Investigating Factors that Contributed to the Large Reduction and Subsequent Increase in Roadway Fatalities in the United States between 2005 and 2016

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Word Count: 5,984 words + 6 tables = 7,484 words

Submitted August 1, 2019

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ABSTRACT
The substantial decline in motor-vehicle fatal crashes over the period of 2008 to 2011 and a subsequent increase afterwards in the United States has been subjected to extensive research in the last few years. Following the perceptible reduction in traffic fatalities beginning in 2008, which concurred with a major recession, researchers focused on finding the relative influence of the recession on fatalities using statistical modeling. The Project 17-67 by the National Cooperative Highway Research Program (NCHRP) conducted an in-depth investigation, where the researchers developed two Poisson-gamma regression models, Model Controlling State (MCS) effect and Model Not Controlling State (MNCS) effect to analyze the factors associated with the decline in fatalities. This study sought to serve as an extension of the NCHRP Project 17-67 to provide a thorough investigation of the factors influencing fatalities during and after the 2008 recession using an updated dataset to 2016. The modeling results showed remarkable improvements, where both the MNCS and MCS models could reflect the fluctuations in fatalities over the focus period. The effect analysis revealed that the economic factors contribute as much as 84% to 86% in the reduction and subsequent increase in fatalities during and after the recession. The unemployment rate of 16 to 24 years old, median household income, and the price of gasoline were found to be the most statistically significant parameters in both the models. Changes in vehicle-miles traveled (VMT), government expenditure, and regulatory measures were not significant factors in affecting the number of fatalities over the analysis period.

Keywords: Fatalities, unemployment, economy, regression, negative binomial model

INTRODUCTION

Traffic fatalities are one of the major causes of death in the United States (U.S.). According to the Annual U.S. Road Crash Statistics (ASIRT, 2017), over 37,000 people die from traffic crashes causing nearly $230.6 billion economic loss every year to the nation. Although historical data from the last 50 years (1975-2015) show a downward trend of fatalities in the U.S., highway designers, safety engineers and analysts are always concerned about fatal crashes because of the unquantifiable distress these impose on human lives. Statistics provided by the National Highway Traffic Safety Administration (NHTSA, 2016) showed a drastic decline in fatalities all over the U.S. during the period of 2005 to 2011. This drew the attention of researchers and safety engineers, and they started looking for potential factors that could be associated with this large decline in the number of fatalities. Traffic fatalities declined from 43,510 to 32,479 from 2005 to 2011 which quantifies to an aggregated total of over 25 percent decline in fatalities during that period (NHTSA, 2016). Although from 2005 to 2007 showed some substantial decline, a historically marked 21 percent decrease in traffic fatalities occurred from 2008 to 2011, reaching the lowest count over the last 50 years in 2011. Data from the subsequent years show a gradual increase in traffic fatalities. **Figure 1** presents a graphical depiction of the yearly change in fatalities from 2001 to 2016 in the U.S.

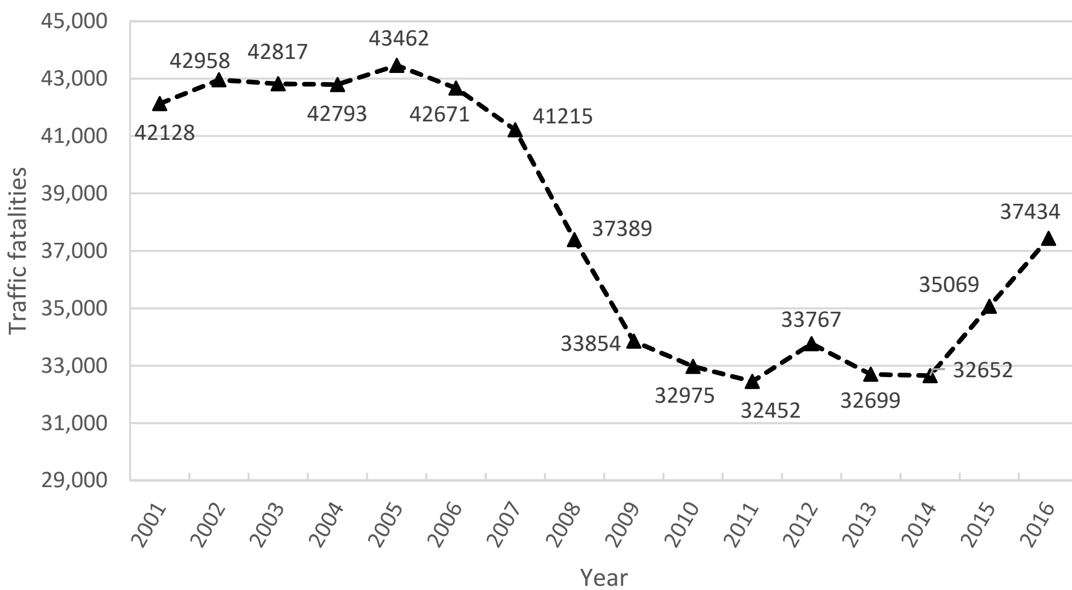


Figure 1 Traffic fatalities, 2001-2016.

