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Daily motor vehicle traffic volume and other risk factors associated with road deaths in U.S. counties

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A R T I C L E I N F O

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A B S T R A C T

Introduction: Road death risk is often characterized as deaths per volume of traffic in geographic regions, the denominator in miles or kilometers supposedly indicative of the magnitude of risk exposure. This paper reports an examination of the differences in the predictive value of factors hypothesized to influence traffic volume and road death risk. *Method:* The association of 11 risk factors in U.S. counties during the first 7 months of 2020 was examined for consistency of predictions of road death and traffic volume measured by cell phone and vehicle location data. The study employed least squares regression for traffic volume and Poisson regression for deaths with the population as the offset variable. *Results:* The directions of the regression coefficients for traffic volume and odds of road deaths per population were opposite from one another for 9 of the 11 variables in the analysis of vehicle occupant deaths. Only the coefficients for maximum daily temperature and Saturday travel were in the same direction. The confidence intervals of three risk ratios for pedestrian deaths indicated low reliability but most of the predictor variables were opposite in association with traffic volume and odds of death. Although traffic volume plunged in the first weeks of the pandemic, the results for the months before and during the COVID-19 pandemic were similar. *Practical applications:* Traffic volume is an inverse risk factor for road deaths at the local level, likely the result of lower speeds on congested roads. Without the application of countermeasures aimed at reducing speed and other risk factors, the reduction of road congestion is likely to increase deaths.

1. Introduction

Risk factors correlated with deaths may be factors that influence the probability of exposure to a hazard and the probability of death when exposed. To inform the choice of preventive measures, that is not a problem if the association between the rate of death and the predictive value of a hypothesized risk factor is consistently positive or negative for both stages of risk. There are instances in which the latter is not true, however. In the case of road deaths, factors that contribute to road use and factors that increase the risk of death to people on the roads may differ. For example, researchers have found increases in road deaths associated with precipitation (Datla & Sharma, 2008; Eisenberg & Warner, 2005; Stevens, 2019), but often do not consider that some people decide not to travel during inclement weather (Black and Mote, 2015). The resultant death rate per population is the net consequence of reduced aggregate exposure due to people not traveling and the increased risk when people travel on wet or icy roads. This paper presents new evidence on traffic volume and its predictors in association with road deaths and its implications for changes in road deaths per population when road congestion is reduced.

Reports of deaths per traffic volume have been criticized as of dubious value (Redelmeier, 2014). While traffic counts at selected sites are reliably measured, they may not represent the traffic volume in relatively large geographic areas around them. The reliability and validity of aggregate traffic volume are implausible when annual traffic volume is divided by the number of vehicles in use in various countries (Robertson, 2020). Yet the death rate per traffic volume is often cited as an indicator of fatal crash risk per exposure to traffic (Shen et al., 2020). The metric implies that reducing traffic volume would reduce deaths, but distances traveled in traffic congestion are far less risky than higher-speed travel in light traffic during other times of the day or week (Farmer & Williams, 2005). Most research on traffic volume and crashes includes all police-reported crashes (Retallack & Ostendord, 2019). This is problematic because property damage and slight injury crashes that impede heavy traffic are likely to come to police attention, while some of those in light or no traffic may not be reported. A study of injuries seen in emergency rooms in Cleveland OH and five surrounding counties found that 30% of road injuries were not reflected in official police statistics

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(Barancik et al., 1983). Similar results have been found in other studies in the United States and elsewhere (e.g., Sciortino et al., 2005; Watson et al., 2015). Also, the inclusion of the far more frequent property damage crashes is likely to obscure patterns that differ for severe crashes. Deaths are not likely to go unreported and are far more important than fender benders.

When the COVID-19 pandemic emergency was announced in the United States on March 13, 2020, all but seven states soon issued stay-at-home orders for nonessential travel during various periods in mid to late spring 2020. Among the states without such orders, all but South Dakota ordered some business closures and all states closed schools. Road traffic declined precipitously but road deaths declined less and were increasing by late April. Road deaths in 2020 were 6.8% higher than in 2019 (National Highway Traffic Safety Administration, 2022) but estimated total miles accumulated declined by about 14% (Federal Reserve Economic Data, 2023). Monthly road deaths among U.S. states were not associated with new COVID-19 cases. Higher temperatures, increased truck registrations, and reduced fuel prices in 2020 compared to 2019 predicted the aggregate change in road deaths per population among U. S. states from 2019 to 2020 (Robertson, 2023) as they did when the road death rate per population reversed its downward trend in 2015–2016 (Robertson, 2018).

