AN ANALYSIS OF FACTORS DRIVING THE INCREASES IN TRAFFIC FATALITIES IN THE UNITED STATES

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ABSTRACT

According to the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA), 37,461 people died in the United States in traffic crashes in 2016, a 5.6% increase in fatalities from 2015. It was the second consecutive year of increasing fatalities following an 8.4% increase from 2014 to 2015. This study applies random-effects generalized linear mixed modeling techniques to examine the association of changes in traffic fatality counts with changes in explanatory factors, by state, between 2005 and 2016. Three regressions modeled different outcomes: 1) passenger vehicle occupant fatalities, 2) pedestrian fatalities, and 3) motorcycle fatalities

Motor vehicle-related traffic fatalities were collected by year and by state using NHTSA's Fatality Analysis Reporting System (FARS). A variety of sources provided measures on explanatory factors. The Fatality counts (outcome) and explanatory factors were then combined as panel data by year (2005-2016) and state (51 states including the District of Columbia). The models tested the association between fatalities and more than seventy explanatory factors including economic, exposure, behavioral and vehicle factors.

The study found that the increases in passenger vehicle fatality counts were associated with increases in vehicle miles traveled (exposure) and an improving economy. In addition, the increase in the population age 65 and older and an increase in the percent of this population in the workforce also was associated with increasing fatality counts. Several behavioral factors were associated with changes in fatality counts, including non-belt use and increased drunk driving. Conversely, improved vehicle safety design was associated with a decline in occupant fatalities. A rise in motorcycle fatalities was associated with increased exposure (motorcycle registrations and overall vehicle miles travelled) and an improving economy. Among pedestrian and motorcycle fatalities, there is some evidence that driver distraction plays a role.

While the quasi-experimental study design does not allow for inferences of causality, the models can be applied to forecast future fatality counts based on expected or observed environmental, behavioral and vehicle factors or to evaluate the potential impact of prospective interventions.

Increased exposure, the improving economy, and behavioral factors drove increases in fatality counts between 2005 and 2016. However, improved vehicle safety design substantially countered these effects, mitigating the increases.

INTRODUCTION

According to the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA), 37,461 people died in the United States in traffic crashes in 2016, a 5.6% increase in fatalities from 2015 the second consecutive year of increasing fatalities following a 8.4% increase from 2014 to 2015 [1]. The data further showed traffic deaths rising across nearly every segment of the population. The last single-year increase of this magnitude was in 1966, when fatalities rose 8.1 percent from the previous year.

These figures come after a decade of progress. Eleven years ago, the number of traffic deaths was nearly 25 percent higher, with 42,708 fatalities reported nationwide in 2005 [2]. In the past two decades, behavioral safety and enforcement programs have helped lower the number of deaths by increasing seat belt use and reducing impaired driving [3][4]. Vehicle improvements, including air bags and electronic stability control, have made substantial contributions to reducing traffic fatalities [5].

Increased exposure in terms of vehicle miles travelled (VMT) does not account for all of the increases. In 2014 there were 1.08 traffic-related deaths per 100 million VMT. This increased to 1.12/ 100 million VMT in 2015 and 1.18/100 million VMT in 2016, a 6.5% and 2.5% change, respectively [1][2]. Changes in fatality counts varied by person type, with non-occupants contributing more to the increases than occupants[2]. The toll was particularly high among and older drivers (age 65+) in 2015 and 2016.

Risk factors for traffic crashes and deaths are fairly well understood. One tool for analyzing an injury event and ways to either prevent the injury or reduce the harm done is the Haddon Matrix. In 1970, William Haddon Jr. proposed a matrix that allows simultaneous consideration of the stages over time of an injury event (pre-, during, and post-event) with all the possible host, agent/carrier, and environment factors involved in the event. Table 1 presents a Haddon Matrix that identifies factors relevant to traffic fatalities. Important person-level factors include restraint use, driver impairment, and driver distraction, age and gender. Important vehicle factors include speed, vehicle size, age and safety design. Environment factors are differentiated as either physical (i.e. road conditions, weather, proximity to emergency medical services) or social (i.e. existing safety laws and economic conditions).

Table 1. Haddon Matrix of factors relevant to traffic deaths

	Person Factors	**Vehicle/Equipment Factors**	**Environment**	
			Physical	**Social/Economic**
Pre-Crash	Driver Experience Impairment Gender Driver condition Risk-taking behavior	Vehicle condition Driving Speed Load characteristics Safety package	Road quality Road characteristics Weather Conditions	Existing laws Enforcement of laws Safety culture Economy Congestion Travel time/Exposure
Crash	Helmet use Restraint use Injury Propensity Health Age	Speed Crashworthiness/safety design of vehicle Vehicle size/Body Type Vehicle condition Type of crash	Road features Type and size of object struck	Laws relevant to human/ vehicle/ physical factors
Post-Crash	Health Age Impairment	Integrity of fuel and battery systems Availability of automated crash notification and GPS locator	EMS response speed and quality Distance to trauma care Availability of rehabilitation programs Accessibility to crash victims	EMS protocols Public support for trauma care and rehab

Changes in these factors will influence the number of crashes or reduce the severity of crashes resulting in fewer fatalities. Depending on the factor or the combination of factors, small changes can have large impacts and vice versa. State or local level policies, laws, enforcement, and education can influence many of these factors.

