Effects of Vehicle Miles Traveled and Highway Speeds on the Frequency and Severity of Motor Vehicle Accidents: Evidence from COVID-19

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Abstract

Highway fatalities are a leading cause of death in the U.S. and other industrialized countries. Using highly detailed accident, speed and flow data, we show highway travel and motor vehicle accidents fell substantially in California during the response to the COVID-19 pandemic. However, we also show the frequency of severe accidents increased due to lower traffic congestion and higher highway speeds. This "speed effect" is largest in counties with high pre-existing levels of congestion, and we show it partially or completely offsets the "VMT effect" of reduced vehicle miles traveled on total fatalities. During the first eleven weeks of the COVID-19 response, highway driving decreased by approximately 22% and total accidents decreased by 49%. While average speeds increased by a modest 2 to 3 miles-per-hour across the state, they increased between 10 and 15 miles-per-hour in several counties. The proportion of severe accidents increased nearly 5 percentage points, or 25%. While fatalities decreased initially following restrictions, increased speeds mitigated the effect of lower vehicle miles traveled on fatalities, yielding little to no reduction in fatalities later in the COVID period.

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1 Introduction

Each year more than 30,000 motor vehicle fatalities occur in the United States (National Highway Traffic Safety Administration, National Center for Statistics and Analysis, 2019), with 1.35 million deaths worldwide World Health Organization (2018). Fatal accidents reflect a tremendous amount of driving, over 3 trillion vehicle miles traveled (VMT) (United States Department of Transportation, Bureau of Transportation Statistics, 2020), and a large number of accidents, over 6 million, each year in the U.S. (National Highway Traffic Safety Administration, National Center for Statistics and Analysis, 2020). During the national response to the COVID-19 pandemic, travel restrictions substantially reduced driving and, anecdotally, motor vehicle accidents in the US. We exploit detailed data on driving, accidents, weather and fatalities in California to study the effect of COVID-19-related restrictions on traffic accidents and fatalities. We show these restrictions in California led to large reductions in VMT and accidents, while increasing highway speeds and accident severity. More generally, we document and quantify an important trade-off that emerges for any reduction in traffic congestion.

While increased VMT and higher speeds should clearly affect motor vehicle fatalities, isolating and quantifying their individual effects is empirically challenging due to the interplay between the demand for driving, traffic congestion, speeds and accidents. Cross-sectional analysis of the effect of these factors on fatalities is prone to omitted variable bias (e.g. differences in road conditions, funding, policing, underlying attitudes, etc.). Time-series analysis is complicated by reverse causality in the timing of accidents and congestion related speed reductions - that is, accidents that cause congestion, or time-varying trends in driving, accidents and fatalities (e.g. changes in vehicle technologies and safety).

We overcome these challenges by exploiting the reduction in travel due to COVID-19 restrictions to estimate the causal effects of VMT and average vehicle speeds on accidents and motor vehicle fatalities. Decreased demand for driving led to large reductions in VMT and higher average vehicle speeds in congested urban areas. We measure these shifts using hourly data on VMT and traffic speeds at thousands of locations across California from the Freeway Performance Measurement System (PeMS) (California Department of Transportation, 2020).

We combine these data with reports from the California Highway Patrol (CHP) Incident Report System, also collected through PeMS. Using a text analysis of these detailed incident reports (several tens of millions of individual entries at the minute time-scale), we categorize accidents by severity and whether a fatality occurs. Because weather plays a role in many accidents, we collect hourly weather data from the NOAA ISD-lite system (National Oceanic and Atmospheric Administration, 2020) and match station-level observations to California counties based on proximity. Combined, these are the most comprehensive micro-level data on motor vehicle-related fatalities available - a key factor in selecting California for this analysis.

Trends in driving and accidents before and after COVID-19 restrictions for six large California counties show large decreases in vehicle miles traveled and accidents, as well as large increases in average speeds. The share of severe accidents increases substantially. Regression analysis across all California counties in our PeMS dataset show travel restrictions decreased VMT by approximately 22 percent and total accidents by approximately 49 percent. Average highway speeds increased by 2 to 3 miles per hour across all counties, but increased as much as 10 to 15 miles per hour during peak hours in some counties. The share of severe accidents increased nearly 5 percentage points, or approximately 25 percent, during the COVID period.

We use the shift in travel demand due to COVID-19 restrictions to estimate the causal effects of VMT and average vehicle speed on fatalities. We find a 1 percent increase in VMT increases fatalities by about 1 percent and cannot reject an elasticity of one. A 1 percent increase in average speed increases fatalities by about 4 percent. These parameter estimates imply reduced VMT during the COVID period would have reduced fatalities in California by approximately 50 percent. However, higher average speeds due to reduced congestion mitigates this effect by half, such that the total decrease in fatalities is approximately 25 percent. Further, increases in VMT several weeks after initial COVID-19 restrictions, which were not coupled with substantial speed decreases, contributed to a rise in fatalities later in our sample. This result follows from the convex relationship between travel time and congestion - when traffic is uncongested, changes in the number of cars on the road have little-to-no effect on average speed.

Using detailed data on the characteristics of drivers and accidents in California during this period, we investigate the potential role of compositional shifts in increased fatalities. For example, if lower congestion allowed riskier drivers to drive at higher speeds, then the observed increase in accident severity may reflect compositional shifts in driver types. During the COVID period, younger drivers and male drivers make up a larger share of parties involved in accidents. Vehicles involved in accidents are older, and alcohol and poor weather are more likely to contribute to accidents during the COVID period. An analysis of the fatality age distributions for single car accidents indicates an increase in fatalities among both younger and middle-age drivers. This suggests the increase in accident severity we document is not isolated to younger and potentially riskier drivers.

We contribute to a large literature that investigates the causes of motor vehicle fatalities. Earlier cross-sectional studies have explored the relationship between VMT and fatalities (Clark and Cushing, 2004; Yeo, Park, and Jang, 2015). The relationship between vehicle speeds and fatalities has been studied in the context of increases in speed limits on rural interstates during the 1980s and 1990s following changes to U.S. national speed limits. While a 10 mph higher speed limit increases average speed between 2 and 4 mph (Ashenfelter and Greenstone, 2004; McCarthy, 2001; Retting and Greene, 1997; Van Benthem, 2015), fatalities increase substantially, between 15 and 60 percent (Ashenfelter and Greenstone, 2004; Baum, Wells, and Lund, 1990; Farmer, Retting, and Lund, 1999; Farmer, 2017; Greenstone, 2002; Van Benthem, 2015). However, extending these results to urban areas or metro-area highways has been challenging in part because urban vehicle speeds are often limited by congestion rather than speed limits (Burger and Kaffine, 2009). Further, systematic differences in factors such as hospital access, emergency vehicle response times, vehicle fleet composition and the prevalence of divided highways imply the effect of speed on fatalities is likely different in urban areas. Understanding effects in urban areas is especially important as over 80 percent of U.S. population lives in urban areas (United States Census Bureau, 2018).

Our results have implications beyond the current COVID crisis. State and local policies that reduce congestion and increase average highway speeds are likely to experience similar increases in accident severity. In contrast to earlier studies that identified the effects of higher speed limits on fatalities on rural highways, the effects identified here are largest on congested urban highways, which carry a substantial fraction of total vehicles. Further, since the effects we estimate move in opposite directions (decreased VMT reduces fatalities, increased speed increases fatalities), we note that our results have important implications for the choice of congestion relief policy. For example, highway expansions that increase both the amount of driving and vehicle speeds will increase fatalities through both channels. By contrast, congestion charges that reduce VMT but increase speeds can either increase or decrease fatalities depending on the relative strength of these channels.

2 Data

We combine detailed data on motor vehicle travel and fatalities from several sources. Vehicle miles traveled and average speeds are from the California Department of Transportation Performance Measurement System (PeMS) (California Department of Transportation, 2020). PeMS reports hourly traffic data for major highways in 42 of California's 58 counties (additional information on PeMS monitoring network is provided in the appendix). Hourly data are collected for the period from March 1, 2015 through May 31, 2020. Observations are county-level VMT totals and mean speeds calculated from thousands of traffic sensors (loop detectors) throughout the state. We sum hourly VMT to the daily total within each county. We calculate mean speed as the average across all detectors within a given county.

Detailed accident data are collected by the California Highway Patrol (CHP) Incident Report System and made available through PeMS (California Department of Transportation, 2020). Each record contains the time, location, duration and a description of the accident. The CHP data also include police dispatch codes that we use to classify accidents as minor, severe or unknown. Severe accidents are those where the dispatch code reports a fatality (1144), requests an ambulance (1179, 1141) or reports a major injury (1180). Minor accidents are those with dispatch codes reporting minor injuries (1181) or no injuries (1182, 20002) and accidents classified as unknown are those reported with unknown injuries (1183, 20001).

Fatality data are also derived from a text analysis of the CHP incident reports. Dispatch codes reported in CHP incident reports denote probable fatalities (1144). However, many incidents with different initial dispatch codes ultimately result in a fatality. More detailed notes accompanying each incident report indicate whether a fatality subsequently occurred. Therefore, we scrape CHP's detailed incident notes and perform a text analysis to determine an accurate fatality count. Specifically, we search the detailed incident notes for words such as "coroner" and "veh 1144" to determine whether a fatality has occurred.

Because weather, in particular rainfall, is a key factor in many traffic accidents (Saha et al., 2016), we collect weather data from the National Oceanic and Atmospheric Administration (2020). We collect hourly precipitation, cloud cover, wind speed, wind direction, temperature and pressure. Hourly data are collapsed to daily average precipitation, wind speed, wind direction, cloud cover, temperature and pressure. Stations are matched to counties based on the shortest distance between each station and county's population-weighted centroid. Because the effect of rainfall on accidents may be non-linear, our main empirical results include an indicator variable that equals one if the daily total rainfall in a county exceeds 5mm. In specifications using weekly data, heavy rainfall is defined as weeks with weekly total rainfall greater than 10mm. Robustness checks presented in Section 4.3 include additional weather controls.

