. To ensure the validity of our results, we perform several robustness checks. We run placebo regressions of traffic on lagged crime, relax the spatial assumptions regarding traffic assignment, and employ alternative methods to generate measures of unexpected traffic (maximum travel time and moving average estimates).

5 Results

5.1 Main Results

Table 1 presents the impact of high traffic (above 95th percentile) on domestic violence. Column (1) uses all traffic and crime observations in Los Angeles to estimate equation (1), and shows that domestic violence is significantly higher when traffic exceeds the 95th percentile. Given that we are using a Poisson model the coefficients can be interpreted as the approximate percentage change in crime once traffic exceeds the 95th percentile. Columns (2) - (4) focus on subsamples that should be more affected by traffic. Column (2) investigates the impact of high traffic on domestic violence, excluding the downtown area. We exclude crimes that occurs downtown since either these crimes are not affected by the typical commuting pattern, or we cannot be sure which roads the offender traveled to reach downtown. Column (3) excludes weekends and holidays, since the conventional commuting patterns do not hold and traffic is inherently less predictable. Column (4) excludes downtown, weekends and holidays. All specifications show that there is significantly more domestic violence when there is unexpectedly high traffic. The effects are larger when restricting the sample to those areas and time periods that represent conventional commuting behavior. Our preferred specification is column (4), which we use for the remainder of the paper. All subsequent regressions also include zip code, year-month and day-of-week fixed effects, as well as weather and recent traffic controls.

Next, we examine how different high traffic thresholds impact crime. Figure 4 shows estimates of indicator variables for high traffic using percentiles ranging from the 75th to the 99th. Each bar represents the coefficient estimate of that percentile indicator, and the error bars are 95% confidence intervals generated from the robust standard errors clustered at the zip code level. Each coefficient is estimated using our preferred specification shown in column (4) of Table 1. There is almost a monotonic effect of moving to higher traffic thresholds. The effect of high traffic is small and insignificant when defining the threshold from the 75th percentile to the 84th percentile. For thresholds above the 85th percentile the coefficients become statistically significant and generally increase in magnitude as the percentile threshold increases. The effect at the 90th percentile is 5.8% and the effect at the 98th percentile is 9.2%.[18] This is consistent with threshold effects, where only traffic in the right tail can be considered to be unexpected and cause the necessary stress to induce domestic violence. The damages of traffic can also experience thresholds effects. For example, drivers may account for certain levels of traffic when commuting, but extreme traffic will cause them to be late to work and miss important appointments.

Table 2 estimates the effect of traffic on different types of crimes. Column (1) replicates our preferred specification using domestic violence as the outcome variable. In column (2), we regress all crimes on traffic, and find that extreme traffic leads to a 1.3% increase in any type of crime. Column (3) - (5) present results using assaults, property crimes, and homicides as the outcome variables. Since domestic violence is categorized as an assault we remove domestic violence incidents from the assault category. There are no significant effects for assaults, property crime, or homicides.[19] The results show that traffic predominantly effects domestic violence as opposed to other crimes, which is consistent with a model of emotional cues where unexpected traffic shocks increase psychological stress. It is unlikely that the psychological stress from traffic would cause an increase in robberies or homicides.

5.2 Heterogeneity

Next, we examine heterogeneous impacts by the timing of unexpected traffic. In particular, we examine the effect of both morning (AM) and evening (PM) traffic shocks on crime in addition to each effect separately. Column (2) of Table 3 shows that both the morning and evening effects are similar in magnitude and significance, which is also corroborated when examining each effect in isolation (columns (3) and (4)). The effects of PM traffic on crime are slightly larger but not statistically different from the effects of AM traffic. Column (5) estimates the effect of traffic that exceeded the 95th percentile in both the morning and the evening. The effect increases from roughly 6% to over 8%, but the effects are not statistically different from each other. Lastly, as a placebo test we estimate the effect of traffic in the

[18] An exception is traffic above the 99th percentile, which is smaller with a very large confidence interval. These extreme events are very rare and noisy, and may be due to something other than conventional traffic jams. As a robustness check we replicate Figure 4 when removing all observations above the 99th percentile of traffic. The results, presented in Figure B.4 are quantitatively and qualitatively similar.

[19] The coefficient of the effect on homicides is reasonably large, but is very noisy, because homicides are very rare events.

evening on domestic violence that occurs in the morning (column (6)). Reassuringly, we find no effect of traffic later in the day on crime in morning.

Table A.3 investigates if the emotional cues due to unexpected high traffic leads to an increase in domestic violence incidents in the following days. Column (1) of Table A.3 presents results at time T and replicates our preferred specification of Table 1. Columns (2), (3), and (4) present results at time $T+1$, $T+2$ and $T+3$. The results indicate that the negative impact of high traffic carries on the following day (T+1) but not after that (not for T+2 and T+3). Column (5) uses domestic violence incidents at time T or $T+1$, as an outcome variable, showing the cumulative impact of unexpected high traffic on domestic violence. Including crimes that occur the day after an extreme traffic event increases the effect size slightly to over 7%.

Next, we examine heterogeneity in the effect of traffic on crime by dividing zip codes along three dimensions: crime, income and distance to downtown. In each specification we subset zip codes in the sample by being either above or below the sample median for each variable.[20] Crime and income are correlated, but there are zip codes that are high crime and high income. Table 4 shows that traffic increases domestic violence in predominantly high-crime and low-income zip codes. We also find that most of the effect appears to come from zip codes that are closer to downtown, which may arise for two reasons. First, households living closer to downtown are more likely to work downtown, and therefore we are assigning them the appropriate traffic conditions. Secondly, a traffic shock for a household with a very long commute may be a smaller proportion of their total commute and a traffic shock might be more expected.

In order to assess the policy levers available to mitigate the effect of traffic on domestic violence, we examine how access to public transportation affects our results. Table 5 studies how the proximity to a metro station moderates the effect of traffic on domestic violence. Table 5 presents results for our measure of unexpected traffic (above the 95th percentile) but limits the sample to zip codes near a metro station. Columns (1) - (4) of Table 5 limit the sample to zip codes within 0.5 mile - 3 miles from a metro station. Table 5 shows

[20] The median fraction of low income households is 68%, the zip code median crime rate is 2 crimes per day, and the median commute distance is 10.9 miles.

once again than unexpected high traffic leads to an increase in domestic violence incident, and that the negative impact of unexpected high traffic is not reduced by access to public transportation.[21]

5.3 Robustness

We perform several robustness checks to test the validity of the results. Our first exercise is a placebo test where we regress traffic information at time T and crime information in the previous days: at times $T-1$, $T-2$, $T-3$, and $T-4$. High traffic at time T should not affect crime in previous periods. Table 6 shows that high traffic at time T has no significant impact on domestic violence incidents in previous days. This is reassuring as high traffic at time T leads to higher incidence of domestic violence at time T but no increase is observed in the days prior to the unexpected high traffic.