Engineering approaches (e.g. traffic calming, rumble strips, advanced driving systems in vehicles, vehicle safety design) may also counter some factors.

The growth in the population of motor vehicles and the increase in VMT that accompanies economic growth is associated with an increase in road traffic crashes. According to NHTSA, job growth and low fuel prices were two factors that led to increased driving, including increased leisure driving and driving by young people [2].

Weather and regional demographic distributions are other examples of high-level factors shown to play a role in crash rates. Consistently, studies have shown that increases in temperature are associated with an increase in fatal traffic crashes due to an increase in VMT and exposure for pedestrians, bicyclists, and motorcyclists [6][7].

Nevertheless, even when state characteristics are similar, considerable variability in traffic deaths exists. For example, states with similar populations and seat belt laws have substantially different outcomes with respect to vehicle occupant deaths, seat-belt-use rates, and unbelted vehicle occupant fatalities.

This paper examines the association of these factors with the number of traffic deaths in the United States to identify key factors driving the changes in deaths over the past twelve years. This study quantifies the contribution of high-level factors like the economy and VMT to distinguish the role of key factors relevant to intervention by state and local governments and vehicle manufacturers.

METHODS

This study analyzes changes in traffic death counts in U.S. states from 2005 to 2016 using generalized linear mixed modeling. These regressions model the association of changes in measurable factors (explanatory variables) with changes in traffic death counts by state (outcome variable). Three regressions modeled different outcomes: 1) passenger vehicle occupant fatalities, 2) pedestrian fatalities, and 3) motorcycle fatalities.

Explanatory Variable Selection

The Haddon matrix (Table 1) was used as a guide in selecting explanatory variables to test in the model. To be included in the model, the variable had to be available by state and year. Over seventy variables were tested. These are listed in Appendix A.

Data Sources

Table 2, Table 3, and Table 4 detail the data sources for the outcome, exposure and explanatory variables included in the final models.

Table 2. Data Sources for the Outcome Measure

Measure of Outcome	Data Source and Description
Fatality Counts	Fatal Analysis Reporting System (FARS)

Table 3. Data Sources for Exposure Measures

Measures of Exposure	Data Source and Description
Vehicle Miles Travelled	Highway Statistics, Federal Highway Administration
Population	United States Census Bureau
Number of Vehicles	National Vehicle Population Profile, R.L. Polk
Motorcycle Registrations	Motorcycle Sales Report, 2000-2016, Motorcycle Industry Council

Table 4. Data Sources for Explanatory Measures

Measure of Key Factors	Data Source and Description
U.S. Population Counts, demographic	United States Census Bureau

distributions	
Gross Domestic Product	United States Bureau of Economic Analyses
Employment percentages by age	United States Census Bureau
Average Annual Temperature	National Oceanic and Atmospheric Administration
Motorcycle Registrations	Motorcycle Sales Report, 2000-2016, Motorcycle Industry Council
Alcohol Consumption	National Institute of Alcohol Abuse and Alcoholism
Self-Reported Belt Use	Behavioral Risk Factor Surveillance System, Centers for Disease Control
Self-Reported Drunk Driving	Behavioral Risk Factor Surveillance System, Centers for Disease Control
Observed Driver Handheld Use while Driving	National Occupant Protection Use Survey, National Highway Traffic Safety Administration
Average IIHS crash test rating of vehicle fleet	Insurance Institute for Highway Safety crash test ratings
Average NCAP Score of vehicle fleet	National Highway Traffic Safety Administration, New Car Assessment Program
Percent of vehicle fleet ESC-equipped	Safercar.gov, National Highway Traffic Safety Administration
Average, Median, Vehicle Mass and Mass distribution of state vehicle fleet	National Vehicle Population Profile, R.L. Polk

State motor vehicle traffic deaths counts were tabulated using the NHTSA-administered Fatality Analysis Reporting System (FARS). VMT was tabulated by state using annual data from the Federal Highway Administration. Gross Domestic Product (GDP), based on data from the U.S. Bureau of Economic Analysis, was the primary economic measure included in the final model. United States Census Bureau data provided information on state demographic distributions over time, means of transportation to work, and population employment characteristics.

The Center for Disease Control's Behavioral Risk Factor Surveillance System (BRFSS) provided data on risk behaviors. The BRFSS is a national random digit dial telephone survey. Data are collected at the state level among a representative sample of the population over 18 years of age. Regarding belt use, the survey asks the question: "How often do you use seatbelts in your car?" The possible responses are: always, nearly always, sometimes, seldom, and never. For this study we defined "rarely belted" as those responding "sometimes", "seldom", or "never". Regarding drunk driving, the survey asks the question: "In the past 30 days, have you driven after drinking too much?" with a yes or no response. The BRFSS also includes a question on binge drinking (5 or more drinks for men and 4 or more drinks for women in one drinking session).