Finally, for our analysis of compositional changes we obtain detailed data on the characteristics of drivers involved in accidents from the California Highway Patrol Statewide Integrated Traffic Records System (California Highway Patrol, 2021). These data report driver characteristics such as sex, age and ethnicity as well as accident characteristics such as vehicle type, weather, crash severity and whether alcohol was involved. We calculate the mean values of driver and accident characteristics immediately before and then during the initial COVID period and interpret differences in these values as evidence of compositional shifts during COVID-19 driving restrictions.

3 Traffic changes during initial COVID-19 related restrictions

Figure 1 plots daily vehicle miles traveled, average highway speeds, weekly accidents and accident severity for Los Angeles, Sacramento, San Diego, San Francisco and Santa Clara Counties (these represent approximately 44% of highway VMT in the state - authors' calculations using PeMS data). We note three dates: First, March 4, 2020, the day California Governor Gavin Newsom declared a state of emergency related to the COVID-19 pandemic. Second, March 12, 2020, the date of the Governor's executive order limiting large gatherings and enacting social distancing measures. Third, March 19, 2020, the beginning of the California stay-at-home order. Each of these events likely had a different effect on driving within the state and their relative importance is not clear *a priori*.

The VMT and accident data in Figure 1 are normalized to account for differences in scale across cities. For VMT, panel a, we account for daily traffic patterns by first regressing VMT on day-of-week fixed-effects, using observations from 2020 prior to the Governor's executive order. We estimate the model separately for each city to account for differences in daily traffic patterns and mean VMT levels across cities, and then plot the ratio of observed VMT to predicted VMT. For accidents, panel b, we aggregate accidents to the weekly level to smooth day-to-day variability and better illustrate the county-level trends. We again estimate separate models for each county and plot the ratio of observed accidents to model predictions based on rainfall and week-of-year fixed effects. For accident severity, panel d, we expand the sample to five years prior to March 2020 to preserve statistical power. We predict the mean severe accident share for each week and county during 2020 and plot the difference between the observed and predicted shares, based on week-of-year fixed effects and an indicator for heavy rainfall. This measure gives the change in the share of severe accidents, in percentage points, over time.

Panel a of Figure 1 shows VMT trends for the six counties, which are are essentially constant through the state of emergency declaration and are decreasing only slightly prior to the March 12 executive order. However, following the executive order, VMT decreased

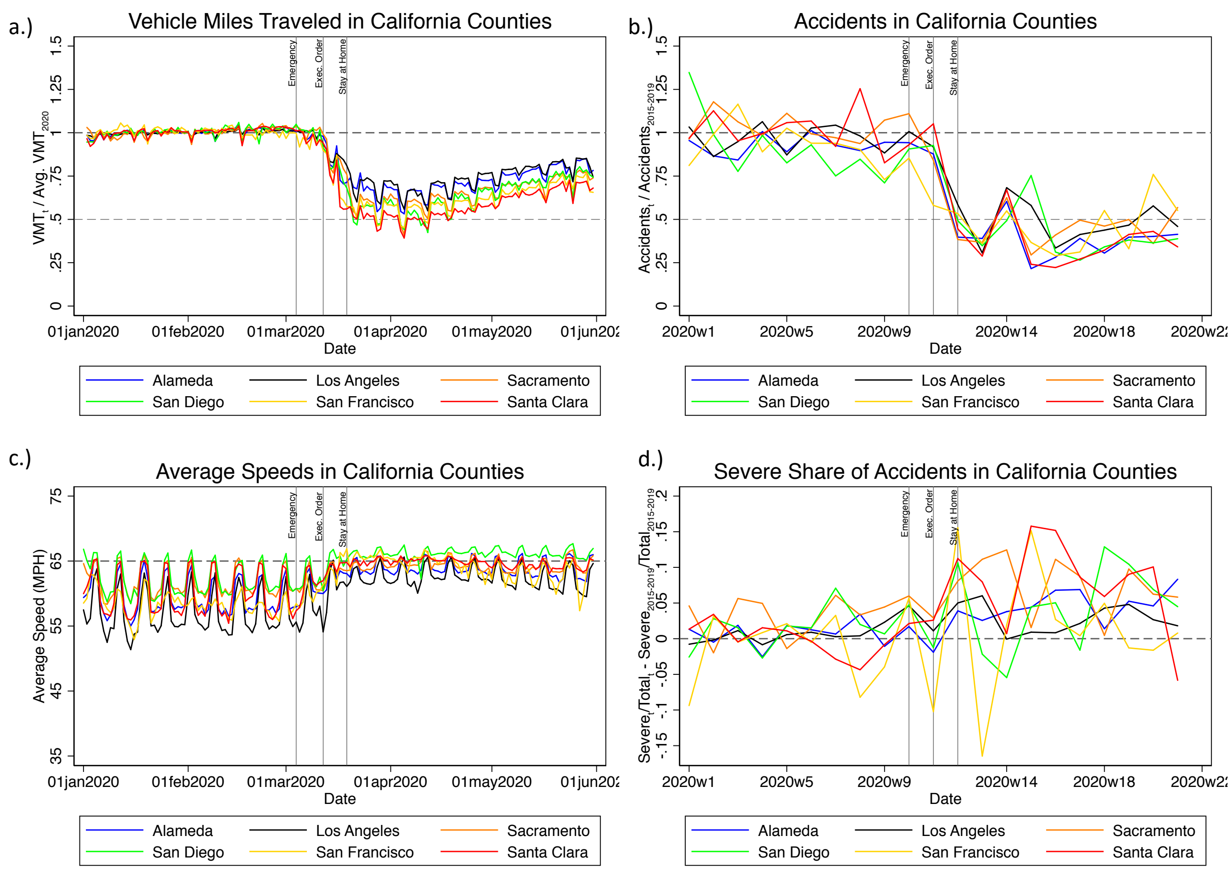

Figure 1: Time-series of traffic patterns in six California counties before and after COVID-19 related travel restrictions. a.) vehicle miles traveled; b.) weekly accident totals; c.) average highway speeds; and d.) changes in the share of severe accidents.

sharply for several weeks, falling as much as 50 percent by the beginning of April. The largest decreases are for Santa Clara and San Diego counties, while the decline in VMT is smaller in Alameda and Los Angeles Counties. Following several weeks of declining VMT, driving begins to increase during the month of April. By the end of May, VMT rises to near 75 percent of pre-COVID levels. Panel b of Figure 1 shows similar accident trends for the six counties. Accident totals are noisy but essentially constant during the first part of 2020. Accidents begin to decrease around the time of the executive order, falling to below 50 percent of pre-COVID levels. However, by week 16, 4 to 5 weeks following the executive order, accidents begin to increase slightly.

Panel c of Figure 1 shows average speeds for the six counties increased as VMT declined. Prior to COVID-19 restrictions, average speeds in counties such as Los Angeles do not reach free flow levels, even on weekends, and range between 55 mph and 60 mph. Speeds begin to increase in the week before the Governor's executive order. Following the order, average speeds are 5 to 10 mph higher across the six counties, which suggests that when accidents do occur, they are likely more severe. Throughout the month of April, speeds remain high despite the increase in VMT, as highways were still largely uncongested. However, by May average speeds begin to decrease, indicating a return to congested conditions.

Panel d of Figure 1 shows the share of severe accidents in the six counties over time, coded based on police dispatch codes from the CHP incident reports. The share of severe accidents post COVID-19 restrictions increases between 5 and 10 percentage points, providing evidence of a substantial increase in accident severity, as this represents a doubling of severe accident share in some counties. The largest effects are in San Francisco and Santa Clara, counties that saw the largest speed increases in panel c. Overall, the trends illustrated in Figure 1 suggest COVID-19 restrictions had large effects on vehicle travel and accidents in California. We quantity the average effects across all PeMS counties in the section below.

4 Empirical analysis

To quantify the mean effects of COVID-19 travel restrictions on traffic, accidents and fatalities across California, we estimate a series of models of the form:

$$y_{it} = \beta_0 + EO_t + \delta_{it}^{hr} + \epsilon_i + \epsilon_{it}, \tag{1}$$

where y_{it} is an outcome of interest (VMT, average speed, accidents or accident severity) in county i on date t. We account for mean differences across counties using county fixed-effects ϵ_i. We model the effect of rainfall on traffic patterns and accidents with an indicator variable δ_{it}^{hr} that is equal to 1 if rainfall is heavy, as described above. We show in Section 4.3 that the results presented below are robust to alternate specifications. The main parameter of interest is an indicator variable for the start of COVID-19 travel restrictions EO_t. Observations occurring after Governor Newsom's March 12, 2020 executive order are coded as 1, based on the timing of the VMT decline in Figure 1 panel a. Therefore, EO_t measures the mean effect of the COVID-19 travel restrictions across all counties during the treated period.

For VMT, we specify the dependent variable as the natural logarithm of vehicle miles traveled to account for differences in scale in the treatment effect across counties with widely varying levels of driving. We account for changes in the size of the PeMS monitoring network over time by including the number of PeMS "lane-points" (or lanes-monitoring locations) in each county on each day as an additional explanatory variable in our VMT model.

We model average highway speed in miles per hour, *i.e.* levels. Because the effect of changes in speed on fatalities also varies with the number of drivers exposed to these changes in speed, we estimate a weighted average treatment effect using weighted least-squares where the weights are county-level VMT. Accident severity is modeled as the share of severe accidents as indicated by CHP dispatch codes on each day in each county. We model the number of accidents and fatalities per day in each county as count variables and estimate Equation 1 using Poisson regression.