Our next set of robustness checks relax the assumptions that allow us to match zip codes to traffic conditions. Columns (1) - (5) of Table 7 restrict the sample to zip codes that are within one to five miles to the closest on-ramp. Households in these zip codes are more likely to use the roads that we assign to them. Once again we find that unexpected high traffic leads to increase in domestic violence incidents. The effects of traffic on domestic violence in these specifications are larger (7% to 12.1%). These zip codes represent less stringent assumptions regarding the typical commuting patterns, indicating that our preferred specification may in fact be a lower bound. We also restrict the sample to zip codes that have a clear choice of route (I-5 or I-10) by removing zip codes that have similar distances to the two routes. Table 8 replicates our preferred specification for zip codes where the distance between the nearest on-ramp for I-10 and I-5 is at least 2, 3, 4, and 5 miles. These zip codes are more likely to be assigned the appropriate traffic conditions. The results do not change substantively; all the effects are of similar magnitude and statistically significant at the 5% level.

Table 9 presents different measures of high traffic. In column (1) we replace the metric of travel time with the maximum daily travel time (by hour of day) instead of the cumulative travel time. Maximum daily travel time is the maximum travel time for all hours in the

[21] The effects are actually larger in zip codes close to a metro stations. This result is likely driven by the fact that these zip codes are closer to downtown, and Table 4 shows that impact of crime on domestic violence is concentrated in zip codes closer to downtown.

morning or evening commute. The effect is smaller in magnitude, but still positive and statistically significant. Next, we model traffic expectations with a variety of moving average models. In our preferred specification we define unexpected traffic as traffic above the 95th percentile for each zip code while controlling for recent traffic. The moving average models use recent traffic to generate a predicted travel time and then examine the deviations from the prediction as unexpected traffic. In particular, a deviation above the 95th percentile of all deviations is defined as unexpected extreme traffic. We use three specifications of moving averages, presented in Table 9. Column (2) uses deviation above the 95% percentile from the moving average based on the last 5 working days. Column (3) uses a weight of 1/10 for the last 5 working days and 1/30 for the following 15. Column (4) uses deviations above the 95% percentile from the moving average based on the last 30 working days as a measure of extreme traffic. All the moving average models produce positive and statistically significant effects of extreme traffic, indicating that our results are robust to various models of traffic expectations. Column (5) presents instrumental variable estimates using accidents causing traffic delays above one hour as our instruments.[22] While traffic and accidents are correlated we believe that the timing and location of severe accidents exploits one specific source of quasi-random variation in our empirical strategy. Once again, the results indicate that unexpected high traffic leads to an increase in domestic violence incidents. The coefficient is slightly larger (+11.45%) and significant at the 10% level.[23]

Overall, the results are robust to alternative specifications. These numerous robustness checks and heterogeneity investigation provide confidence that the emotional cues due to unexpected high traffic leads to high domestic violence incident.

[22]The accident data is collected from Caltrans.

[23]The correlation between our instrument (accident with long delays) and traffic conditions is 0.22 and the F-test of the first stage is 12.81.

6 Conclusion

This paper investigates the impact of emotional cues due to unexpected high traffic on domestic violence. We combine traffic data in Los Angeles from 2011 to 2015 to police incident reports from the Los Angeles Police Department and the Los Angeles Sheriff Department. This rich dataset allows us to link traffic with criminal activity at a fine spatial and temporal dimension. Our identification relies on extreme deviations from normal traffic to isolate the impact of abnormally high traffic on domestic violence incidents.

We find that extreme traffic (above the 95th percentile) significantly increases the incidence of domestic violence by approximately 6%. We control for static unobserved effects across space with fixed effects, and time-varying measures of traffic in the most recent week and month to control for changes in traffic expectations. We also find that the increase in domestic violence are concentrated in low-income and high-crime areas. Our results are consistent with a model of emotional cues, and are robust to several specifications and falsification tests. There is no effect of traffic on lagged crime, no effect of evening traffic on morning crimes, and no effect of traffic on other categories of crime such as property crime.

The results highlight a new externality associated with traffic in addition to congestion, pollution, and health impacts that have been established in the literature. This is important as the direct and indirect costs of a domestic violence incident is estimated to be up to $107,020 (McCollister et al. (2010)). Our estimates of the economic cost of traffic-induced domestic violence range from $5-10 million dollars per year depending on the specification. Since we expect that most people who suffer some psychological costs of traffic do not actually commit crimes we consider our estimates to be an extreme lower bound; they are the tip of the iceberg. Documenting the psychological costs of traffic provides additional support for congestion management policies that not only reduce average travel times but improve reliability by reducing the variance of travel times. Building new capacity is unlikely to reduce congestion in the long-run since the elasticity of travel demand change with respect to capacity is equal to one (Duranton and Turner, 2011). Alternatively, Peirce et al. (2013) document that drivers report less stress after time-of-day pricing was implemented on a major road in Seattle. Therefore, our research documents additional benefits of congestion pricing policies, but more research is needed on how different types of tolling structures improve travel reliability and driver satisfaction.[24] There are also implications for how resources are deployed after extreme traffic events. More police and/or counseling services should be available when there is high traffic.

References

Anderson, Michael L, "As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality," *NBER Working Paper Series*, 2015, (21578).

_ **, Fangwen Lu, Yiran Zhang, Jun Yang, and Ping Qin**, "Superstitions, Street Traffic, and Subjective Well-Being," *Journal of Public Economics*, Forthcoming.

Beland, Louis-Philippe and Dongwoo Kim, "The effect of high school shootings on schools and student performance," *Educational Evaluation and Policy Analysis*, 2016, *38* (1), 113–126.

Borger, Bruno De and Stef Proost, "Traffic externalities in cities: the economics of speed bumps, low emission zones and city bypasses," *Journal of Urban Economics*, 2013, *76*, 53–70.

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

Cui, Lin and Randall Walsh, "Foreclosure, vacancy and crime," *Journal of Urban Economics*, 2015, *87*, 72–84.

Currie, Janet and Maya Rossin-Slater, "Weathering the storm: Hurricanes and birth outcomes," *Journal of Health Economics*, 2013, *32* (3), 487–503.

[24] A technical report by the Washington State Department of Transportation shows that dynamically priced high-occupancy toll lanes reduce peak congestion in a road in metro Seattle (WSDOT, 2012).

— **and Reed Walker**, "Traffic Congestion and Infant Health: Evidence from E-ZPass," *American Economic Journal: Applied Economics*, 2011, *3* (1), 65–90.