Observed belt use data are available by state from the annual National Occupant Protection Use Survey (NOPUS), coordinated by NHTSA. This probability-based survey collects observations on driver and right-front passenger seat belt use. Observations of driver hand held use are also included in the NOPUS and used in this study.

Weather data (precipitation and temperature) were obtained from the National Oceanic and Atmospheric Administration (NOAA). The NOAA maintains and collects data from automated weather stations distributed across all 50 states.

Changes in state laws (in particular alcohol, motorcycle, and graduated drivers licensing) were assessed using information available from the IIHS and the Governors Highway Safety Association.

This study includes a detailed focus on the role of vehicle fleet characteristics (age, safety design, mass disparity). To compute measures of these characteristics, we compiled, by state and year, counts of the vehicle population by vehicle make, model and model year using data published by R.L Polk and Co. Vehicle mass (from NHTSA) and crash testing data (from the Insurance Institute for Highway Safety and from NHTSA's New Car Assessment Program) are available by make, model and model year. IIHS ratings were converted to numeric scores: poor=1, marginal=2, acceptable=3 and good=4. Using these data merged with R.L. Polk vehicle population data (by make, model and model year), the study computed safety-related measures of the vehicle fleet for each state over time. Therefore, changes in these measures represent the improved safety design of new vehicles as they penetrate the fleet. including average IIHS rating, average NCAP rating, average vehicle mass, and fleet age. In addition, we computed several measures of mass disparity to characterize any changing distribution of passenger vehicles by mass.

Other measures tested in the regression models but not included in the final models were obtained from an additional number of data sources: Gasoline prices (from the U.S. Energy Information Administration), driving and walking time per day (from the American Time Use Survey, Bureau of Labor Statistics), drug- and opioid-related fatalities (Multiple Cause of Death File, CDC), number of mobile phone subscribers (Voice Telephone Services Report, Federal Communications Commission).

A full list of measures and data sources is compiled in Appendix A.

Data Preparation
Outcome and explanatory variables were compiled as panel data by year (2005-2016) and state, resulting in 612 observations (12 years x 51 states/DC). Because the scales of the explanatory variables varied dramatically, all variables were standardized and centered. For some data sources the data were missing in one year. In this case, the variable was imputed as the mid-way between the previous year and the following year. No 2016 estimates (last values) were missing in the final analysis.

Statistical Modeling
Generalized linear mixed models (GLMM) were created modeling the relationship between changes in the explanatory variables with fatality counts by year and state. GLMM is an extension of linear mixed models that combines the characteristics of generalized linear models and mixed models. The mixed model includes variables on two levels, time and state. This type of regression is appropriate for panel data with repeated measures over time.

While the outcome variables are count data (count of traffic fatalities), the assumptions for Poisson regression (equality of mean and variance of the outcome variable given the explanatory variables) were not met. Therefore, we used the negative binomial log link function.

Model Specification
GLMMs were fitted at two levels (state and time) using the panel data. The model allows for independent random effects for the intercept and slope for each subject (i.e. state). The model allows for an independent state-level random effect to incorporate the data structure of years nested in a state.

Measures to be included as explanatory variables were collected from multiple sources. Often there was more than one way to measure a key factor; either in different ways by different sources or by defining one source in different ways. For example, we developed three measures of belt use: 1) percent reporting rarely belted, 2) percent reporting always belted in the BRFSS, and 3) the percent observed daytime belted rate reported in the NOPUS. Different measures of the same key factor were tested separately for inclusion in the model. In determining which variable to use in the final model we considered measure's significance in the model and its contribution to model fit (measured by Bayesian Information Criterion, BIC).

Criteria for inclusion in the final model included testing for significance, collinearity, interaction effects, examining the impact on the coefficients of other explanatory variables, and the variable's contribution to model fit. The number of explanatory variables included in the final model was limited to between eight and ten due to the model degrees of freedom. Highly correlated variables (Pearson correlation coefficient>0.8) were not included simultaneously in specifying or in the final model.

This study further estimates the individual contribution of each key factor in the change in fatalities from 2015 to 2016 by applying the model to the known change in that key factor from 2015 to 2016 holding the other variables at 2015 values. For example, the contribution of the change in percent of adults reporting driving drunk is determined by predicting the number of fatalities in 2016 based on the change in this variable where all other explanatory variables remain at 2015 levels. The individual factor contributions by this method are not additive as their effects interact.