Table 1 presents results for our estimates of Equation 1. Column 1 shows that log daily VMT decreases by -0.249 across all counties, or about 22 percent, after implementation of the COVID restrictions. Column 2 presents results for accidents, which fall by -0.647 or approximately 48 percent. While accidents decrease overall, Column 3 shows that the share of severe accidents increases by 4.8 percentage points, or about 25 percent during this period. In column 4 we see average speeds decrease by about 2.0 mph as a result of COVID-19 restrictions. However, this figure ignores the fact speed increases are greater when more drivers are affected, *i.e.* in the more congested counties with greater traffic volumes. Column 5 presents the estimated speed increase from a weighted least squares regression where counties are weighted by daily VMT, whereby the estimated effect is over 50 percent larger, approximately 3.1 mph. While decreases in VMT reduce fatalities, the corresponding increase in speed and accident severity likely increase fatalities. The estimate in Column 6 shows the net effect of these factors could be slightly positive, about 7 percent, though the estimate is not statistically significant.

COVID-Related Traffic Effects

	ln(VMT)	ln(Accidents)	Severe Share	Avg. Speed	Avg. Speed VMT Wgt.	ln(Fatalities)	ln(Fatalities)
Post Exective Order	-0.249***	-0.647***	0.048***	2.033***	3.066***	0.072	
	(0.0480)	(0.0370)	(0.0060)	(0.2710)	(0.5520)	(0.1130)	
Daily rainfall > 5mm	-0.040**	0.475***	-0.017***	-0.508***	-0.583***	0.182**	-0.352
	(0.0160)	(0.0360)	(0.0040)	(0.1640)	(0.0940)	(0.0890)	(0.5750)
ln(VMT)							1.048***
							(0.1080)
ln(Speed)							4.352**
							(1.8980)
Lanepoints	Yes	No	No	No	No	No	No
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78990	77488	58048	78990	78990	70341	6074
Adj. R-sq.	0.97		0.05	0.41	0.48		

Table 1: Regression analysis of COVID-19 related travel restrictions on VMT, accidents, highway speeds and fatalities. Notes: Vehicle miles traveled (VMT) measured in millions of miles per county per day for PeMs counties. Accidents are the sum of CHP severe, minor and unknown incidents by CA county and day. The severe share is the share of all accidents classified as severe according to CHP dispatch codes. Average speed is the average speed on PeMs highways over all hours of the day. Weights are total county level daily VMT. Fatalities are CHP reported deaths by county and date for 2020. Standard errors clustered at the date level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

To identify the relationships between driving, vehicle speeds and traffic deaths we model fatalities as:

$$ln(Fatalities_{it}) = \beta_0 + \beta_1 lnVMT_{it} + \beta_2 lnSpeed_{it} + \delta_{it}^{hr} + \epsilon_i + \epsilon_{it}, \tag{2}$$

where $lnVMT_{it}$ is the natural logarithm of vehicle miles traveled and $lnSpeed_{it}$ is the natural logarithm of average speed in county i on date t. Again, δ_{it}^{hr} is an indicator variable for days with heavy rainfall and ϵ_i are county fixed-effects. A common challenge in modeling fatalities is that unobserved factors that are correlated with vehicle miles traveled and speeds may also be correlated with fatalities leading to omitted variable bias. Here, we exploit the COVID-19 travel restrictions to isolate exogenous variation in VMT and highway speeds. We focus on a narrow window of time, approximately ten weeks prior and ten weeks following the implementation of travel restrictions to isolate plausibly exogenous shifts in travel behavior. We estimate Equation 2 using Poisson regression. Parameter estimates are reported in column 7 of Table 1. The coefficient β_1 can be interpreted as the "VMT effect" on fatalities, while the coefficient β_2 can be interpreted as the "speed effect" on fatalities. The relationship between vehicle flow or VMT and speed is well known to be backward bending, i.e. at high levels of congestion speed and flow decrease simultaneously. The reduction in driving during the COVID period shifted many California counties out of these highly congested hyper-congestion conditions to less-congested travel. Because of these shifts, the data have sufficient variation in both VMT and speed to allow separate estimation of both effects. Specifically, we find a 1 percent increase in VMT increases fatalities by about 1 percent. A 1 percent increase in average speed increases fatalities by approximately 4 percent.

To gauge whether these estimates are reasonable, consider a conceptual model for traffic fatalities where the probability a driver is involved in an accident is a constant ρ (per mile driven), such that the product $\rho \times VMT_{it}$ is the expected number of accidents in county i and day t. Some fraction of these accidents will be severe enough to result in a fatality. For simplicity, assume the likelihood of a fatal accident is proportional to the amount of kinetic energy in the collision (proportional to vehicle speed squared). Under these assumptions, the expected number of fatalities is:

$$Fatalities_{it} = \alpha \rho VMT_{it} \times Speed_{it}^2, \tag{3}$$

where α is a constant. Taking the natural logarithm yields the following equation, where $\gamma = ln(\alpha\rho)$:

$$\ln Fatalities_{it} = \gamma + 1 \times \ln VMT_{it} + 2 \times \ln Speed_{it}.$$

Under this model, the VMT coefficient would be 1, and if one could measure each vehicle's speed, the speed coefficient would be approximately 2. However, since the relative infrequency of fatal accidents requires some amount of aggregation, our regression analysis only measures changes in average speed at the daily level. This average reflects relatively larger increases in speed in congested counties during hours with the most driving and a near-zero change during uncongested evening and early morning hours. Therefore, we expect the speed coefficient to be somewhat larger than 2, as found in Table 1.

4.1 Heterogeneity and aggregate effects

The mean effects presented in Table 1 hide important heterogeneity in the data, as counties with different baseline levels of driving and congestion have different impacts from COVID-19 restrictions. Figure 2 decomposes the effect of COVID-19 restrictions on speed into different periods of the day (AM peak, mid-day, PM peak, and night) for county quintiles based on historical (5 year) measures of congestion. In the most congested counties (top row, Q5), there are large increases in average speeds during the daytime periods, ranging from 5 to over 15 mph. The largest increases occur during the afternoon peak. Less congested counties experience smaller speed increases, on the order of 5 to 10 mph for counties in the fourth quintile of congestion and 0 to 5 mph for counties in the third quintile. The least-congested counties (bottom row, Q1) see little-to-no change in average speeds, and there are no nighttime effects outside of the fifth quintile.

Figure 3 uses the estimates from Equation 2 to decompose county-level changes in fatalities into a VMT effect and a speed effect. To facilitate comparisons across counties, the VMT effect is the decrease in fatalities solely due to VMT reductions under COVID-19 restrictions normalized relative to a no-COVID counterfactual. The speed effect is defined as the increase in fatalities due to higher speeds under COVID-19 restrictions relative to the no-COVID baseline counterfactual. The x-axis shows percentage reductions in fatalities due to lower driving and the y-axis shows percentage increases due to higher speeds, such that the 45-degree line is where the two effects exactly cancel, implying no net effect on fatalities. In most counties, reduced VMT lowers fatalities between 20 and 40 percent. In uncongested counties (green), the speed effect is essentially zero. In moderately congested counties, higher speeds increase fatalities between 10 and 20 percent, negating about half of the VMT effect. In the most congested counties (red), the speed effect increases to between 20 and 35 percent. This implies San Francisco and Alameda counties experience a small reduction in fatalities, while Los Angeles experiences a small *increase* in fatalities due to COVID-19 restrictions.

Figure 4 shows the total fatalities and model predictions for all California PeMS counties over time. We compare predicted fatalities under COVID-19 restrictions that include both

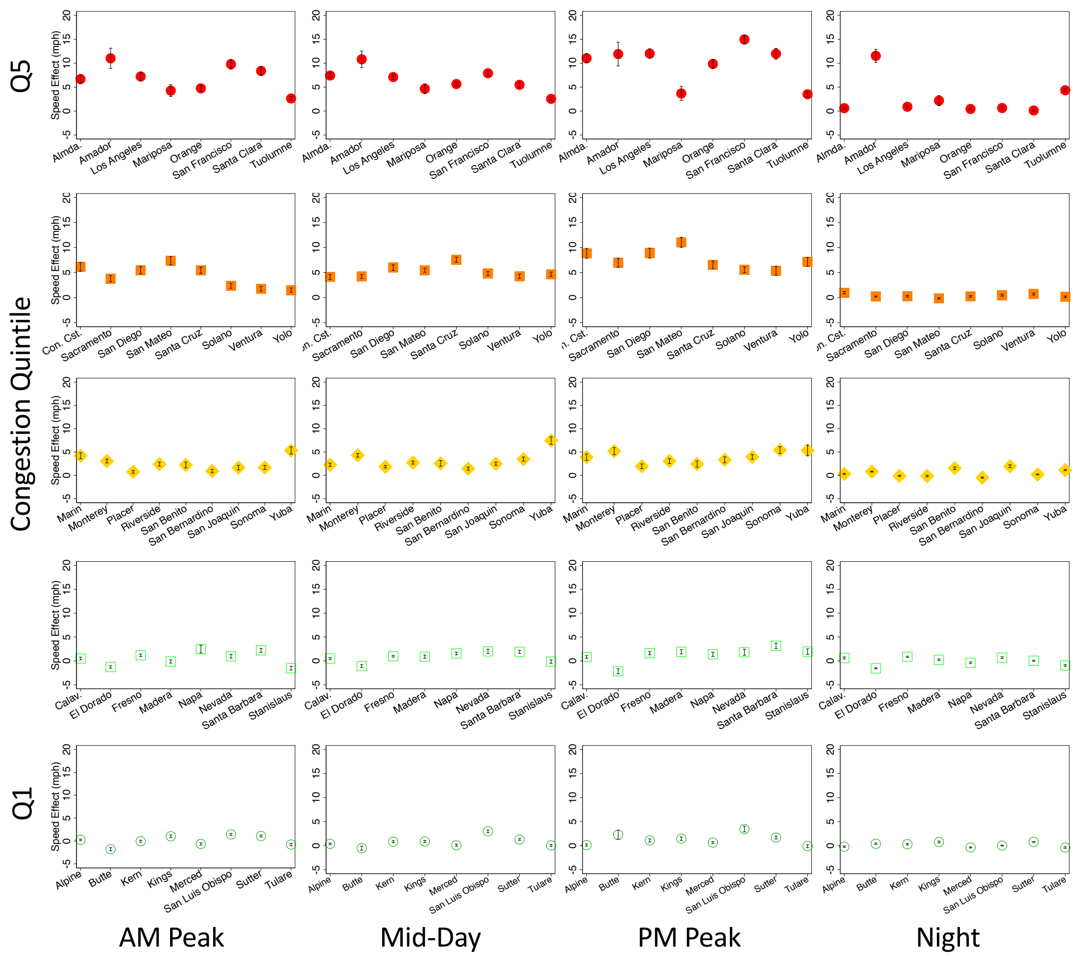

Figure 2: Average COVID-19 related speed effects (change in mph) by time of day: AM Peak is 6 am to 9 am, Mid-day is 9 am to 4 pm, PM Peak is 4 pm to 7 pm and Night is 7 pm to 6 am. The counties are grouped into quintiles of traffic congestion defined as historical average delay using a free-flow speed of 65 mph. Q5 is the most congested quintile, Q1 is the least.