Duncan, Brian, Hani Mansour, and Daniel I Rees, "It's Just a Game: The Super Bowl and Low Birth Weight.," *Journal of Human Ressources*, 2016.

Duranton, Gilles and Matthew A Turner, "The Fundamental Law of Road Congestion: Evidence from US Cities," *American Economic Review*, 2011, *101* (6), 2616–2652.

Eren, Ozkan and Naci Mocan, "Emotional Judges and Unlucky Juveniles," 2016, *22611.*

Eskenazi, Brenda, Amy R Marks, Ralph Catalano, Tim Bruckner, and Paolo G Toniolo, "Low birthweight in New York City and upstate New York following the events of September 11th," *Human Reproduction*, 2007, *22* (11), 3013–3020.

Gee, Gilbert C and David T Takeuchi, "Traffic stress, vehicular burden and well-being: a multilevel analysis," *Social Science & Medicine*, 2004, *59* (2), 405–414.

Gibson, Matthew and Maria Carnovale, "The effects of road pricing on driver behavior and air pollution," *Journal of Urban Economics*, 2015, *89*, 62–73.

Gottholmseder, Georg, Klaus Nowotny, Gerald J Pruckner, and Engelbert Theurl, "Stress perception and commuting," *Health Economics*, 2009, *18* (5), 559–576.

Gross, Austin and A. Daniel Brent, "Dynamic Road Pricing and the Value of Time and Reliability," *LSU Working Papers*, 2016.

Heaton, Paul, "Sunday liquor laws and crime," *Journal of Public Economics*, 2012, *96* (1), 42–52.

Hennessy, Dwight A and David L Wiesenthal, "Traffic congestion, driver stress, and driver aggression," *Aggressive Behavior*, 1999, *25* (6), 409–423.

Herrnstadt, Evan and Erich Muehlegger, "Air Pollution and Criminal Activity: Evidence from Chicago Microdata," Technical Report, National Bureau of Economic Research 2015.

Imberman, Scott A, Adriana D Kugler, and Bruce I Sacerdote, "Katrina's children: Evidence on the structure of peer effects from hurricane evacuees," *The American Economic Review*, 2012, pp. 2048–2082.

Künn-Nelen, Annemarie, "Does commuting affect health?," *Health Economics*, 2016, *25*, 984–1004.

McCollister, Kathryn E, Michael T French, and Hai Fang, "The cost of crime to society: New crime-specific estimates for policy and program evaluation," *Drug and alcohol dependence*, 2010, *108* (1), 98–109.

Ossokina, Ioulia V and Gerard Verweij, "Urban traffic externalities: Quasi-experimental evidence from housing prices," *Regional Science and Urban Economics*, 2015, *55*, 1–13.

Parkinson, Brian, "Anger on and off the road," *British Journal of Psychology*, 2001, *92* (3), 507–526.

Peirce, Sean, Sean Puckett, Margaret Petrella, Paul Minnice, and Jane Lappin, "Effects of Full-Facility Variable Tolling on Traveler Behavior: Evidence from a Panel Study of the SR-520 Corridor in Seattle, Washington," *Transportation Research Record: Journal of the Transportation Research Board*, 2013, (2345), 74–82.

Ranson, Matthew, "Crime, weather, and climate change," *Journal of Environmental Economics and Management*, 2014, *67* (3), 274–302.

Roberts, Jennifer, Robert Hodgson, and Paul Dolan, "It's driving her mad: Gender differences in the effects of commuting on psychological health," *Journal of Health Economics*, 2011, *30* (5), 1064–1076.

Schneider, Daniel, Kristen Harknett, and Sara McLanahan, "Intimate partner violence in the Great Recession," *Demography*, 2016, *53* (2), 471–505.

Schrank, David, Bill Eisele, and Tim Lomax, "TTI's 2012 urban mobility report," *Proceedings of the 2012 annual urban mobility report. Texas A&M Transportation Institute, Texas, USA*, 2012.

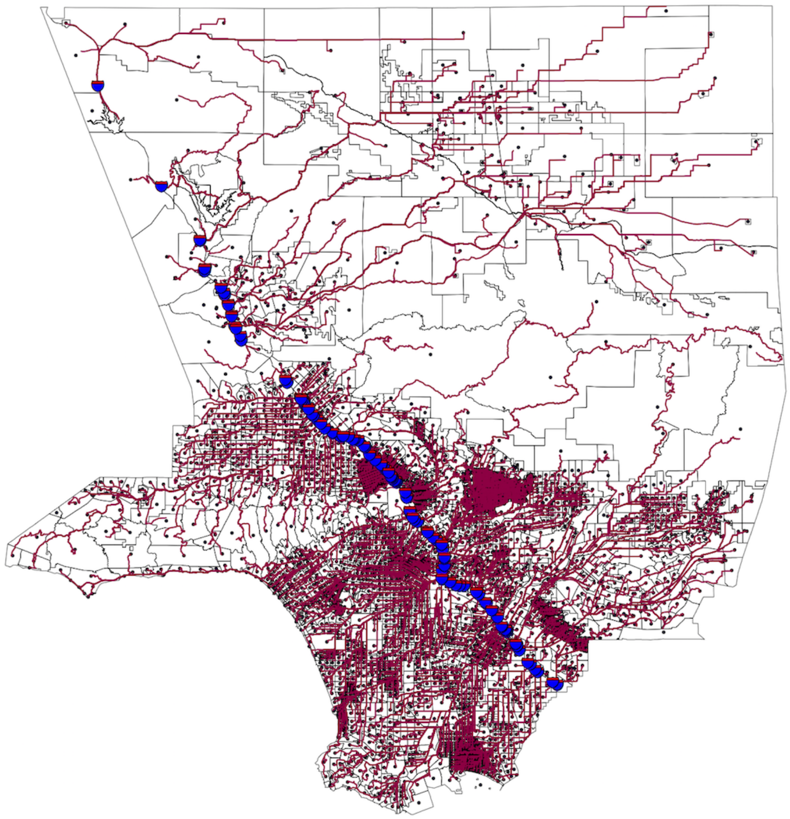
Small, Kenneth A., Clifford Winston, and Jia Yan, "Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability," *Econometrica*, 2005, *73* (4), 1367–1382.

Sorensen, Paul, "Moving Los Angeles," *ACCESS Magazine*, 2009, *1* (35).