RESULTS

Figure 1 presents the counts of traffic-related fatalities over time, by person type. Changes in fatality counts varied by person type, with non-occupants contributing more to the increases than occupants. Fatalities decreased monotonically until 2012. In 2015 and 2016 traffic-related deaths increased again. Increases among non-occupant fatalities were greater than vehicle occupant fatalities. Fatality counts increased by 11.9% and 9.0% among pedestrians in 2015 and 2016, respectively, and 13.7% and 1.3%, respectively, among pedalcyclists. Motorcyclist deaths increased 9.5% and 5.1% in 2015 and 2016, respectively. Passenger vehicle occupant deaths increased 7.5% and 4.7%, respectively.

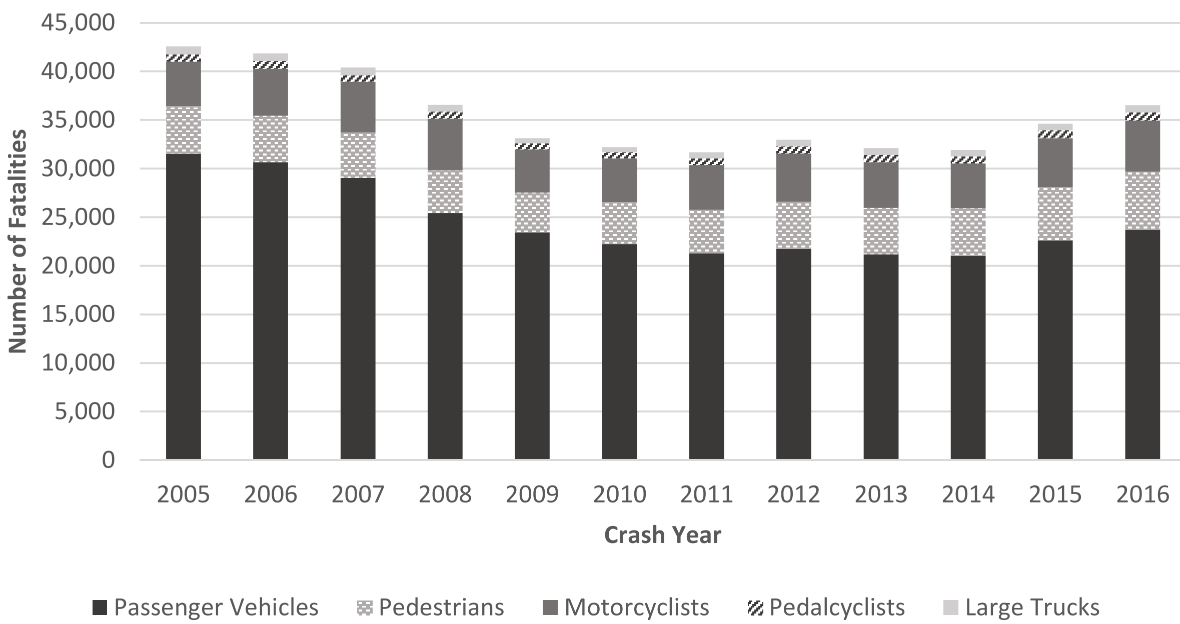

Figure 1. Number of Fatalities by Crash Year and Person Type (Source: Fatality Analysis Reporting System, National Highway Traffic Safety Administration)

Figure 2 plots state VMT versus the count of traffic-related fatalities for the 50 states and Washington D.C. for each of the years between 2005 and 2016. The trendline shows that fatality counts are highly correlated with exposure. However, the points do not cluster tightly around the line indicating that state- and time-related variability in risk exists that is not fully explained by changes in VMT alone.