This study was undertaken to increase understanding of the association between traffic volume and risk of road deaths. Estimates of daily vehicle miles (1.61 km) traveled within U.S. counties in the coterminous 48 states during the first seven months of 2020 provided the opportunity to examine social and economic factors related to traffic volume and the odds of road deaths per population before and during the first five months of the pandemic in the United States. Hypothesized predictors of traffic volume and road deaths include daily high temperatures, precipitation, the COVID-19 shutdown, weekend days, linear miles of Interstate Highway and, separately, other state-maintained highways, population density, median family income, percent of the population in the workforce, and percent of those unemployed. The association of these variables with vehicle occupant and pedestrian deaths was compared to their association with daily traffic volume to discern whether associations with traffic volume were consistent with associations with risk of road death.

Temperature and precipitation are included because of their consistent association with road death risk. The length of different classes of highways in a county is included because of the different risks of road deaths on limited-access highways and other roads. Population density is included as a proxy of the likelihood of availability of forms of transportation (bus, rail) other than privately owned vehicles. The economic variables are proxies for the extent to which newer safer vehicles are affordable as well as their likely effect on travel.

2. Methods

Streetlight Data, Inc. (2019) donated estimates of daily miles traveled in each U.S. county from 1 January through 31 July 2020 based on vehicle and cell phone location data. The R^2 of data from traffic counter sites and Streetlight's estimates at the sites is 0.98 and has been validated by independent researchers (Kodjoe et al., 2020; Grond et al., 2022). Daily road deaths by county and the date of the crash were gleaned from the Fatality Analysis Reporting System, a census of fatal crashes where the case is included if the deceased expired within 30 days of the crash (National Highway Traffic Safety Administration, 2023). Data for both daily maximum temperature and total precipitation were obtained by using the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) gridded temperature and precipitation data which have a spatial resolution of 0.5° latitude $\times$ 0.5° longitude (NOAA Physical Sciences Laboratory, 2023). Using these gridded datasets, sorted by NOAA gridded latitude and longitude, the data were considered a match to a county when the geographic center point position of each county was within 0.5° of the NOAA coordinates. Remote counties with no match to weather data were excluded. The lengths of segments of Interstate and state-maintained roads in each county were summed using a file downloaded from the U.S. Bureau of Transportation Statistics (2023a). Population and number per square kilometer (density) by county in 2020 were downloaded from the U.S. Census (2023). Median household income, people in the workforce, and unemployment in each county during 2020 were from the U.S. Department of Agriculture (2023). The data sets were matched by county and dates into a file for statistical analysis. The file contains data on 643,688 county days during which 17,430 vehicle occupants and 4277 pedestrians were killed.

Least squares regression was used to examine the association of the predictor variables with the logarithm of daily kilometers of vehicle travel and Poisson regression was used to estimate their association with daily road deaths, with log (population) as the offset variable. Friday, Saturday, and Sunday were included as binary variables, assigned 1 if applicable and 0 if not. The variance of skewed frequency distributions was reduced by computing the square root of variables that could be zero and logarithms of the others where appropriate. Vehicle occupant deaths and pedestrian deaths were examined separately, each during the pre-pandemic and pandemic periods.

3. Results

Within a few days after the COVID-19 emergency was declared on March 13, 2020 vehicle kilometers traveled per capita declined to their nadir in both shutdown and the other states (Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, and Wyoming), and then trended upward until an abrupt increase during the first week in June 2020 after most shutdown orders were loosened or abandoned (Fig. 1).

The trends in daily deaths of vehicle occupants and pedestrians did not decline as dramatically as traffic volume when the COVID-19 emergency was declared and the pedestrian trend increased less than that of occupant deaths in late spring and the summer (Fig. 2). The day-of-week variation is evident in both trends but as noted in the regression analyses, weekend days with a lower proportion of mileage have a higher proportion of road deaths.

The regression coefficients for predictors of daily kilometers and risk ratios of daily road deaths for the hypothesized predictors pre-pandemic are presented in Table 1. Only 2 of the 11 variables had associations in the same direction for vehicle kilometers traveled and occupant deaths – temperature and Saturday. Kilometers traveled were higher in counties with more length of limited access Interstate highways and state-maintained highways, but the odds of death were less per population in those counties. All of the economic variables were associated with more road use but with fewer occupant fatalities among counties. Road use was lower on Sundays but deaths were more frequent. The results for pedestrian deaths were not as consistent. The confidence intervals of the odds of pedestrian deaths with precipitation, on Friday, and Sunday vary from negative to positive, indicative of unreliable association. Counties with higher median income have more kilometers traveled and more pedestrian deaths corrected for the other factors. Otherwise, the results are similar to those for vehicle occupants. Criteria for the goodness of fit of the models were acceptable.