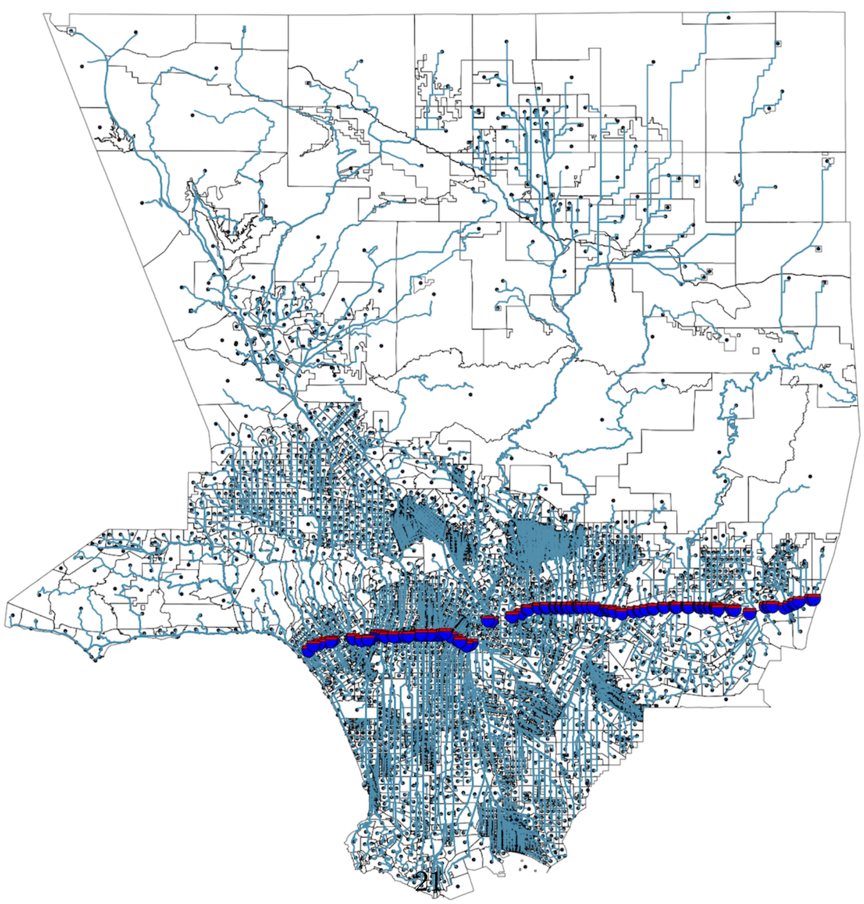
WSDOT, "SR 167 HOT Lanes Pilot Project Fourth Annual Performance Summary," Technical Report May 2008, WSDOT 2012.