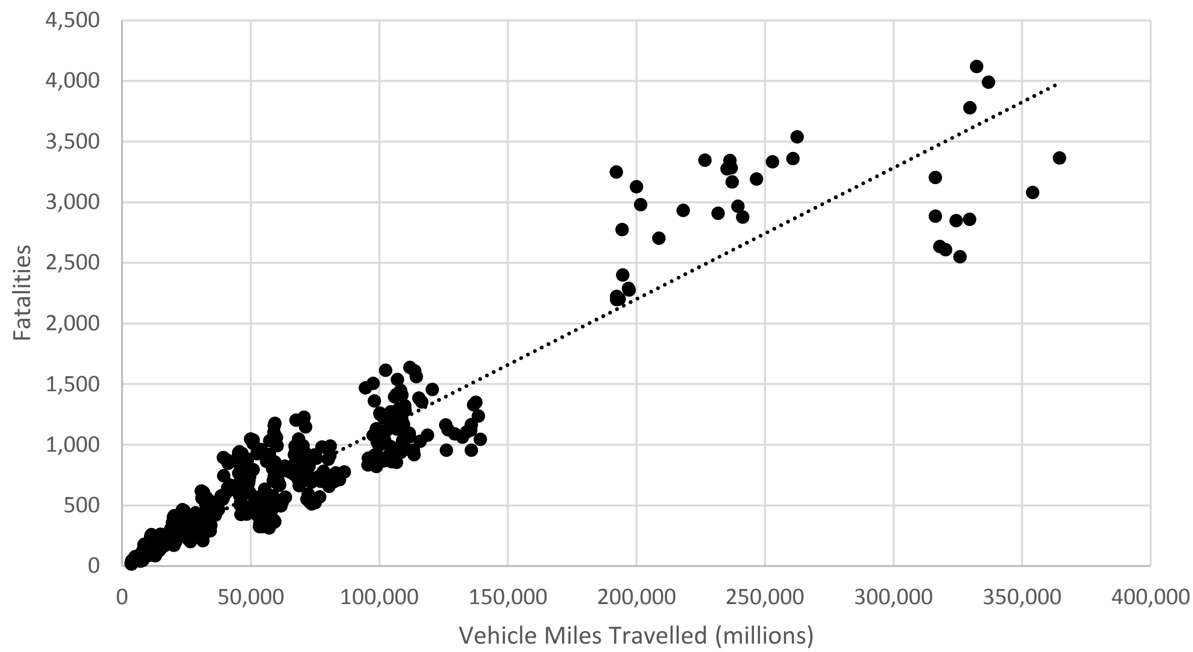

Figure 2. Count of Fatalities Versus Vehicle Miles Travelled, for 50 states and the District of Columbia between 2005 and 2016.

Table 5, Table 6, and Table 7 present the modeled fixed effects parameter estimates of the explanatory variables and the direction of this relationship for passenger vehicle occupant fatalities (Table 5), pedestrian fatalities (Table 6), and motorcycle fatalities (Table 7). "Positive" indicates that as the explanatory variable changes, fatalities change in the same direction; i.e. an increase in the explanatory variable is associated with increasing fatalities, and vice versa. "Negative" indicates that as the explanatory variable changes, fatalities change in the opposite direction; i.e. an increase in the explanatory variable is associated with decreasing fatalities, and vice versa.

Passenger Vehicle Occupant Fatalities

Eight explanatory variables were included in the final model predicting passenger vehicle occupant fatalities (Table 5). The final model controlled for high-level factors related to exposure (VMT per capita), the economy (GDP) and temperature. With the exception of average IIHS rating, all explanatory variables showed a positive association with fatality counts, i.e. an increase in the explanatory variable was associated with an increase in fatality counts. The models found that an increase in the average IIHS rating was associated with a decrease in fatality counts.

Table 5. Fixed Effects Parameter Estimates of Explanatory Variables Included in the Final Model of Passenger Vehicle Occupant Fatalities

Explanatory Variable	Estimate	p-value	Association with Fatalities
Average fleet IIHS Rating	-0.204	< 0.001	Negative
Employment Rate for the Population Age 65+ (%)	0.211	< 0.001	Positive
Population Age 65+ (% of total population)	0.167	< 0.001	Positive
Adults Reporting Rarely Belted (% reporting sometimes, seldom or never wear seatbelt)	0.116	< 0.001	Positive
Adults Reporting Drunk Driving in the past 30 days (%)	0.012	0.016	Positive
Average Temperature (degrees F)	0.137	< 0.001	Positive
VMT per Capita (millions)	0.196	< 0.001	Positive

GDP (Billions)	0.004	0.292	Positive

Pedestrian Fatalities

Nine explanatory variables were included in the final model predicting pedestrian fatalities (Table 6). The final model controlled for high-level factors related to exposure (VMT per capita), the economy (GDP) and temperature. With the exception of percent of workers who walk to work and GDP, all explanatory variables showed a significant positive association with fatality counts. The models found that an increase in the percent of workers who walk to work was associated with a decrease in fatality counts. GDP, however, was included in the model because it significantly modified the effect of VMT in urban areas: increasing urban VMT with a concurrent increase in GDP was associated with a decrease in pedestrian fatalities.

Table 6. Fixed Effects Parameter Estimates of Explanatory Variables Included in the Final Model of Pedestrian Fatalities

Explanatory Variables (Key Factors)	Estimate	p-value	Association with Fatalities
Walk to Work (% of workers)	-0.122	0.012	Negative
% Vehicles with Mass above the U.S. 90^{th} %ile	0.121	0.002	Positive
Observed Using Hand-Held Device (% of drivers)	0.016	0.027	Positive
Population Age 65+ (% of total population)	0.151	< 0.001	Positive
VMT in Urban Areas (% of overall VMT)	0.089	0.140	Positive
Average Temperature (degrees F)	0.175	< 0.001	Positive
VMT per Capita (millions)	0.060	0.060	Positive
GDP (Billions)	0.453	< 0.001	Positive
Police per Million	-0.044	0.005	Negative
Interaction effect: VMT in Urban Areas x GDP	-0.116	0.003	Negative

Motorcycle Fatalities

Eight variables were included in the final model predicting motorcycle fatalities (Table 7). The final model controlled for high-level exposure-related factors (Total VMT and registered motorcycles), economic changes (GDP), motorcycle registrations, and temperature. With the exception of implementing a universal helmet law and population density, all explanatory variables showed a significant positive association with fatality counts. The presence of a universal helmet law was included in the model because it significantly modified the effect of total VMT: the presence of a universal helmet law where there was a concurrent increase in total VMT was associated with decreased fatalities.