Table 2 contains the regression coefficients on travel and risk ratios of predictor variables during the early 5.5 months of the pandemic. The results are very similar to those in Table 1. Corrected for the reduction in travel and deaths during the period of shutdowns, except for temperature, the association of the predictors of travel is the reverse of predictors of occupant deaths. The association of pedestrian deaths with the shutdown period was within the bounds of chance and the other associations were similar to those in Table 1.

The least-squares correlation coefficients among the predictor variables were examined for potential distortion of the regression coefficients because of collinearity (Table 3). The coefficients are low enough that substantial distortion is not possible.

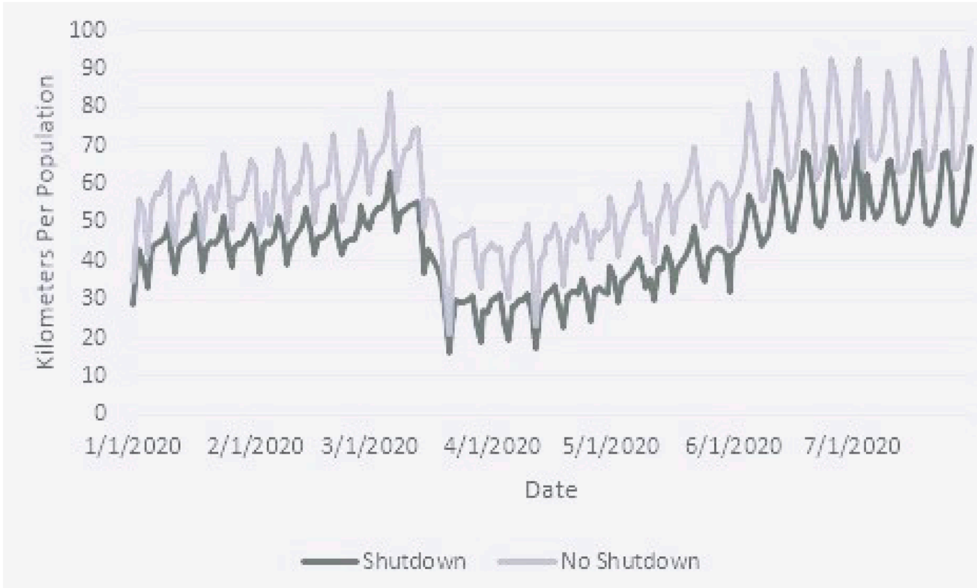

Fig. 1. Daily vehicle kilometers traveled per population in U.S. states that shut down in Spring, 2020 and those that did not, January-July 2020. Source: Streetlight Data, Inc., adjusted from miles to kilometers.

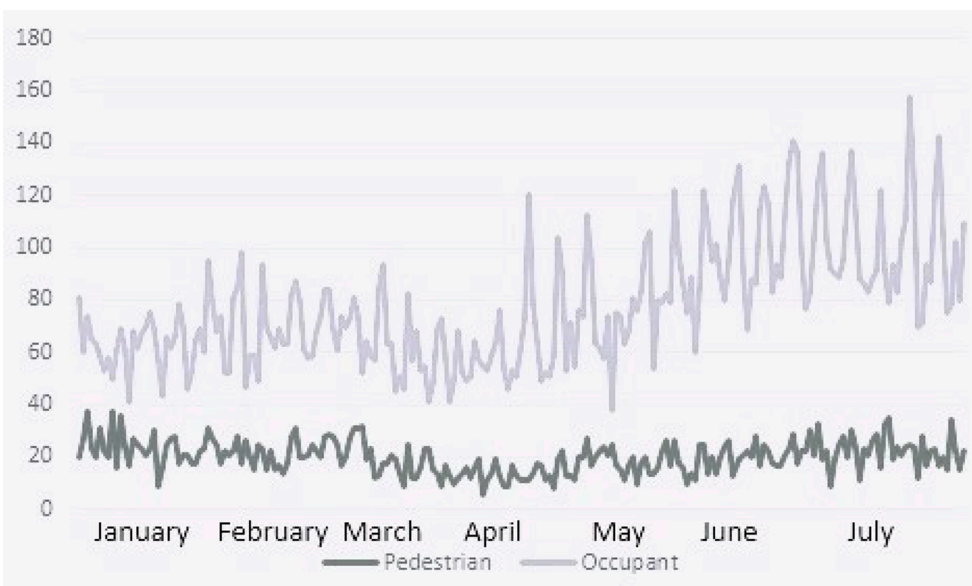

Fig. 2. Daily Road Deaths in the U.S., January-July 2020. Source: National Highway Traffic Safety Administration, Fatal Analysis Reporting System.