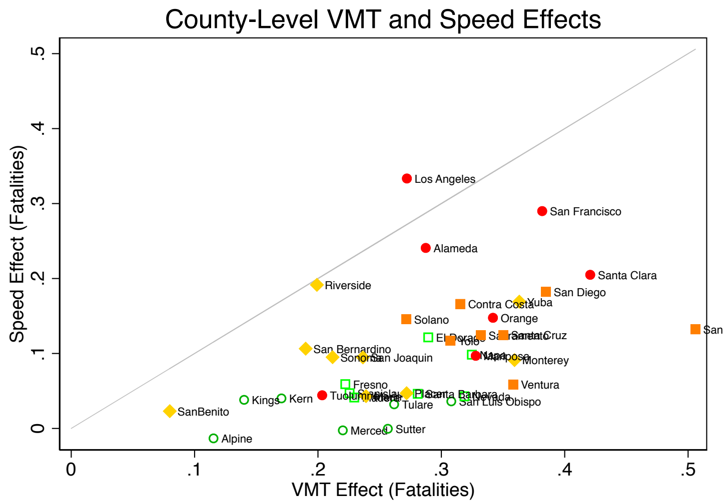

Figure 3: Decomposition of total fatalities into decreases from lower vehicle miles traveled and increases due to higher speeds. County-level estimates are shown based on Equation 2. The 45-degree line indicates no net change in fatalities. Color coding is based on quintiles in Figure 2

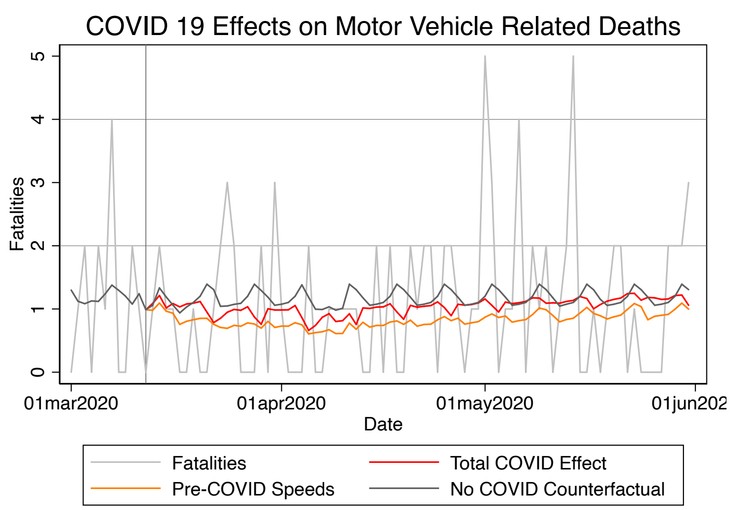

Figure 4: Estimated effects of COVID-19 related travel restrictions on California motor vehicle fatalities. Observed fatalities are shown in light-gray. The estimated no-COVID counterfactual based on Equation 2 is plotted in dark gray. Plotted in red are (smoothed) fatalities under COVID restrictions, *i.e.* taking into account the combined effects of reduced VMT and increased speed. Plotted in orange is the counterfactual prediction assuming no average speed increase due to COVID-19 restrictions. The difference between the red and orange plots shows the estimated increase in daily fatalities due to higher speeds from lower traffic congestion during the treated period.

the speed and VMT effects (red), with the no-COVID counterfactual (dark grey) and a counterfactual excluding the speed effect (orange). Fatalities fall by approximately 30 percent during the initial COVID-period relative to the counterfactual. By May, as VMT increases but speeds remain high, the COVID fatality rate increases to a level comparable with the no-COVID counterfactual. Importantly, without the COVID-19 speed effects (orange) the fatality rate during the COVID period would have been substantially lower, by approximately 25 percent.

4.2 Driver and accident characteristics

In this section, we exploit detailed accident and driver data from the California Highway Patrol Statewide Integrated Traffic Records System to explore potential mechanisms for the accident and fatality effects. We focus on characteristics that may be associated with riskier drivers or more dangerous driving conditions. For example, one hypothesis is that the composition of drivers changed, as riskier drivers were relatively less likely to stay home during the COVID period. A reduction in congestion, that previously constrained these drivers' speeding or otherwise risky behavior, might now enable more speeding thereby increasing crash severity. Such compositional changes have been found in other contexts, such as Maheshri and Winston (2016) who show that changes in the composition of drivers during the Great Recession reduced the number of fatal highway accidents in Ohio.

Our analysis focuses on two periods: the ten-week period in 2020 immediately before the California Executive order and the ten-week period immediately following the order. Our sample includes all accidents on all types of roadways during the period. Table 2 presents the mean of each characteristic in each period.

Accident Characteristics	Pre-Covid	Covid Period	Change	p-value
Driver Age (years)	40.06	39.00	-1.07	0.000
Driver Over 65	0.080	0.065	-0.014	0.000
Driver Under 25	0.197	0.211	0.014	0.000
Driver Male	0.614	0.674	0.060	0.000
Young Male Driver	0.119	0.140	0.021	0.000
Alcohol Involved	0.089	0.113	0.024	0.000
Speeding (Fatal Acc.)	0.169	0.194	0.025	0.244
Rain	0.021	0.060	0.039	0.000
Wet Roadway	0.059	0.140	0.081	0.000
Darkness	0.371	0.276	-0.095	0.000
Fatal Acc.	0.0048	0.0082	0.0034	0.000

Table 2: Characteristics of drivers and accidents in the 10 weeks prior and 10 weeks following the California Executive Order.

Beginning with driver age, we see the mean age of drivers involved in an accident in the pre-COVID period is approximately 40 years. The mean age falls by approximately 1 year during the COVID period. This change is largely driven by a decrease in the proportion of older drivers and an increase in younger drivers. In the pre-COVID period, approximately 8 percent of drivers involved in accidents were over the age of 65. The share of older drivers involved in accidents decreased to 6.5 percent during the COVID period. For drivers under the age of 25, the share grew from 19.7 percent to 21.1 percent. Drivers involved in accidents are 6 percentage points more likely to be male during the COVID period. Overall, these shifts mean the proportion of accidents involving young males increases from approximately 12 percent to 14 percent.

There is some evidence these shifts led to riskier driving behavior. During COVID, the percentage of accidents where alcohol use is indicated increased from 8.9 percent to 11.3 percent. There is also suggestive evidence speed was more likely a factor in fatal accidents, increasing from 16.9 percent to 19.4 percent. Though this effect is not statistically significant, it is consistent with our regression results above indicating increases in highway speeds led to increases in fatalities. Further, one would expect increases in speed to be less of a factor in the statistics reported in Table 2, since this sample included accidents on all California roadways - many of which may have seen less congestion relief during COVID than the PeMS sample of major highways used in the analysis above.

If the shifts above imply riskier drivers are more likely on the road and involved in accidents during COVID, we would expect an increase in fatalities for these groups. We focus on driver age as the main risk factor, as well as single car accidents to remove the influence of drivers of other vehicles on fatalities, though effects for accidents involving multiple vehicles are quite similar to those presented here. Figure 5 plots the distribution of fatalities by driver age in the pre-COVID and COVID periods. During the COVID period we see increases in the number of fatalities among younger drivers. However, we also see similar increases in fatalities among middle aged drivers. There is a small decrease in fatalities for older drivers during the COVID period.

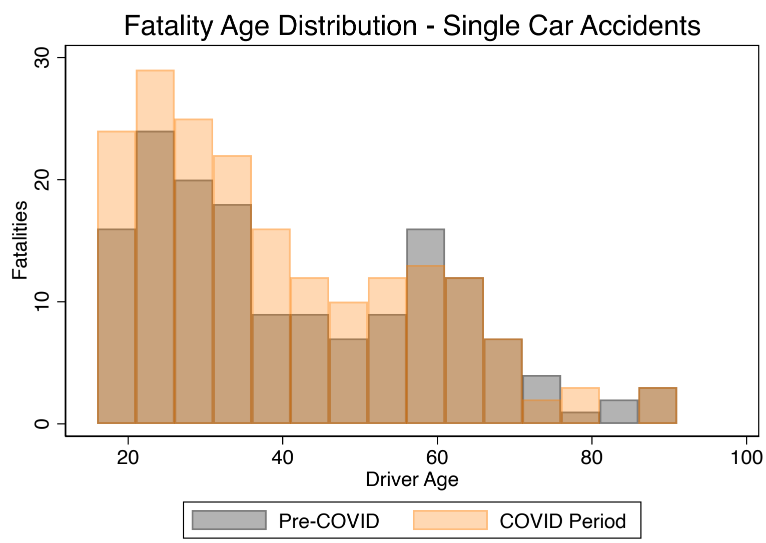

Figure 5: The distribution of driver ages involved in fatal single car accidents in the 10 weeks prior and 10 weeks following the California Executive Order.