Table 7. Fixed Effects Parameter Estimates of Explanatory Variables Included in the Final Model of Motorcycle Fatalities

Variables (Key Factors)	Estimate	p-value	Association with Fatalities
Statewide Universal Helmet Law (1=Yes/0=no)	-0.048	0.513	Negative
Beer Consumption (gallons of ETOH/capita)	0.083	0.002	Positive
Observed Using Hand-Held Device (% of drivers)	0.021	0.008	Positive
Population Density (Population/square mile)	-0.361	< 0.001	Negative
Registered Motorcycles (#)	0.111	0.001	Positive
Average Temperature (degrees F)	0.239	< 0.001	Positive
Total VMT (millions of miles)	0.437	< 0.001	Positive
GDP (Billions)	0.225	0.041	Positive

Interaction effect: Universal Helmet Law x Total VMT	-0.208	0.030	Negative

The models were applied to estimate the contribution of each key factor to changes in fatality counts. Table 8, Table 9, and Table 10 present the estimated change in the number of fatalities between 2015 and 2016 for the observed changed in each individual key factor between 2015 and 2016, holding the other factors constant. (Note: The factor-related contributions by this method are not additive as their effects interact)

In general, high-level factors (i.e. VMT, GDP, Temperature) are related to the highest corresponding changes in fatalities (Table 8, Table 9, Table 10). Increases in non-belt use (reporting rarely belted) and drunk driving (in the past 30 days) were substantial and corresponded to an estimated increase of 220 and 371 occupant fatalities, respectively (Table 8, Table 9). The 2.6% increase in the over-65 population corresponded to an increase in 647 occupant fatalities (Table 8) and 162 pedestrian fatalities (Table 9). The proportion of this population working has increased in the past decade, by 2.3% from 2015 to 2016, and corresponded to an increased 352 occupant fatalities (Table 8). Distracted driving, measured with the NOPUS of observed driver cell phone use, decreased and corresponded with a decline in vulnerable road user fatalities (49 fewer pedestrian fatalities and 60 fewer motorcycle fatalities).

Improved vehicle safety design, as measured by the average IIHS score of the vehicle fleet, was the one factor that corresponded with a substantial decrease in fatalities; 1,325 fewer occupant fatalities. Mass discrepancy, measured by the percent of vehicles in the fleet whose mass is above that of the 90th U.S. percentile declined and corresponded with a decrease of 42 in pedestrian fatalities.

No change, or an insignificant change, in a key factor will not play a role in driving the number of traffic deaths (e.g. no states changed their motorcycle helmet laws between 2015 and 2016).

Table 8. Estimated Individual Contribution of each Key Factor in the Change in Passenger Vehicle Occupant Fatalities from 2015 to 2016

Key Factor	Change 2015 to 2016	Corresponding change in Fatalities
Average IIHS Score	+7.0%	-1,325
Employment Rate for Age 65+ (%)	+2.3%	+352
Population Age 65+ (%)	+2.6%	+647
Adults Reporting Rarely Belted (%)	+6.9%	+220
Adults Reporting Drunk Driving (%)	+14.7%	+371
Average Temperature (degrees F)	+1.5%	+223
Total VMT (millions of miles) per Capita	+1.2%	+293
GDP (Billions)	+1.5%	+417

Table 9. Estimated Individual Contribution of each Key Factor in the Change in Pedestrian Fatalities from 2015 to 2016

Key Factor	Change 2015 to 2016	Corresponding change in Fatalities
Workers who Walk to Work (%)	-1.9%	+18
% Vehicles with Mass above the U.S. 90^{th} %ile	-3.2%	-42
Drivers Observed Using Hand-Held Device (%)	-11.5%	-49
Population Age 65+ (%)	+2.6%	+162
VMT in Urban Areas (%)	+0.9%	+55
Average Temperature (degrees F)	+1.5%	+53

Total VMT (millions of miles) per Capita	+1.2%	+27
GDP	+1.5%	+74

Table 10. Estimated Individual Contribution of each Key Factor in Motorcycle Fatalities from 2015 to 2016

Key Factor	Change 2015 to 2016	Corresponding change in Fatalities
Universal Helmet Law	No change	0
Beer Consumption (gallons/capita)	+0.2%	+9
Drivers Observed Using Hand-Held Device (%)	-11.5%	-60
Population Density (Population/square mile)	+0.8%	-2
Motorcycle Registrations (#)	+2.2%	+2
Average Temperature (degrees F)	+1.5%	+81
Total VMT (millions of miles)	+1.2%	+99
GDP	+1.5%	+45

To gauge the accuracy of the models, we compared the modeled predicted 2016 fatality counts using data from 2005 to 2015 to actual fatality counts (Table 11).