A simple Poisson regression model of deaths as a function of log (kilometers) yielded a risk ratio of .419 (95%CI .415,.423) for occupants and .422 (95%CI .413,.431) for pedestrians. In an attempt to assess variation because of interaction among predictor variables and log(kilometers), the same Poisson regression was applied to subsets of the predictor variables – temperatures above and below freezing, precipitation vs. none, Interstate miles vs. none, Saturday, Sunday and weekdays separately, and above and below average on the other predictor variables. As indicated in Table 4, there is no evidence of major differences in risk ratios among the subsets of the risk factors that would change the conclusion that traffic volume is an inverse risk factor for road deaths. Because the number of county days examined is in the hundreds of thousands, the confidence intervals are very narrow and not shown in the table.

4. Discussion

The results support the hypothesis that the association of higher temperature with more deaths is a function of discretionary travel based partly on temperature. Also, there is an increased risk to those who choose to travel on wet, snowy, or icy roads, but fewer vehicles are on the roads in inclement weather. The inconsistencies in the direction of most of the predictors of road travel and road deaths adjusted for population support the position that the rate of deaths per travel volume can be a misleading indicator of risk. For example, the lower death rate per mile on Interstate highways compared to other roads in the United States is often used to argue that those highways "save lives" (Trip, 2021). If all traffic on Interstate highways were shifted to other roads that might be true but the resulting increase in traffic volume on other roads would likely reduce the death rates per population.

Table 1
Predictors of log(daily kilometers traveled) using least squares regression and risk ratio of daily road deaths using Poisson regression among U.S. counties in 48 coterminous states, January 1 – March 13, 2020.

	Log (vehicle kilometers)		Occupantdeaths		Pedestrian deaths	
Predictor	Coefficient	95% Confidence	Risk Ratio	95%Confidence	Risk Ratio	95%Confidence
Temperature	.007	.007,.007	1.011	1.010,1.012	1.003	1.002,1.004
√Precipitation	−.172	−.179,-.165	1.164	.097,1.211	1.004	.954,1.057
√Interstate linear miles	.134	.133,.135	.906	.898,.914	.901	.885,.917
√State highway linear miles	.056	.056,.056	.969	.966,.972	.991	.985,.997
Log(population density)	.548	.547,.549	.508	.502,.514	.458	.366,.550
Median Income (1000 s)	.015	.015,.015	.991	.990,.992	1.006	1.003,1.009
Percent unemployed	.086	.085,.087	.916	.908,.922	.969	.953,.985
Labor force/ population	1.462	1.432,1.492	.406	.292,.520	.062	.032,.092
Friday	.045	.040,.050	.849	.865,.950	1.042	.946,1.138
Saturday	.022	.017,.027	1.242	1.118,1.366	1.127	1.027,1.227
Sunday	−.132	−.137,-.127	1.115	1.064,1.166	1.038	.941,1.135
Intercept	9.729					
Model fit criteria	$R^2 = .75$		Deviance/ df = .18		Deviance/ df = .08	

Table 2
Predictors of log(daily kilometers traveled) using least squares regression and risk ratio of daily road deaths using Poisson regression among U.S. counties in 48 coterminous states, March 14 − July 31, 2020.

	Log (vehicle kilometers)		Occupantdeaths		Pedestrian deaths	
Predictor	Coefficient	95% Confidence	Risk ratio	95%Confidence	Risk ratio	95%Confidence
Temperature	.014	.014,.014	1.013	1.011,1.015	1.016	1.014,1.018
√Precipitation	−.116	−.021,-.007	1.278	1.203,1.353	1.149	1.000,1.298
√Interstate linear miles	.124	.123,.125	.898	.889,.907	.889	.869,.909
√State highway linear miles	.055	.055,.055	.974	.970,.978	.996	.989,1.003
Log(population density)	.520	.518,.522	.512	.506,.518	.471	.459,.483
March 14 −May 31 shutdowns	−.117	−.124,-.110	.750	.699,.801	1.094	.954,1.234
Median Income (1000 s)	.014	.014,.014	.992	.990,.994	1.005	1.001,1.009
Percent unemployed	.084	.081,.087	.903	.894,.912	.951	.932,.970
Labor force/ population	1.499	1.465,1.533	.310	.216,.484	.096	.044,.148
Friday	.025	.019,.031	.888	.840,.936	.982	.877,1.087
Saturday	−.033	−.039,-.027	1.288	1.226,1.350	.970	.865,1.075
Sunday	−.138	−.144,-.132	1.135	1.079,1.191	1.003	.888,1.145
Intercept	9.175					
Model fit criteria	$R^2 = .74$		Deviance/ df = .22		Deviance/ df = .07	