Figure 1: Mapping Zip Codes to Roads

(a) I-5

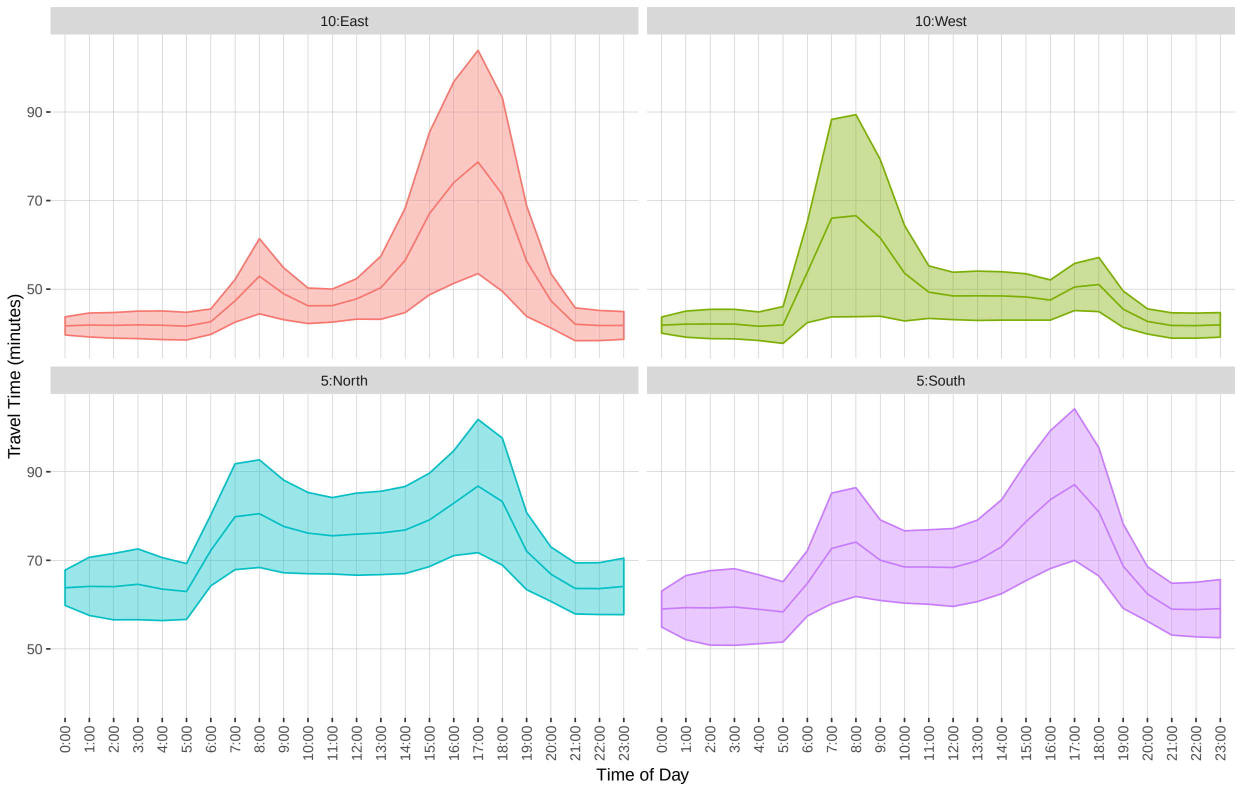


(b) I-10



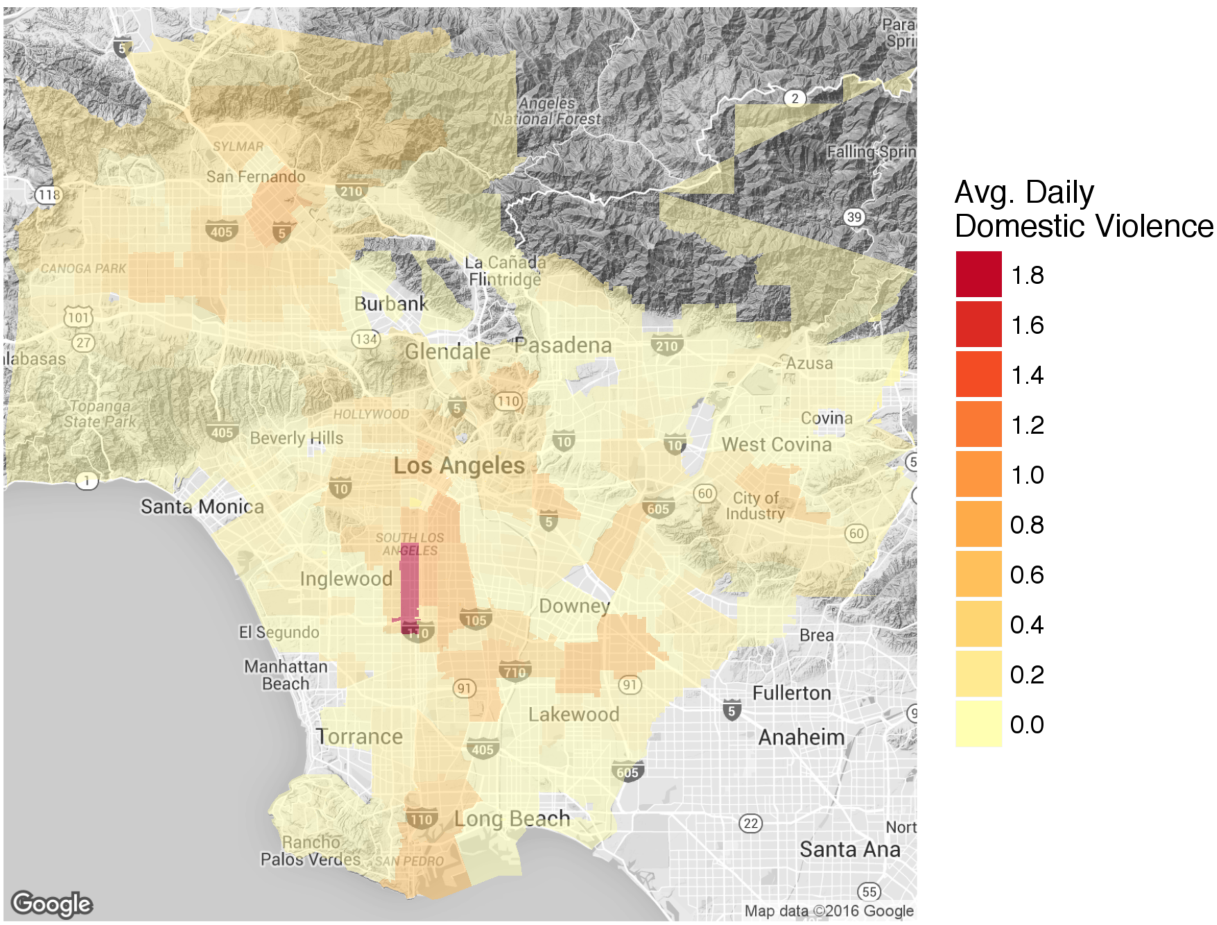
Sources: California Department of Transportation

Figure 2: Traffic by Route, Direction and Time of Day



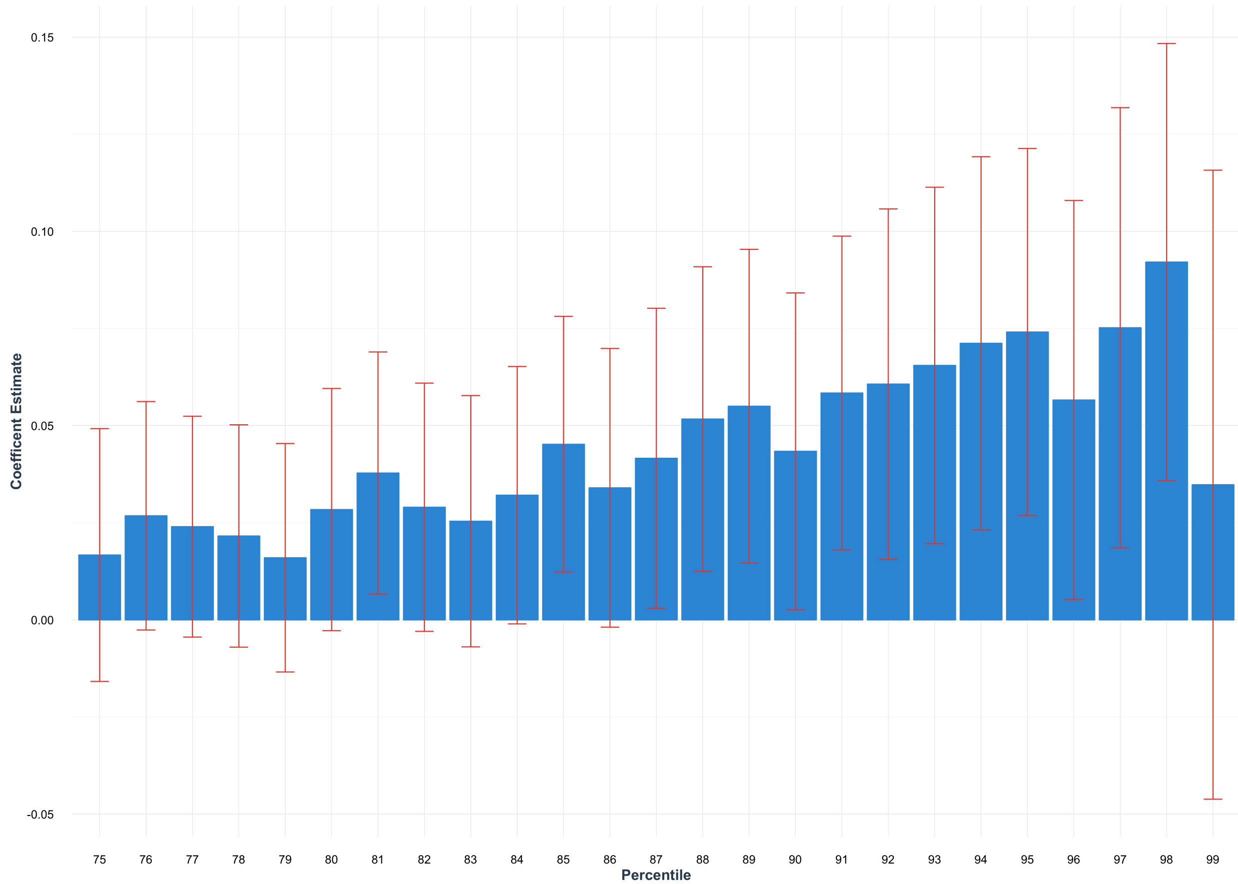
Sources: California Department of Transportation

Figure 3: Map of Domestic Violence in Los Angeles



Sources: Los Angeles Police Department and Los Angeles Sheriff Department.