Table 11. Modeled Predicted 2016 Fatality Counts versus Actual 2016 Fatality Counts

Model	Forecasted 2016	Actual 2016	% difference (Forecasted versus Actual)
Passenger Vehicles	23,102 (2.5%)	23,714	-2.5%
Pedestrians	5,671 (5.2%)	5,987	-5.2%
Motorcycles	5,271 (0.2%)	5,286	-0.2%

CONCLUSION

The models presented in this study suggest that observed increases in passenger vehicle fatality counts in 2015 and again in 2016 were driven by measurable changes in vehicle miles of travel (exposure) and an improving economy. Beyond these high-level factors, changes in the elderly population age 65 and older, the percent of this population employed, non-belt use, and drunk driving were associated with increasing fatality counts. However, improved vehicle safety design that accompanied the new vehicles as they entered the fleet substantially countered these effects, thereby tempering fatality increases.

Increases in motorcycle fatalities were associated with increased motorcycle registration, overall VMT (exposure), and an improving economy. Among pedestrian and motorcycle fatalities, there is some evidence that other factors like driver distraction plays a role but could not be easily measured.

DISCUSSION

Newer vehicles, for the most part, receive higher IIHS ratings and NCAP scores. Therefore, IIHS average rating is a surrogate measure of new vehicles penetrating the fleet and the accompanying improving overall safety design. However, it is important to note that the attrition from the fleet of older vehicles without airbags and other safety features is also contributing. The other measure of average safety design, average NCAP score, had the same effect in the models and was collinear with the measure of average IIHS rating. Because both could not be included at the same time, the average IIHS rating was chosen because model fit was slightly better.

The method presented in this paper provides a resource to study the impact of year-to-year changes in factors known to impact fatalities. For vehicle manufacturers the models can be used to examine how vehicle fleet changes are influencing fatality counts in the context of other factors. For example, the models can be applied to estimate fatalities prevented if fleet turnover is accelerated given expected economic changes. This method can be further applied to study how fleet changes influence fatality counts in different crash segments (for example, intersection crashes, rural crashes) to identify opportunities for vehicle safety advancements or detailed follow-up studies.

The models are useful to policy- and decision-makers to identify opportunities for intervention. The resulting models can be applied to forecast future fatality counts, given that a known set of input parameters exists, on at a national level or by state. For example, the model can be applied to predict the number of deaths prevented if seat belt use increased to 95%.

An insignificant change, in a key factor will not contribute to a change in the number of traffic deaths. For example, because there were no changes in universal helmet laws between 2015 and 2016, there was no estimated contribution of this key factor to fatality counts.

Even proven effective countermeasures will not appear to have an impact on fatality counts unless their year to year change is significant. For example, one might expect that the belt use rate should have a large effect on the number of deaths occurring. While safety belts are proven effective in preventing fatalities, no significant change in the belt use rate has been observed in recent years (Enriquez and Pickrell, 2019). However, if safety belt use rates were to increase dramatically to, for example, 95% from their national average of 90%, the impact would be measurable.

The quality of these forecasting models relies on a number of critical factors. First, the data must be available and consistently collected per state for the full study period. A smaller number of training data points would degrade model performance. In many cases data have become available only recently (i.e. self-reported drunk driving), however no historical record exists in earlier years. Next, the homogeneity of each state becomes important for each factor sampled. Since a single value represents each parameter for each state and input year, we assume that this value appropriately represents that condition for the entire state. While this assumption is true in many ways, there are exceptions. For example, average precipitation may provide a useful metric for smaller states while large states may have widely varying conditions depending on the specific region. Depending on the population distribution, these region-specific disparities can be important. A third factor that impacts the quality of models is the representativeness of the data. For example, the model uses observed driver handheld device use as a surrogate for driver distraction. While the use of a handheld device certainly plays a role, it is not the only factor impacting the likelihood of distraction while operating a vehicle.

Finding a suitable measure for some factors was challenging and sometimes not available. In particular, measures of distracted driving, motorcycle helmet use, and speeding were difficult to obtain in a consistent way.

The models generated by this study provide a resource to study the impact of year to year changes in factors known to impact fatalities among passenger vehicle occupants, motorcycle riders and pedestrians.

Limitations

An important limitation of the current study is availability of direct measures to characterize important known risk factors including motorcycle helmet use, distraction, drunk driving and speeding.

In addition, in order to understand any relationship, the measure or a proxy must exist for each state and year. Forecasting the impact of factors that are not yet measurable is also not possible. For example, forecasting the impact of the newest emerging technologies is challenging because limited data exist.

The model examines the relationship of changes in factors with changes in fatality counts. Due to the quasi-experimental design, cause and effect cannot be inferred from the modeled relationships.