Table 3
Least squares correlation of predictor variables except for weekdays, U.S. counties in 48 coterminous states, January 1 − July 31, 2020.

	√precip	√Interstatelinear miles	√state hwy. linear miles	Log(pop density	Med income	Percent unemp	Labor force/pop
Temperature	.011	.089	.008	.071	−.118	.056	−.154
√precipitation		−.032	.004	.067	.422	.310	.166
√Interstate			.003	.015	.020	.060	−.004
√state highway				.003	.007	.024	.039
Log(population density)					.372	.328	.073
Median income						−.188	.591
Percent unemployed							−.394

The risk of road death per population is consistently lower on days when traffic volume is higher in U.S. counties. While the disruption of travel during the first months of the COVID-19 pandemic was associated with reduced road deaths, the reduction was not commensurate with the reduction in travel. Yet the associations of temperature, precipitation, types of roads, and economic factors to traffic volume and risk of death were similar during the pandemic as before it began. Except for unemployment, the lower risk of death in more prosperous counties appears to be at least partly a result of the higher congestion on roads in those counties. Other research indicates that unemployment is not a consistent predictor of fatality risk year-to-year (Robertson, 2018).

The most likely reason for the association between traffic volume and lower road death risk is that reduced traffic congestion results in higher speeds, the most important element in the energy exchange in a crash. A study of the changes in road deaths in 20 countries comparing deaths per kilometer based on Apple mobility data in 2020 and prior years found substantial variation among the countries (Wegman & Katrakazas, 2021). The study did not account for changes in temperature and precipitation or most of the other risk factors that might account for the differences, but did report that travel speeds during the pandemic increased in Great Britain more than expected from prior years, peaking in April 2020 and trending downward afterward through the year.

More than half (58%) of the fatal collisions on U.S. roads in 2020 involved only one motor vehicle striking a pedestrian, bicyclist, fixed object, or rolling over. The number of other vehicles in proximity at the time is unknown but the data suggest that fatal "traffic crashes" occur more frequently when there is less, if any, traffic. Higher occupant death rates per population on weekend days when travel volume is lower are

Table 4
Risk ratios of traffic volume and daily road deaths for subsets of other risk factors using Poisson regression among U.S. counties in 48 coterminous states, March 14 – July 31, 2020.

	Occupant		Pedestrian	
	High	Low	High	Low
Temperature	.412	.405	.428	.402
Precipitation	.423	.416	.434	.413
√Interstate	.432	.420	.412	.425
√state highway	.419	.432	.431	.412
Log(population density)	.453	.508	.487	.518
Median income	.409	.442	.393	.453
Percent unemployed	.444	.396	.430	.398
Labor force/pop	.402	.484	,411	.489
Friday	.417	.419	.412	.422
Saturday	.432	.417	.431	.420
Sunday	.426	.418	.460	.414

likely a function of increased alcohol consumption (Morrison et al., 2019) in addition to increased speed on less congested roads on weekends. There were various health and environmental benefits associated with reduced traffic volume during the COVID-19 shutdowns (Musselwhite et al., 2021), including reduced road deaths during shutdowns found in this study.

5. Limitations

The limitations of this study include the lack of data on pedestrian exposure and the lack of specification of the amount of traffic, weather, and speed at the time of day of the collisions. Case-control studies would provide a better indication of the influence of specific risk factors. Driver, pedestrian, and vehicle factors have been studied by comparison to people and vehicles at the same time of day and day of week, and location of the crash. Environmental factors at the site can be compared to those that the vehicle passed on the way to the crash (Robertson, 2022). In the case of traffic volume, the volume at the same time of day, day of week, and location should be compared to other times of day on the same day of the week as the fatality.

6. Practical applications

The results of this study suggest that efforts to reduce road congestion will increase road deaths without mitigation of speed, alcohol use by drivers and other road users, roadside hazards, and other environmental changes (Elvik et al., 2009) at times and places where congestion is reduced.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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