Figure 4: Effect of Traffic on Domestic Violence - Different Thresholds



Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 1: Base Results

	(1) All Observations	(2) No Downtown	(3) Workdays	(4) No Downtown & Workdays
95th Percentile	0.0623***	0.0610***	0.0630***	0.0650***
	(0.0210)	(0.0211)	(0.0236)	(0.0239)
Observations	469,025	452,600	318,780	307,440

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 2: Different Crimes

	(1) Domestic Violence	(2) All Crimes	(3) Assault	(4) Property	(5) Homicide
95th Percentile	0.0650***	0.0131**	0.00950	0.00518	-0.0673
	(0.0239)	(0.00621)	(0.0190)	(0.00891)	(0.129)
Observations	307,440	356,580	337,680	350,280	199,080

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 3: Crimes by Time of Day

	(1) Base	(2) AM & PM Traffic	(3) AM Traffic	(4) PM Traffic	(5) Both AM & PM	(6) AM Crime
95th Percentile	0.0650***					
	(0.0239)					
95th Percentile (AM)		0.0627***	0.0588***			
		(0.0210)	(0.0209)			
95th Percentile (PM)		0.0695***		0.0659***		0.00142
		(0.0207)		(0.0207)		(0.0541)
95th Percentile (AM & PM)					0.0837***	
					(0.0309)	
Observations	307,440	307,440	307,440	307,440	307,440	284,760

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 4: Heterogeneity by Crime and Income

	(1) Low Crime	(2) High Crime	(3) Low Income	(4) High Income	(5) Close Zips	(6) Distant Zips
95th Percentile	-0.141	0.0733***	0.0692**	0.0540	0.0836***	0.0187
	(0.0986)	(0.0246)	(0.0283)	(0.0390)	(0.0307)	(0.0312)
Observations	132,300	175,140	134,820	172,620	139,860	167,580

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Sources: California Department of Transportation, U.S. Census American Community Survey, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 5: Heterogeneity by Access to Public Transportation

	(1) 0.5 mile	(2) 1 mile	(3) 1.5 miles	(4) 2 miles	(5) 2.5 miles	(6) 3 miles
95th Percentile	0.0807**	0.0867**	0.0920***	0.0815**	0.0659**	0.0595*
	(0.0363)	(0.0345)	(0.0341)	(0.0317)	(0.0327)	(0.0305)
Observations	83,160	104,580	118,440	137,340	151,200	162,540

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Open Data website, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 6: Placebo Test - Lag of Domestic Violence on Traffic

	(1) T-1	(2) T-2	(3) T-3	(4) T-4
95th Percentile	0.00155 (0.0347)	0.0498 (0.0312)	0.0147 (0.0231)	0.0325 (0.0236)
Observations	285,157	295,466	301,515	300,212

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 7: Zip Codes Near On-ramps

	(1) 1 mile	(2) 2 miles	(3) 3 miles	(4) 4 miles	(5) 5 miles
95th Percentile	0.0710	0.0740*	0.121***	0.106***	0.0894***
	(0.0931)	(0.0445)	(0.0378)	(0.0305)	(0.0312)
Observations	25,200	55,440	100,800	128,520	154,980

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 8: Zip Codes with Clear Choice of Route

	(1) 2 miles	(2) 3 miles	(3) 4 miles	(4) 5 miles
95th Percentile	0.0688***	0.0672**	0.0647**	0.0643**
	(0.0264)	(0.0273)	(0.0279)	(0.0284)
Observations	262,080	249,480	234,360	223,020

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Table 9: Robustness: different measures of high traffic

	(1) Max Travel Time	(2) MA 5days	(3) MA 5days and 15days	(4) MA 30days	(5) IV accidents
Domestic Violence	0.0364**	0.0478**	0.0549***	0.0579***	0.1145*
	(0.0168)	(0.0220)	(0.0189)	(0.0204)	(0.0657)
Observations	307,440	303,292	301,340	300,120	248,229

Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Appendix

Table A.1: Descriptive Statistics table, daily average traffic by zip code in AM & PM

	Mean	SD	Min	Max
AM	70.22	13.72	50.35	83.23
PM	77.68	18.02	50.90	90.44

Notes: It presents key descriptive statistics (Mean, SD, Min and Max) for daily average traffic in AM and PM.
Sources: California Department of Transportation

Table A.2: Descriptive Statistics table, daily average crime by zip code.

	Total Crime				Evening Crime			
	Mean	SD	Min	Max	Mean	SD	Min	Max
All	3.695	4.14	0	22.84	2.181	2.46	0	13.65
Assault	0.528	0.81	0	6.23	0.344	0.50	0	3.32
Domestic	0.157	0.23	0	1.72	0.108	0.15	0	1.10
Property	1.603	1.76	0	8.96	0.931	1.02	0	4.93
Homicide	0.004	0.01	0	0.07	0.003	0.01	0	0.05

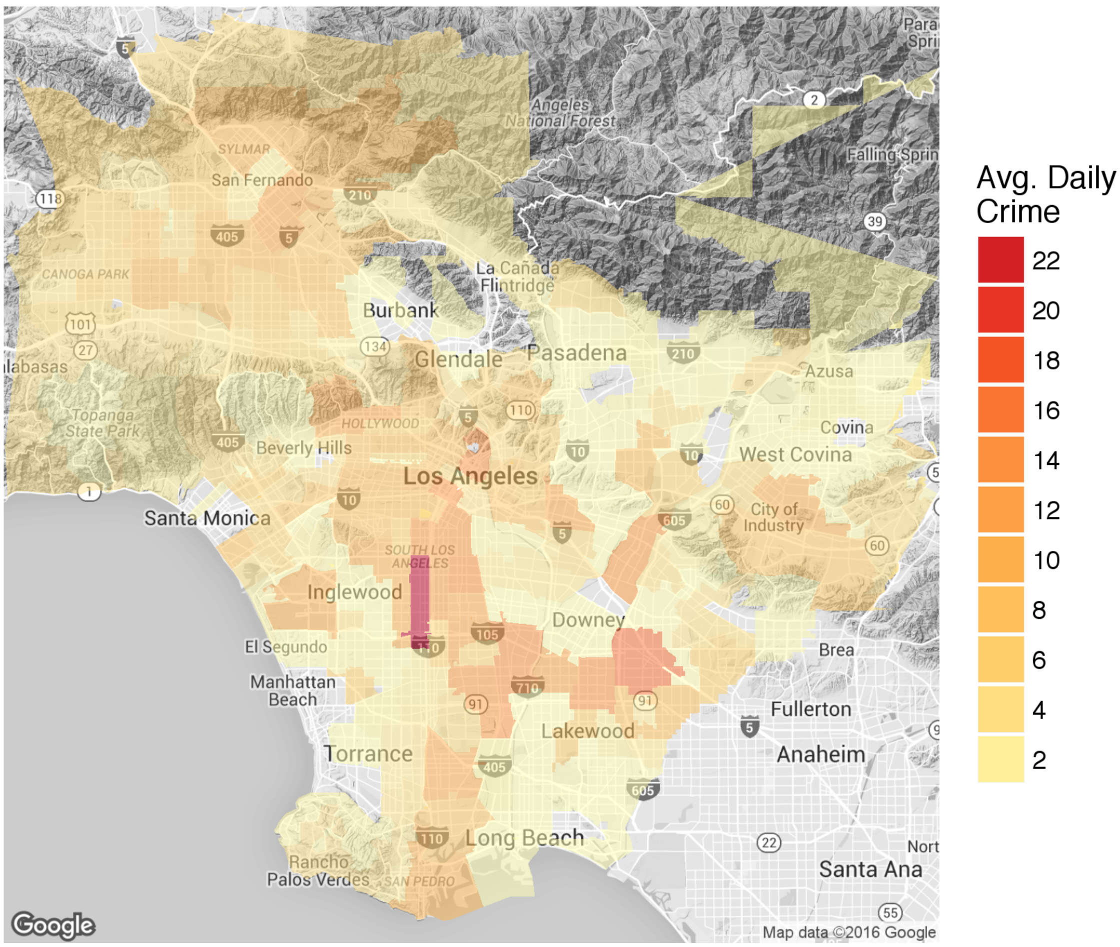
Notes: It presents key descriptive statistics (Mean, SD, Min and Max) for daily average crime by zip code for total crime and evening crime.
Sources: Los Angeles Police Department and Los Angeles Sheriff Department.