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APPENDIX A: MEASURED KEY FACTORS TESTED AS EXPLANATORY VARIABLES IN THE MODELS

CATEGORY	VARIABLE	SOURCE
Weather	Annual Precipitation	National Oceanic and Atmospheric Administration
	Annual Average Temperature	National Oceanic and Atmospheric Administration
Urban/Rural	Urban VMT (million) per Capita	Federal Highway Administration (FHWA)
	VMT in Urban Areas	FHWA
	Urban VMT/Total VMT	FHWA
	VMT in Rural Areas	FHWA
	Rural VMT per Capita	FHWA
Social	Education Level: High School and Higher	United States Census (US Census)
	Police per Capita	US Census
Policies/Laws	Alcohol Policy	Governors Highway Safety Association
	GDL - strength of policy	Insurance Institute for Highway Safety (IIHS); strength based on [9]
	Universal Motorcycle Helmet Law	IIHS
Regulations	FMUSS 214 (side impact protection) implemented	NHTSA
	% of registered vehicles with ESC	R.L. Polk U.S. Vehicle registrations
Economy	Mean Travel Time to Work	US Census
	Gross Domestic Product	Bureau of Economic Analyses

CATEGORY	VARIABLE	SOURCE
	Gas Price per Gallon	Energy Information Administration (EIA)
	Poverty	US Census
	Employment Rate for People 65	US Census
	Population without Health Insurance (%)	US Census
	Average Gas Price per BTU	EIA
	Household Income	US Census
	Employment Rate	US Census
	No Health Insurance	US Census
Exposure	VMT	FHWA (Highway Statistics: 5.4.1. Vehicle-miles of travel, by functional system)
	Total Population	US Census
	Average Driving Minute per Capita per Day	American Time Use Survey
	Number of vehicles	R.L. Polk U.S. Vehicle registrations
	% Who Use Vehicle to Work (Alone)	US Census
	% Who Walk to Work	US Census
	Average Walking Minute per Capita per Day	American Time Use Survey
	Population Density	US Census
	Average Cycling Minute per Capita per Day	American Time Use Survey
	Average Driving Minute per Day for Driver 65	American Time Use Survey
	Total VMT (million) per Capita	FHWA (Highway Statistics: 5.4.1. Vehicle-miles of travel, by functional system)
Demographics	Population age 65 and over	US Census
	Race White%	US Census
	Male Ratio	US Census
	Median age of population	US Census
Car Safety	ESC % of Vehicles on Road	R.L. Polk U.S. Vehicle registrations
	Average IIHS Score	R.L. Polk U.S. Vehicle registrations/IIHS crashworthiness testing
	% of Vehicles with Electronic Stability Control	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 90 Percentile	R.L. Polk U.S. Vehicle registrations
	Average NCAP Score	R.L. Polk U.S. Vehicle registrations/New Car Assessment Program
	Percent of Old Vehicles on Road	R.L. Polk U.S. Vehicle registrations
	Percent of New Vehicles on Road	R.L. Polk U.S. Vehicle registrations
	Average Vehicle Age	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 50 Percentile	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 10 Percentile	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 25 Percentile	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 75 Percentile	R.L. Polk U.S. Vehicle registrations
Vehicle Mass Disparity	Difference of 10th percentile and 90th percentile of Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	% of Vehicles Below the Bottom 10%	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com

CATEGORY	VARIABLE	SOURCE
	National Mass	
	% of Vehicles Above the Top 10% National Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	Average Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	Standard Deviation of the Mass of Vehicles on Road	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	Total % of Vehicles above and below the top 10% and bottom 10% National Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
Belt Use	Self Report Rarely Belted %	Behavioral Risk Factor Surveillance System (BRFSS)
	Self Report NOT Always Belted %	BRFSS
	Self Report Always Belted % for Age 65	BRFSS
	Self Report Always Belted %	BRFSS
	Self Report Rarely Belted % for Age 20-	BRFSS
	Self Report Always Belted % for Age 20-	BRFSS
	Self Report Rarely Belted % for Age 65	BRFSS
	Observed Belted Rate	NOPUS
Alcohol/Drugs	Opioid Related Fatalities	Multiple Cause of Death File, Centers for Disease Control
	Beer Consumption (gallons of ethanol/capita)	National Institute of Alcohol Abuse and Addiction (NIAAA)
	All Beverage Consumption(gallons of ethanol/capita)	NIAAA
	Spirit Consumption(gallons of ethanol/capita)	NIAAA
	Wine Consumption(gallons of ethanol/capita)	NIAAA
	% who Report Binge drinking	BRFSS
	% Self Report Never Drunk Driving	BRFSS
	% Self Report Drunk Driving in Past 30 Days	BRFSS
	Self Report Binge Drinking in Past 30 Days % for Age 65	BRFSS
	Self Report Binge Drinking in Past 30 Days % for Age 20-	BRFSS
Distraction	Phone Subscribers per Capita	FCC (Voice Telephone Services Report) Additional Data
	Phone Subscribers	FCC (Voice Telephone Services Report) Additional Data
	Observed Driver Hand-held Device Use while driving	NOPUS