Overall, these trends suggest substantial compositional shifts in the types of drivers involved in accidents in California during this period. However, the net effect on accident severity and fatalities is less clear. While we do observe shifts toward drivers typically considered risky, mainly young drivers, fatalities increase across a wide range of ages. While age is an imperfect proxy for riskiness, this result suggests to us the speed effects identified above apply more broadly than simply to a subset of risky drivers.

As a final check we investigate weather and daylight hours, as they are conditions typically associated with accident risk. These measures reflect the change in weather during the spring of 2020, namely rainfall increases later in the sample and the sun rises earlier and sets later thereby increasing hours of daylight. Since these effects are offsetting, wet roadways increase risk and better lighting decreases risk, it is difficult to sign the overall affect. However, the weather statistics underscore the need to account for rainfall as we do in our estimates above. Since the speed increases are greatest during uncongested mid-day hours, the effect of longer days seems unlikely to bias our results.

4.3 Robustness

Here we present alternate specifications and robustness checks for the results presented above. For outcomes presented in Table 1, we explore alternate controls for weather, seasonal effects and investigate heterogeneity in COVID-19 restriction effects by day of week.

We begin with the results for vehicle miles traveled in Table 3. For comparison, Model 3 is the base model used in Table 1 of the main text. Model 1 is a more parsimonious specification without controls for rainfall or county-specific mean effects. We see the estimated effect of COVID-19 restrictions is somewhat larger in magnitude, though comparable to the main results. Model 2 adds county fixed-effects. The estimated reduction in vehicle miles traveled during the COVID is smaller in magnitude than in Model 1 but identical to the result presented in Table 1. Model 4 allows for different mean travel patterns by day of week using day of week effects and Model 5 investigates whether COVID-19 restrictions affected travel differently on different days of the week, by interacting the treatment dummy with day of week fixed effects. Sunday is the omitted category. We see very large reductions in log VMT during the weekend, with decreases of -0.346 on Sundays and approximately -0.312 on Saturdays. The weekday effects are smaller, about -0.20, consistent with a smaller share of discretionary travel on weekdays.

Table 3: Alternate specifications for COVID-19 related VMT effects.

COVID-Related VMT Effects	Model 1	Model 2	Model 3	Model 4	Model 5
Post Exective Order	-0.305**	-0.249***	-0.249***	-0.251***	-0.346***
	(0.1160)	(0.0480)	(0.0480)	(0.0530)	(0.0590)
Lanepoints	0.072***	0.125***	0.125***	0.124***	0.124***
	(0.018)	(0.041)	(0.041)	(0.041)	(0.041)
Daily rainfall > 5mm			-0.040**	-0.014	-0.014
			(0.0160)	(0.0140)	(0.0140)
Post E.O. * Monday					0.128***
					(0.0170)
Post E.O. * Tuesday					0.127***
					(0.0200)
Post E.O. * Wednesday					0.129***
					(0.0180)
Post E.O. * Thursday					0.126***
					(0.0170)
Post E.O. * Friday					0.138***
					(0.0160)
Post E.O. * Saturday					0.034**
					(0.0130)
County Fixed-Effects	No	Yes	Yes	Yes	Yes
Week Fixed-Effects	No	No	No	Yes	Yes
DOW Effects	No	No	No	No	Yes
Observations	78990	78990	78990	78990	78990
Adj. R-sq.	0.43	0.97	0.97	0.97	0.97

Notes: The depdendent variable is the natural logarithm of county-level daily vehicle miles traveled. Vehicle miles traveled (VMT) measured in millions of miles per county per day for PeMs counties. Standard errors clustered at the county level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Results for accidents are presented in Table 4. The estimated effects of COVID-19 travel restrictions across different specifications that vary fixed effects are consistent with the base model, again presented as Model 3, ranging from -0.629 to -0.681. Model 4 employs a richer set of weather controls, replacing the heavy rain indicator variable of Model 3 with daily averages for temperature, precipitation, dew point, pressure, wind speed, wind direction and cloud cover. The estimated effect of COVID-19 restrictions is slightly larger in this case, though again comparable to the base model. Therefore, we maintain the simpler specification as our preferred model. Model 6 explores heterogeneity by day of week. The largest estimated reductions in accidents occur mid-week on Tuesdays, Wednesdays and Thursdays, consistent with larger reductions in driving on weekdays.

Table 4: Alternate specifications for COVID-19 related accident effects.

	COVID-Related Accident Effects					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Post Exective Order	-0.660***	-0.638***	-0.647***	-0.681***	-0.629***	-0.468***
	(0.0470)	(0.0350)	(0.0370)	(0.0330)	(0.0370)	(0.0590)
Daily rainfall > 5mm			0.475***		0.478***	0.468***
			(0.0360)		(0.0350)	(0.0350)
Average Hourly Precip.				0.629***		
				(0.0470)		
Average Temperature				0.0010		
				(0.0010)		
Average Dewpoint				0.0010		
				(0.0010)		
Average Pressure				-0.002*		
				(0.0010)		
Average Wind Direction				-0.000***		
				0.0000		
Average Wind Speed				0.011***		
				(0.0040)		
Cloud Cover				0.011**		
				(0.0050)		
Post E.O. * Monday						0.0450
						(0.0850)
Post E.O. * Tuesday						-0.282***
						(0.0710)
Post E.O. * Wednesday						-0.375***
						(0.0730)
Post E.O. * Thursday						-0.238***
						(0.0890)
Post E.O. * Friday						-0.1320
						(0.0970)
Post E.O. * Saturday						-0.125***
						(0.0450)
County Fixed-Effects	No	Yes	Yes	Yes	Yes	Yes
Week Fixed-Effects	No	No	No	No	Yes	Yes
DOW Effects	No	No	No	No	No	Yes
Observations	78990	77488	77488	73655	77488	77488

Notes: Accidents are the sum of CHP severe, minor and unknown incidents by CA county and day. Standard errors clustered at the county level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 5 presents alternate specifications for accident severity. As before, the baseline specification is presented as Model 3. The estimated impacts of COVID-19 restrictions on accident severity is very robust to different fixed effects and a larger set of weather controls. Model 6 presents estimated effects by day of week. While we lack power to precisely estimate heterogenous effects, these estimates suggest large effects on Saturdays and Thursdays, which may reflect differences in the baseline severity across different days.

Table 5: Alternate specifications for COVID-19 related accident severity effects.

	COVID-Related Accident Severity Effects					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Post Exective Order	0.046***	0.048***	0.048***	0.048***	0.044***	0.039**
	(0.0060)	(0.0060)	(0.0060)	(0.0070)	(0.0070)	(0.0180)
Daily rainfall > 5mm			-0.017***		-0.014***	-0.014***
			(0.0040)		(0.0040)	(0.0040)
Average Hourly Precip.				-0.021***		
				(0.0070)		
Average Temperature				0.000*		
				0.0000		
Average Dewpoint				-0.001**		
				0.0000		
Average Pressure				0.0000		
				0.0000		
Average Wind Direction				0.0000		
				0.0000		
Average Wind Speed				-0.0010		
				(0.0010)		
Cloud Cover				0.0000		
				(0.0010)		
Post E.O. * Monday						0.0020
						(0.0280)
Post E.O. * Tuesday						0.0070
						(0.0230)
Post E.O. * Wednesday						-0.0140
						(0.0220)
Post E.O. * Thursday						0.0110
						(0.0280)
Post E.O. * Friday						(0.0010)
						(0.0240)
Post E.O. * Saturday						0.0270
						(0.0270)
County Fixed-Effects	No	Yes	Yes	Yes	Yes	Yes
Week Fixed-Effects	No	No	No	No	Yes	Yes
DOW Effects	No	No	No	No	No	Yes
Observations	58048	58048	58048	55060	58048	58048
Adj. R-sq.	0.00	0.05	0.05	0.05	0.05	0.06

Notes: Accidents are the sum of CHP severe, minor and unknown incidents by CA county and day. Standard errors clustered at the county level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 6 shows the estimated mean speed effects are robust to alternate specifications, ranging from 1.9 to 2.0 mph. Again Model 6 estimates different mean effects by day of week. The mean weekend effect is approximately 1.1 mph. The increase in average speed is approximately 1 mph larger on weekdays, consistent with lower congestion on the most congested days of the week.

Table 6: Alternate specifications for COVID-19 related speed effects.

COVID-Related Speed Effects						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Post Exective Order	2.030***	2.035***	2.033***	2.019***	1.882***	1.126***
	(0.2720)	(0.2710)	(0.2710)	(0.2690)	(0.2970)	(0.2530)
Daily rainfall > 5mm			-0.508***		-0.647***	-0.638***
			(0.1640)		(0.1440)	(0.1470)
Average Hourly Precip.				-0.831***		
				(0.1720)		
Average Temperature				-0.009*		
				(0.0050)		
Average Dewpoint				-0.018***		
				(0.0060)		
Average Pressure				-0.0060		
				(0.0040)		
Average Wind Direction				0.0000		
				0.0000		
Average Wind Speed				-0.088***		
				(0.0150)		
Cloud Cover				0.044**		
				(0.0180)		
Post E.O. * Monday						0.805***
						(0.1520)
Post E.O. * Tuesday						1.056***
						(0.2210)
Post E.O. * Wednesday						1.009***
						(0.2230)
Post E.O. * Thursday						1.117***
						(0.2460)
Post E.O. * Friday						1.005***
						(0.1920)
Post E.O. * Saturday						0.162*
						(0.0890)
County Fixed-Effects	No	Yes	Yes	Yes	Yes	Yes
Week Fixed-Effects	No	No	No	No	Yes	Yes
DOW Effects	No	No	No	No	No	Yes
Observations	78990	78990	78990	75113	78990	78990
Adj. R-sq.	0.02	0.40	0.41	0.41	0.42	0.53

Notes: Accidents are the sum of CHP severe, minor and unknown incidents by CA county and day. Standard errors clustered at the county level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 7 shows estimates for the reduced form effect of COVID-19 restrictions on fatalities. Models 1 through 5 suggest a small increase in fatalities during the COVID period, though none of the estimates are statistically significant.