Table A.3: Leads of traffic: persistence of the effect

Domestic violence	(1) at T	(2) at T+1	(3) at T+2	(4) at T+3	(5) at T or T+1
95th Percentile	0.0650**	0.0811***	0.0359	-0.0188	0.0735***
	(0.0239)	(0.0242)	(0.0234)	(0.0215)	(0.0197)
Observations	307,440	309,959	306,178	309,957	311,219

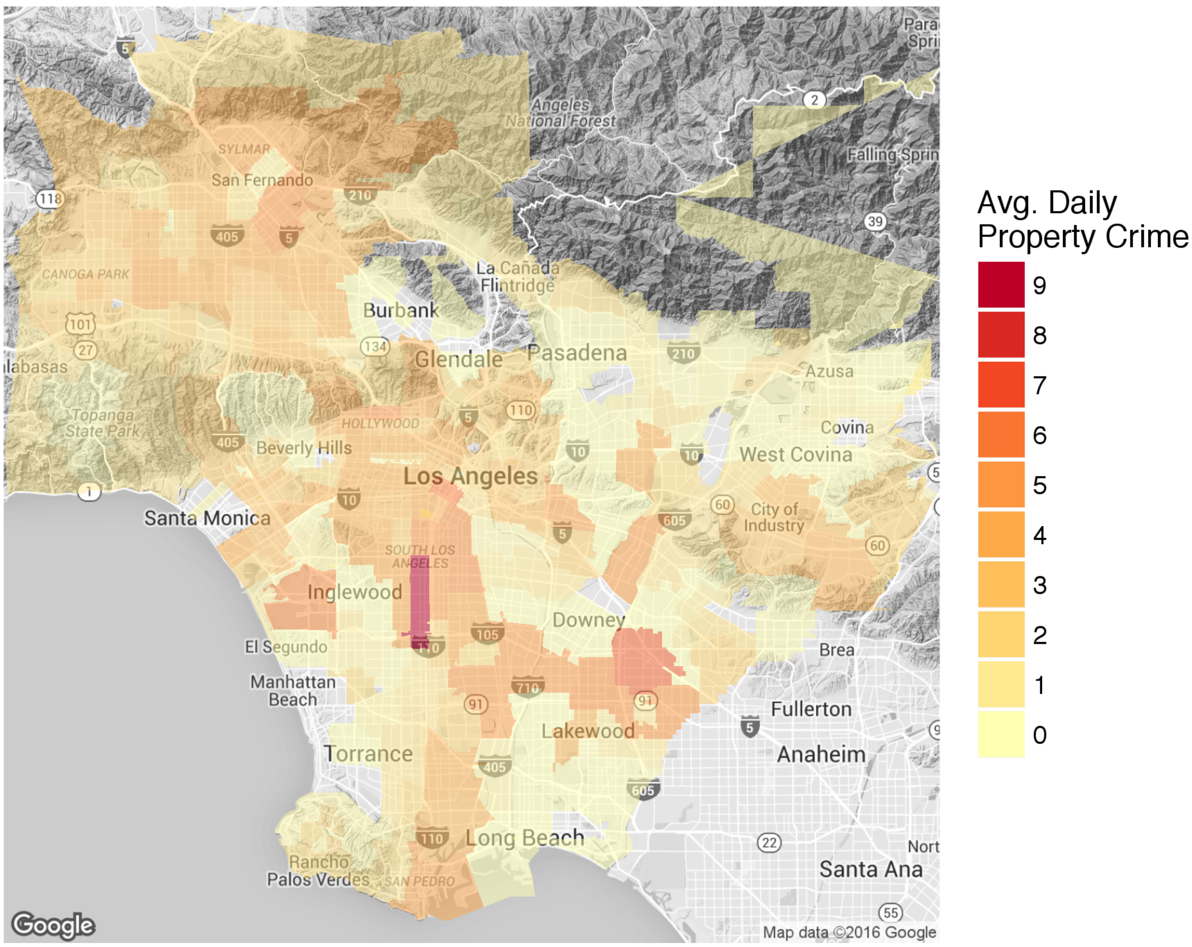
Notes: The estimates include zip code, year-month, and day of week fixed effects, a quadratic time trend, rain, maximum temperature, wind speed. The regressions also include measures of expected traffic: average traffic in the last week and the last month for the given zip code. Robust standard errors clustered at the zip code are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.