Table 7: Alternate specifications for COVID-19 related fatality effects.

	COVID-Related Fatality Effects					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Post Exective Order	0.052 (0.1160)	0.074 (0.1110)	0.072 (0.1130)	0.024 (0.1110)	0.060 (0.1170)	0.032 (0.2400)
Daily rainfall > 5mm			0.182** (0.0890)		0.231*** (0.0850)	0.238*** (0.0840)
Average Hourly Precip.				0.1900 (0.1600)		
Average Temperature				0.006* (0.0030)		
Average Dewpoint				-0.0010 (0.0050)		
Average Pressure				-0.0020 (0.0090)		
Average Wind Direction				0.0000 0.0000		
Average Wind Speed				-0.0070 (0.0250)		
Cloud Cover				0.040** (0.0200)		
Post E.O. * Monday						-0.3700 (0.4440)
Post E.O. * Tuesday						0.0320 (0.4090)
Post E.O. * Wednesday						0.4050 (0.3620)
Post E.O. * Thursday						0.1630 (0.4790)
Post E.O. * Friday						-0.0700 (0.3400)
Post E.O. * Saturday						-0.1510 (0.2950)
County Fixed-Effects	No	Yes	Yes	Yes	Yes	Yes
Week Fixed-Effects	No	No	No	No	Yes	Yes
DOW Effects	No	No	No	No	No	Yes
Observations	78990	70341	70341	64985	70341	70341

Notes: Fatalities are county totals by day as indictated by the CHP incident reporting system. Standard errors clustered at the county level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Finally, Table 8 shows alternate specifications for estimating the relationships between vehicle miles traveled, speeds and fatalities, Equation 2. Each specification is estimated using Poisson regression. Recall, these estimates use only weeks from 2020 immediately before COVID-19 restrictions were adopted. Therefore, week of year fixed effect are (essentially) co-linear with the COVID-19 treatment effect.

Table 8: Alternate specifications for fatality model.

	COVID-Related Fatality Effects					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ln(VMT)	0.992***	0.992***	1.048***	1.000#	0.798	1.048***
	(0.0780)	(0.0790)	(0.1080)		(0.7180)	(0.1330)
ln(Speed)	3.963**	4.062**	4.358**	3.995**	4.0640	2.2170
	(1.5400)	(1.6190)	(1.8960)	(1.5510)	(3.5160)	(2.0110)
Daily rainfall > 5mm	-0.389	-0.378	-0.352	-0.360	-0.348	
	(0.5630)	(0.5600)	(0.5740)	(0.5680)	(0.5680)	
Average Hourly Precip.						-0.2360
						(0.7900)
Average Temperature						0.0060
						(0.0110)
Average Dewpoint						0.048*
						(0.0260)
Average Pressure						0.0220
						(0.0230)
Average Wind Direction						0.0020
						(0.0020)
Average Wind Speed						0.135**
						(0.0640)
Cloud Cover						0.0460
						(0.0810)
Population Average Model	No	Yes	No	No	No	No
County Random-Effects	No	No	Yes	Yes	No	Yes
County Fixed-Effects	No	No	No	No	Yes	No
Observations	6226	6226	6226	6226	3949	5979

Notes: Fatalities are county totals by day as indictated by the CHP incident reporting system during 2020.
vmt coefficient (exposure) constrained to 1. Standard errors clustered at the county level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Model 1 is a simple pooled model and model 2 is a pooled population average model that accounts for the correlations within fatality shocks over time. Both alternate approaches yield VMT and speed parameter estimates comparable to the base model. Model 3 is the base specification and uses random effects to capture differences in baseline fatality rates across counties. We adopt the random effects specification as they can be more efficient than fixed effects in this setting, and because the fixed-effect estimator does not make use of data from any county where zero fatalities occur. This latter issue is less problematic for our accident and reduced-form fatalities specifications in Table 1 since those results leverage 5 years of data. Here however, our identification strategy relies on a short period of time around the implementation of COVID restrictions and fatalities are relatively rare events, and the fixed-effect estimator would exclude 15 of the 41 counties in our sample. The trade-off in using the random effects model is the implicit assumption that VMT and average highway speeds are exogenous regressors. As a check on this assumption, model 5 replaces the county random-effects with fixed-effects, which produces unbiased estimates if the only correlations between independent variables and the error-term are time invariant. This yields a somewhat smaller estimated VMT effect, but a speed effect comparable to the base model. Much of the difference in the estimated VMT-effect comes from the sample restriction, excluding counties that do not record a fatality in 2020, and estimating model 3 (random effects) yields a VMT point estimate of 0.88. As expected, the standard errors are considerably larger than in Model 3. Overall, since the point estimates are comparable, we adopt the more efficient-random effects model in this setting. Next, model 4 assumes fatalities are exactly proportional to accidents and constrains the VMT coefficient to 1. The estimated speed effect is quite similar to the base model. Finally, model 6 employs a richer set of weather controls. Here, the estimated speed effect is smaller though the estimated VMT effect is comparable to the base model. In general, the robustness exercises yield similar qualitative and quantitative insights across a battery of alternative specifications and assumptions.

5 Discussion and conclusions

While we acknowledge our point estimates for California during the COVID period may not translate directly to other settings, our results are roughly consistent with prior cross-sectional studies on VMT and fatalities (Clark and Cushing, 2004; Yeo, Park, and Jang, 2015), and contribute to the broader empirical literature on determinants of road accidents and fatalities (e.g. Loeb (2001), Loeb and Clarke (2007), Welki and Zlatoper (2014), Burger, Kaffine, and Yu (2014), de Vries et al. (2017)). However, an important contrast is that our approach exploits exogenous variation in travel demand and is therefore less susceptible to bias as in these cross-sectional studies. Our VMT results are most comparable to causal estimates using changes in traffic demand from Israeli drivers observing the Jewish Sabbath (Romem and Shurtz, 2016). They find that a 10 percent increase in VMT leads to a 10 percent increase in severe accidents, a figure also comparable to earlier panel data estimates (Michener and Tighe, 1992). More generally, since many parts of the U.S. experienced similar reductions in VMT as California (Cicala et al., 2020), our results likely generalize to congested urban highways outside our sample.

To put our estimates into a broader, policy-relevant context, highway expansion and congestion pricing are oft-discussed policies to manage traffic demand (Lu and Meng, 2017), and given they reduce congestion and increase traffic speeds, they are susceptible to the effects highlighted here. For instance in the fall of 2010, a new 11-mile stretch of carpool (HOV) lane opened on route CA-60 east of Los Angeles. In the months following the opening, rush-hour mainline speeds increased between 10 and 20 mph (authors' estimates from PeMS data). Such an expansion can increase fatalities both through increased VMT and faster speeds - in this case the 16% increase in average VMT would increase fatalities by 16% while the average speed increase of 8% would increase fatalities by 32%. Taken together, our estimates imply that the HOV lane expansion on CA-60 and corresponding increase in speeds increased the accident risk by nearly 50% on that route in the short-run - in the long-run, the well-known phenomenon of induced demand would likely return speeds to near pre-HOV lane levels.

By contrast, congestion pricing can also increase speeds, but it does so by reducing VMT. For example, beginning in 2003 London levied a £5.00 daily charge on vehicles entering central London, which reduced car VMT by 34% and correspondingly increased traffic speeds by 17% (Leape, 2006). Directly applying our estimates suggests that fatalities would increase, on net, by 34% as the increase in fatalities from the traffic speed effect would exceed the reduction via the VMT effect. Noting these potentially offsetting effects of VMT reductions and speed increases, Green, Heywood, and Navarro (2016) empirically estimate the impact of the London Congestion Charge on severe accidents and fatalities using monthly data and find that they actually fell by 25% and 35% respectively. This discrepancy is likely due to the type of roads under consideration - the 17% increase in speeds was from 8.9 mph to 10.4 mph on the surface streets of central London, which is a rather different context than the much higher speed urban highways of California considered here. As such, while the London congestion charge appears to have provided substantial social benefits in the form of reduced fatalities on the surface streets of central London, our findings (e.g. Los Angeles county in

Figure 3) suggest this would be less likely to be true in the context of urban highways.

Finally, our analysis highlights an important secondary effect of COVID-19 travel restrictions. In addition to supporting public health goals, COVID-19 restrictions led to improvements in air quality, reductions in greenhouse gas emissions and energy use (Almond, Du, and Zhang, 2020; Cicala et al., 2020; Le Quere et al., 2020). Here, we show how COVID-19 restrictions had dramatic impacts on vehicle miles traveled, highway speeds, accidents and fatalities. While there was speculation that the sharp decline in driving could lead to a substantial reduction in traffic fatalities, the speed rebound effect we highlight here mitigated those benefits to some extent.

References

Almond, Douglas, Xinming Du, and Shuang Zhang. 2020. "Ambiguous Pollution Response to COVID-19 in China." Tech. rep., National Bureau of Economic Research.

Ashenfelter, Orley and Michael Greenstone. 2004. "Using mandated speed limits to measure the value of a statistical life." *Journal of political Economy* 112 (S1):S226–S267.

Baum, Herbert M, JoAnn K Wells, and Adrian K Lund. 1990. "Motor vehicle crash fatalities in the second year of 65 mph speed limits." *Journal of Safety Research* 21 (1):1–8.

Burger, Nicholas E and Daniel T Kaffine. 2009. "Gas prices, traffic, and freeway speeds in Los Angeles." *The Review of Economics and Statistics* 91 (3):652–657.

Burger, Nicholas E, Daniel T Kaffine, and Bob Yu. 2014. "Did Californias hand-held cell phone ban reduce accidents?" *Transportation research part A: policy and practice* 66:162–172.

California Department of Transportation. 2020. "Performance Measurement System." http://pems.dot.ca.gov/, Accessed on April 29, 2020.