Figure B.1: Map of Crimes in Los Angeles



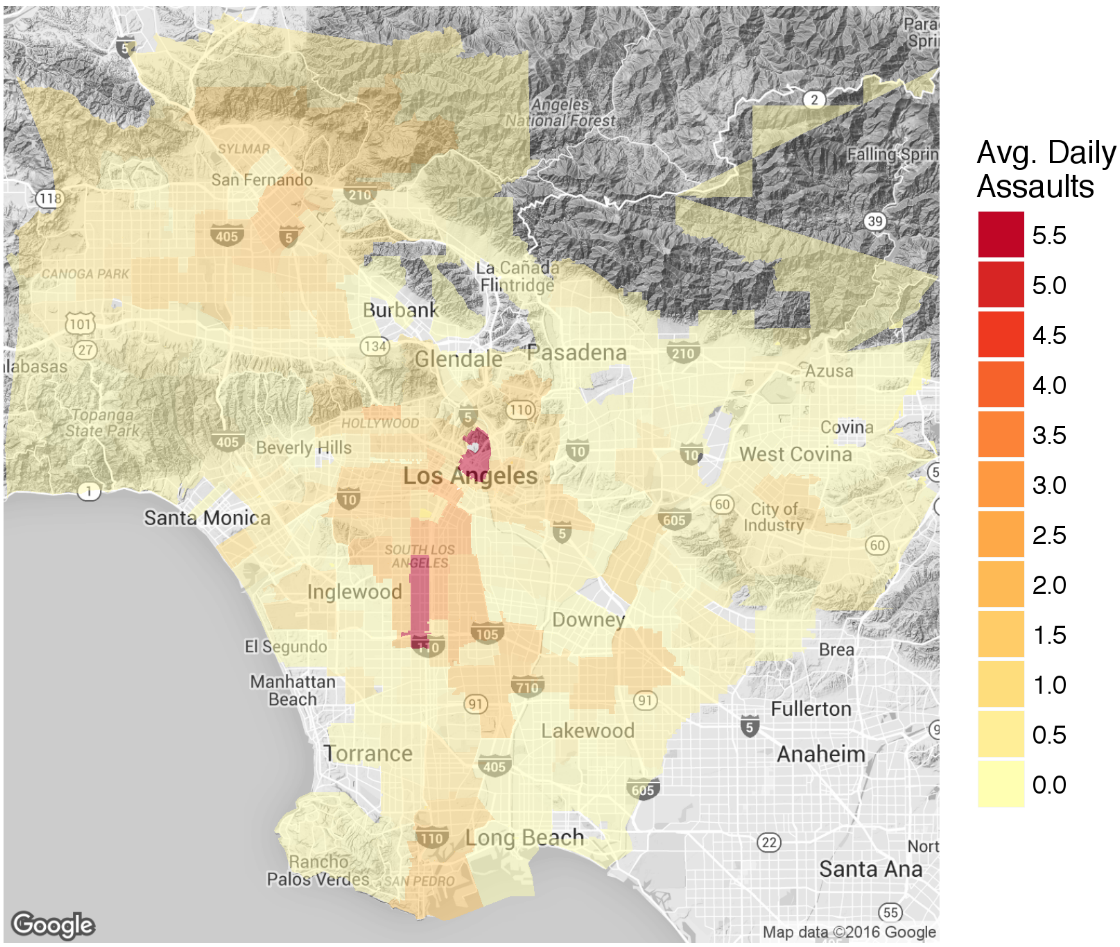
Sources: Los Angeles Police Department and Los Angeles Sheriff Department.

Figure B.2: Map of Property crime in Los Angeles



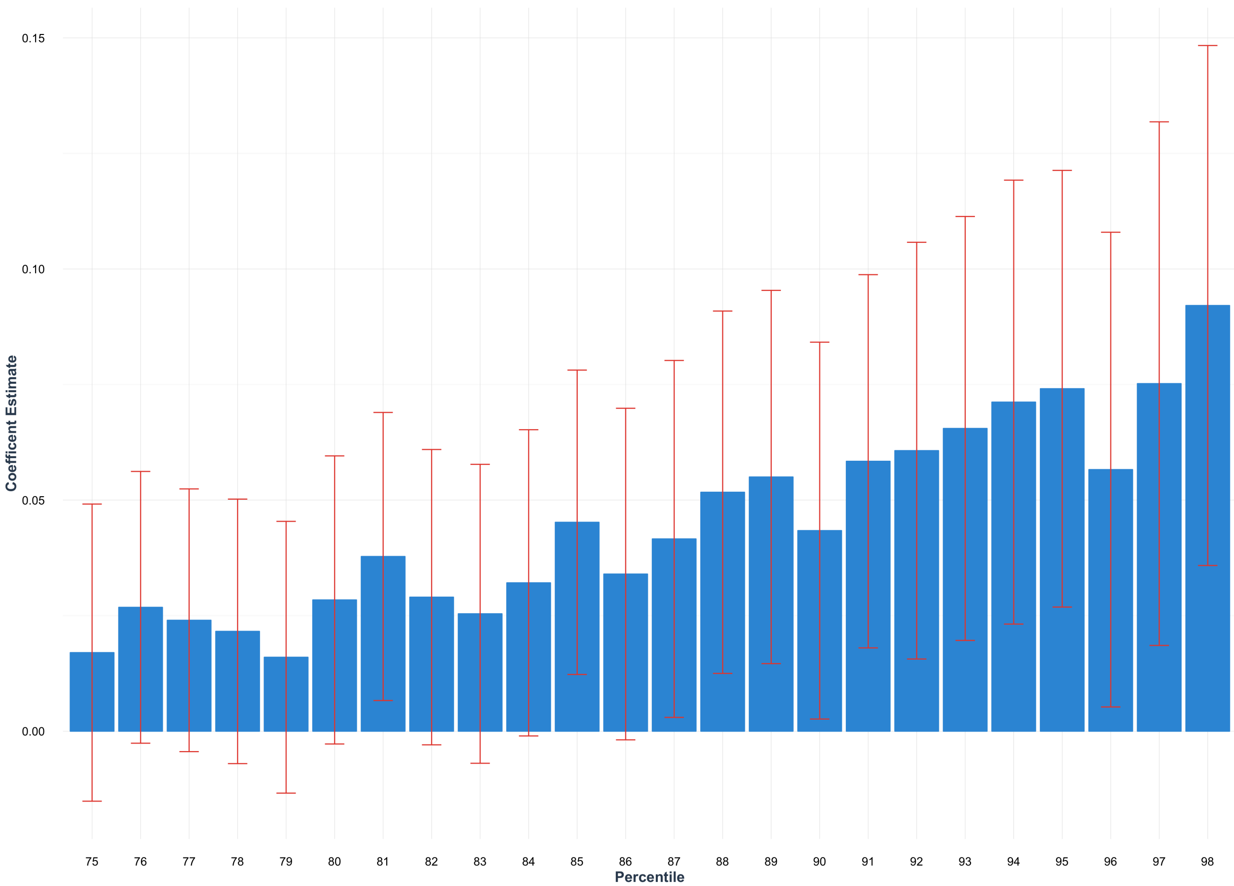
Sources: Los Angeles Police Department and Los Angeles Sheriff Department.

Figure B.3: Map of Assault in Los Angeles



Sources: Los Angeles Police Department and Los Angeles Sheriff Department.

Figure B.4: Effect of Traffic on Domestic Violence - Different Thresholds



Sources: California Department of Transportation, Los Angeles Police Department and Los Angeles Sheriff Department.