California Highway Patrol. 2021. "California Highway Patrol Statewide Integrated Traffic Records System." https://iswitrs.chp.ca.gov/Reports/jsp/CollisionReports.jsp, Accessed on January 29, 2021.

Cicala, Steve, Stephen P Holland, Erin T Mansur, Nicholas Z Muller, and Andrew J Yates. 2020. "Expected Health Effects of Reduced Air Pollution from COVID-19 Social Distancing." Tech. rep., National Bureau of Economic Research.

Clark, David E and Brad M Cushing. 2004. "Rural and urban traffic fatalities, vehicle miles, and population density." *Accident Analysis and Prevention* 36 (6):967–972.

de Vries, Jelle, René De Koster, Serge Rijsdijk, and Debjit Roy. 2017. "Determinants of safe and productive truck driving: Empirical evidence from long-haul cargo transport." *Transportation research part E: logistics and transportation review* 97:113–131.

Farmer, Charles M. 2017. "Relationship of traffic fatality rates to maximum state speed limits." *Traffic injury prevention* 18 (4):375–380.

Farmer, Charles M, Richard A Retting, and Adrian K Lund. 1999. "Changes in motor vehicle occupant fatalities after repeal of the national maximum speed limit." *Accident Analysis and Prevention* 31 (5):537–543.

Green, Colin P, John S Heywood, and Maria Navarro. 2016. "Traffic accidents and the London congestion charge." *Journal of Public Economics* 133:11–22.

Greenstone, Michael. 2002. "A reexamination of resource allocation responses to the 65-mph speed limit." *Economic Inquiry* 40 (2):271–278.

Le Quere, Corinne, Robert B Jackson, Matthew W Jones, Adam JP Smith, Sam Abernethy, Robbie M Andrew, Anthony J De-Gol, David R Willis, Yuli Shan, Josep G Canadell et al. 2020. "Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement." *Nature Climate Change* 10:647–653.

Leape, Jonathan. 2006. "The London congestion charge." *Journal of Economic Perspectives* 20 (4):157–176.

Loeb, Peter D. 2001. "The effectiveness of seat belt legislation in reducing driver-involved injury rates in Maryland." *Transportation Research Part E: Logistics and Transportation Review* 37 (4):297–310.

Loeb, Peter D and William A Clarke. 2007. "The determinants of truck accidents." *Transportation Research Part E: Logistics and Transportation Review* 43 (4):442–452.

Lu, Zhaoyang and Qiang Meng. 2017. "Analysis of optimal BOT highway capacity and economic toll adjustment provisions under traffic demand uncertainty." *Transportation Research Part E: Logistics and Transportation Review* 100:17–37.

Maheshri, Vikram and Clifford Winston. 2016. "Did the Great Recession keep bad drivers off the road?" *Journal of Risk and Uncertainty* 52 (3):255–280.

McCarthy, Patrick. 2001. “Effect of speed limits on speed distributions and highway safety: a survey of recent literature.” *Transport Reviews* 21 (1):31–50.

Michener, Ron and Carla Tighe. 1992. “A Poisson regression model of highway fatalities.” *The American Economic Review* 82 (2):452–456.

National Highway Traffic Safety Administration, National Center for Statistics and Analysis. 2019. “Early estimate of motor vehicle traffic fatalities for 2019.” Tech. Rep. DOT HS 812 806, United States Department of Transportation.

———. 2020. “Traffic Safety Facts 2017 - A Compilation of Motor Vehicle Crash Data.” Tech. Rep. DOT HS 812 946, United States Department of Transportation.

National Oceanic and Atmospheric Administration. 2020. “Integrated Surface Database (ISD).” https://www.ncdc.noaa.gov/isd, Accessed on May 31st, 2020.

Retting, Richard A and Michael A Greene. 1997. “Traffic speeds following repeal of the national maximum speed limit.” *Institute of Transportation Engineers. ITE Journal* 67 (5):42.

Romem, Issi and Ity Shurtz. 2016. “The accident externality of driving: Evidence from observance of the Jewish Sabbath in Israel.” *Journal of Urban Economics* 96:36–54.

Saha, Shubhayu, Paul Schramm, Amanda Nolan, and Jeremy Hess. 2016. “Adverse weather conditions and fatal motor vehicle crashes in the United States, 1994-2012.” *Environmental health* 15 (1):104.

United States Census Bureau. 2018. “Urban Area Facts.” https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/ua-facts.html, Accessed on May 5th, 2018.

United States Department of Transportation, Bureau of Transportation Statistics. 2020. “U.S. Vehicle Miles.” https://www.bts.gov/content/us-vehicle-miles, Accessed on April 29, 2018.

Van Benthem, Arthur. 2015. "What is the optimal speed limit on freeways?" *Journal of Public Economics* 124:44–62.

Welki, Andrew M and Thomas J Zlatoper. 2014. "The effect of cell phones on international motor vehicle fatality rates: a panel-data analysis." *Transportation research part E: logistics and transportation review* 64:103–109.

World Health Organization. 2018. "Global status report on road safety 2018: Summary." Tech. rep., World Health Organization.

Yeo, Jiho, Sungjin Park, and Kitae Jang. 2015. "Effects of urban sprawl and vehicle miles traveled on traffic fatalities." *Traffic injury prevention* 16 (4):397–403.

Appendix

The California Department of Transportation Performance Measurement System (PeMS) employs a vast network of thousands of loop detectors to collect detailed traffic data on California's major highways. Appendix Table A1 lists the freeways included in the PeMS network, the number of detectors on each freeway, miles and lane-miles. Over 100 different routes are monitored. Statistics are reported by route separately for mainline and high-occupancy vehicle (HOV) or "carpool" lanes and by direction of travel. The PeMS network has been designed to capture highway traffic conditions across the state's major metropolitan areas. It therefore captures a large share of California vehicle miles traveled. However, it does not monitor surface streets or smaller roadways in rural areas. Major interstates, denoted by a "I" or "US" prefix are monitored at hundreds or thousands of locations spanning tens or hundreds of miles within the state. Monitoring on smaller state roads, denoted by a "SR" prefix, is more heterogenous with smaller routes monitored in only a few locations. Overall, the PeMS system provides a comprehensive view of highway traffic within the state.

Table A1: California highways and the extent of the PeMS monitoring network.

		Mainline Facilities		HOV Lane Facilities	
Freeway	Detectors	Total Miles	Lane Miles	Total Miles	Lane Miles
I10-E	1,259.0	241.6	695.8	30.6	30.6
I10-W	1,341.0	241.6	679.8	30.6	30.6
I105-E	209.0	18.1	60.3	15.9	15.9
I105-W	214.0	18.1	61.5	15.9	15.9
I110-N	269.0	31.8	122.7	10.7	10.7
I110-S	239.0	31.8	116.5	10.7	10.7
I15-N	1,127.0	293.6	903.5	19.5	23.4
I15-S	1,120.0	294.0	894.1	27.0	38.4
I205-E	58.0	14.3	60.2	0.0	0.0
I205-W	65.0	14.3	61.8	0.0	0.0
I210-E	790.0	87.2	309.5	42.2	42.2
I210-W	828.0	86.2	306.8	42.2	42.2
I215-N	367.0	55.1	169.0	5.3	5.3
I215-S	368.0	55.1	169.2	5.3	5.3
I280-N	226.0	57.5	190.3	10.7	10.7
I280-S	228.0	57.5	193.2	10.7	10.7
I405-N	1,131.0	72.4	328.9	60.5	60.5
I405-S	1,188.0	72.4	327.4	68.4	68.4
I5-N	2,345.0	796.5	1,292.1	50.6	50.7
I5-S	2,406.0	796.3	1,282.8	50.5	50.5
I580-E	527.0	76.2	311.8	5.4	5.4
I580-W	511.0	76.3	266.0	0.0	0.0
I605-N	357.0	28.1	118.5	22.3	22.3
I605-S	367.0	28.1	118.0	22.3	22.3
I680-N	674.0	70.3	227.8	19.6	19.6
I680-S	743.0	70.5	271.3	32.7	32.7
I710-N	205.0	24.2	88.3	0.0	0.0
I710-S	202.0	24.2	88.5	0.0	0.0
I780-E	8.0	6.8	14.5	0.0	0.0
I780-W	8.0	6.8	15.6	0.0	0.0
I8-E	196.0	171.9	97.8	0.0	0.0
I8-W	230.0	172.2	99.3	0.0	0.0
I80-E	1,316.0	204.0	599.6	37.5	117.5
I80-W	1,251.0	204.2	589.9	25.0	25.0
I805-N	323.0	28.7	121.8	0.5	0.5
I805-S	332.0	28.7	132.2	0.0	0.0
I880-N	592.0	46.0	196.2	21.5	21.5
I880-S	620.0	45.7	198.2	24.2	24.2
I880S-N	8.0	1.3	3.9	1.2	1.2
I880S-S	4.0	1.5	2.9	0.0	0.0
I905-E	49.0	8.7	24.6	0.0	0.0
I905-W	58.0	8.7	24.1	0.0	0.0
I980-E	27.0	2.0	6.1	0.0	0.0
I980-W	26.0	2.0	7.0	0.0	0.0
SR1-N	152.0	656.0	117.2	0.0	0.0
SR1-S	153.0	656.0	117.9	0.0	0.0
SR104-E	3.0	27.6	4.9	0.0	0.0
SR104-W	5.0	27.6	4.9	0.0	0.0
SR108-E	9.0	99.3	13.7	0.0	0.0
SR108-W	8.0	99.2	14.1	0.0	0.0
SR11-E	2.0	1.2	2.9	0.0	0.0
SR11-W	8.0	1.4	2.6	0.0	0.0
SR113-N	15.0	60.6	35.2	0.0	0.0
SR113-S	14.0	60.2	27.8	0.0	0.0
SR118-E	299.0	48.0	109.0	11.4	11.4
SR118-W	291.0	48.0	112.2	11.4	11.4
SR12-E	52.0	115.5	46.4	0.0	0.0
SR12-W	50.0	115.5	44.2	0.0	0.0
SR120-E	39.0	152.7	24.2	0.0	0.0
SR120-W	48.0	152.8	23.2	0.0	0.0
SR124-E	3.0	10.3	7.7	0.0	0.0
SR124-W	4.0	10.3	10.5	0.0	0.0
SR125-N	75.0	21.2	38.2	0.0	0.0
SR125-S	76.0	22.9	45.6	0.0	0.0
SR126-E	10.0	47.3	13.2	0.0	0.0
SR126-W	6.0	47.3	10.5	0.0	0.0
SR13-N	2.0	9.7	7.5	0.0	0.0
SR13-S	2.0	9.7	7.5	0.0	0.0
SR132-E	31.0	76.4	21.4	0.0	0.0

		Mainline Facilities		HOV Lane Facilities	
Freeway	Detectors	Total Miles	Lane Miles	Total Miles	Lane Miles
SR132-W	32.0	76.4	21.4	0.0	0.0
SR133-N	77.0	13.6	28.0	0.0	0.0
SR133-S	63.0	13.6	29.2	0.0	0.0
SR134-E	182.0	13.3	54.0	13.3	13.3
SR134-W	152.0	13.3	53.8	13.3	13.3
SR14-N	53.0	116.6	67.8	35.9	35.9
SR14-S	54.0	116.6	66.9	35.9	35.9
SR140-E	8.0	101.6	0.0	0.0	0.0
SR140-W	8.0	101.6	0.0	0.0	0.0
SR142-E	13.0	11.5	8.1	0.0	0.0
SR142-W	13.0	11.5	7.6	0.0	0.0
SR152-E	22.0	104.4	47.0	0.0	0.0
SR152-W	22.0	104.4	47.1	0.0	0.0
SR156-E	15.0	24.2	17.3	0.0	0.0
SR156-W	14.0	24.2	20.1	0.0	0.0
SR16-E	4.0	81.8	5.6	0.0	0.0
SR16-W	3.0	81.8	3.0	0.0	0.0
SR160-N	15.0	49.7	21.3	0.0	0.0
SR160-S	14.0	49.7	11.3	0.0	0.0
SR163-N	73.0	11.1	46.4	0.3	0.3
SR163-S	82.0	11.1	44.2	0.0	0.0
SR165-N	2.0	38.3	5.0	0.0	0.0
SR165-S	2.0	38.3	5.0	0.0	0.0
SR168-E	78.0	5,472.8	34.4	0.0	0.0
SR168-W	85.0	5,402.9	34.2	0.0	0.0
SR17-N	55.0	26.5	64.9	0.0	0.0
SR17-S	49.0	26.5	55.1	0.0	0.0
SR170-N	33.0	7.6	28.3	6.0	6.0
SR170-S	56.0	7.6	28.9	6.0	6.0
SR178-E	4.0	152.4	10.0	0.0	0.0
SR178-W	8.0	152.3	10.5	0.0	0.0
SR180-E	78.0	108.4	45.6	0.0	0.0
SR180-W	105.0	108.4	43.9	0.0	0.0
SR198-E	23.0	141.3	67.0	0.0	0.0
SR198-W	23.0	141.3	67.1	0.0	0.0
SR2-E	91.0	80.2	45.0	0.0	0.0
SR2-W	83.0	80.2	38.6	0.0	0.0
SR219-E	5.0	4.8	10.8	0.0	0.0
SR219-W	6.0	4.8	14.1	0.0	0.0
SR22-E	218.0	14.7	45.4	11.0	11.0
SR22-W	222.0	14.7	47.3	11.0	11.0
SR23-N	74.0	32.0	37.9	0.0	0.0
SR23-S	72.0	32.0	37.3	0.0	0.0
SR237-E	28.0	11.1	28.4	6.5	6.5
SR237-W	51.0	11.1	32.3	6.5	6.5
SR238-N	23.0	16.5	13.2	0.0	0.0
SR238-S	27.0	16.5	14.8	0.0	0.0
SR24-E	141.0	14.0	60.2	0.0	0.0
SR24-W	161.0	14.0	62.0	0.0	0.0
SR241-N	228.0	24.5	71.2	0.0	0.0
SR241-S	208.0	24.5	66.3	0.0	0.0
SR242-N	37.0	3.7	12.3	0.0	0.0
SR242-S	38.0	3.7	11.8	0.0	0.0
SR25-N	6.0	74.6	5.6	0.0	0.0
SR25-S	6.0	74.6	5.6	0.0	0.0
SR26-E	12.0	62.1	0.0	0.0	0.0
SR26-W	12.0	62.1	0.0	0.0	0.0
SR261-N	55.0	6.2	16.4	0.0	0.0
SR261-S	42.0	6.2	12.6	0.0	0.0
SR267-E	2.0	11.7	7.9	0.0	0.0
SR267-W	2.0	11.7	12.9	0.0	0.0
SR28-E	1.0	10.9	5.0	0.0	0.0
SR28-W	1.0	10.9	5.0	0.0	0.0
SR29-N	6.0	105.6	10.6	0.0	0.0
SR29-S	7.0	105.6	10.6	0.0	0.0
SR33-N	6.0	289.7	8.2	0.0	0.0
SR33-S	1.0	289.7	0.0	0.0	0.0
SR37-E	34.0	21.6	32.8	0.0	0.0
SR37-W	36.0	21.5	31.4	0.0	0.0

		Mainline Facilities		HOV Lane Facilities	
Freeway	Detectors	Total Miles	Lane Miles	Total Miles	Lane Miles
SR4-E	384.0	190.9	144.4	8.6	8.6
SR4-W	395.0	190.9	151.8	8.6	8.6
SR41-N	120.0	185.6	64.6	0.0	0.0
SR41-S	111.0	185.6	62.9	0.0	0.0
SR46-E	8.0	110.7	20.1	0.0	0.0
SR46-W	8.0	110.7	20.1	0.0	0.0
SR47-N	10.0	3.3	6.6	0.0	0.0
SR47-S	16.0	3.3	6.9	0.0	0.0
SR49-N	6.0	294.5	15.0	0.0	0.0
SR49-S	7.0	294.5	20.0	0.0	0.0
SR51-N	104.0	8.9	29.4	0.0	0.0
SR51-S	105.0	8.8	29.3	0.0	0.0
SR52-E	59.0	14.8	43.7	0.0	0.0
SR52-W	50.0	14.8	43.5	0.0	0.0
SR54-E	19.0	8.6	21.4	0.0	0.0
SR54-W	18.0	8.6	20.4	0.0	0.0
SR55-N	218.0	17.9	71.1	11.3	11.3
SR55-S	190.0	17.9	68.8	11.3	11.3
SR56-E	58.0	9.3	23.7	0.0	0.0
SR56-W	45.0	9.3	20.2	0.0	0.0
SR57-N	340.0	24.2	109.9	16.2	16.2
SR57-S	321.0	24.2	100.1	16.2	16.2
SR58-E	27.0	235.3	32.8	0.0	0.0
SR58-W	33.0	235.3	32.8	0.0	0.0
SR59-N	2.0	33.7	0.0	0.0	0.0
SR59-S	2.0	33.7	0.0	0.0	0.0
SR60-E	668.0	70.6	255.7	37.2	37.2
SR60-W	654.0	70.6	254.7	37.2	37.2
SR65-N	48.0	94.5	29.2	0.0	0.0
SR65-S	62.0	94.5	27.9	0.0	0.0
SR67-N	8.0	23.8	9.7	0.0	0.0
SR67-S	10.0	23.8	9.7	0.0	0.0
SR68-E	28.0	22.0	28.3	0.0	0.0
SR68-W	12.0	22.0	12.8	0.0	0.0
SR70-E	6.0	179.9	20.0	0.0	0.0
SR70-W	4.0	179.8	10.0	0.0	0.0
SR71-N	101.0	16.5	39.4	8.3	8.3
SR71-S	115.0	16.5	37.8	8.3	8.3
SR73-N	222.0	18.0	64.3	0.0	0.0
SR73-S	229.0	18.0	61.7	0.0	0.0
SR74-E	7.0	111.5	11.5	0.0	0.0
SR74-W	5.0	111.5	13.0	0.0	0.0
SR76-E	11.0	52.2	19.8	0.0	0.0
SR76-W	15.0	52.2	37.1	0.0	0.0
SR78-E	115.0	193.8	57.3	0.0	0.0
SR78-W	149.0	193.8	61.2	0.0	0.0
SR85-N	166.0	24.2	75.9	24.0	24.0
SR85-S	144.0	24.2	76.8	24.0	24.0
SR87-N	80.0	9.1	28.1	7.1	7.1
SR87-S	74.0	9.1	27.8	7.1	7.1
SR88-E	21.0	122.1	20.3	0.0	0.0
SR88-W	22.0	122.1	12.8	0.0	0.0
SR89-N	5.0	243.1	48.3	0.0	0.0
SR89-S	5.0	243.1	53.3	0.0	0.0
SR90-E	25.0	15.7	11.3	0.0	0.0
SR90-W	18.0	15.7	10.2	0.0	0.0
SR91-E	854.0	59.0	251.1	54.3	76.8
SR91-W	834.0	59.1	246.0	54.4	77.0
SR92-E	76.0	27.8	43.7	0.0	0.0
SR92-W	78.0	27.8	52.7	2.8	2.8
SR94-E	89.0	63.3	42.0	0.0	0.0
SR94-W	129.0	63.3	43.8	1.0	1.0
SR99-N	1,201.0	416.2	834.6	0.0	0.0
SR99-S	1,213.0	416.2	831.1	0.0	0.0
US101-N	2,411.0	808.7	1,371.9	64.0	64.0
US101-S	2,403.0	808.7	1,063.5	64.0	64.0
US50-E	355.0	108.6	201.9	25.0	97.0
US50-W	361.0	108.6	216.5	24.0	95.0