While the rapid yearly decline in fatalities was being observed in the U.S. over the period 2008-2011, another major event that coincided with this is the economic plunge experienced nation-wide during the same period. According to the statements of the business cycle dating committee by the National Bureau of Economic Research (NBER, 2010), a major recession, referred to as the "Great Recession," was observed in all U.S. states from December 2007 to June 2009 because of the considerable reduction of 5.1% in GDP growth. Although the Great Recession was officially over in the United States in 2009, the effects of the downturn were felt throughout the upcoming years. During the Great Recession, approximately 9 million jobs were lost, and the nation hit a peak national unemployment rate of 10%, the highest ever observed since the 1982-83 recession (BLS, 2012).

Design and adaptation of safety countermeasures and law enforcement depend on statistical analysis of crash data. Policymakers and safety engineers in practice rely on existing statistical models to estimate the overall road safety performances. However, during a period of recession when traffic fatalities largely decline, all available fatality prediction models fail to forecast the number of fatalities, which creates a setback for the policymakers to design and implement countermeasures. Also, researchers were curious to determine the effects which resulted in a fast-rated road safety improvement during the recession period in order to incorporate the information for designing and developing new countermeasures. After the recession ended in 2012 and a period of economic expansion was observed, the number of traffic fatalities started increasing, which never occurred in the past 50 years. This rare instance created an alarming concern among the traffic safety community and government agencies to explore more into after-recession crash investigation to determine the factors responsible. With these motivations, much research efforts were employed in the investigation of a causal relationship among the processes causing this decline and subsequent increase in fatality counts. This research presents an effort to offer new insights into the substantial changes in number of fatalities between 2005 and 2016.

LITERATURE REVIEW

Numerous studies have documented the association of traffic safety with economic activities starting from the early 1970s. This section summarizes the findings of some of the studies investigating the association of economic and other factors with fatalities.

Multiple studies have found a close association between exposure in terms of vehicle miles traveled (VMT) and the reduction in the number of fatalities during a recession (Wijnen and Rietveld 2015, Forsman et al. 2015, Noble et al. 2015). However, some other studies have argued that during the Great Recession, VMT did not change enough to cause this drastic decline of traffic fatalities (He, 2016), which raises the necessity of investigating other possible factors that might have played a role in reducing traffic fatalities during that period.

Wijnen and Rietveld (2015) provided a distinctive analysis of the studies linking economic factors with fatalities or crash risk separately to impart a better understanding of the mechanisms affecting the number of fatalities and crash risk, which can occur with or without the influence of the other. According to the study, during the time of an economic downturn within a business cycle, a cycle of economic expansion and contraction as defined by the NBER (2010), the most commonly observed phenomena include a decrease in GDP per capita and an increase in the unemployment rate. Other mechanisms involved in the reduction of fatalities during a recession as reported in various literatures are changes in traffic volume, driver class, user behavior, and safety investments (**Table 1**).

Noble et al. (2015) studied the mechanisms associated with the decline in the road traffic crashes from 2007 to 2010 in Great Britain. The authors identified factors, such as decreased VMT by heavy-goods vehicles, decreased proportion of young drivers in the traffic fleet aged between 17 and 24 years, and fewer licenses issued to young drivers that are found to be significant in reducing the number of fatalities during the recession. Forsman et al. (2015) studied the trend of fatalities before and during the period of the Great Recession in Sweden. Based on the findings, the author argued that only studying the causes of reduced fatalities during the night times and those associated with drunk driving alone would explain the drastic reduction in fatalities during the recession.

TABLE 1 Factors identified by literature influencing decline in fatalities during recessions

Studies found in the literature	Study area/nation (Study period)	Factors
Wijnen and Rietveld (2015)	11 nations including the U.S., some European countries, China, New Zealand, Australia, and Canada (1975-2011)	• The volume of traffic in terms of VMT • Modified driver class (reduced young age drivers aged between 16 and 24) • Behavioral changes among users (less drunk driving) • Investments in safety countermeasures (fewer safety features or fewer technologies)
Noble et al. (2015)	Great Britain (2007-2010)	• Decreased VMT by heavy-good vehicles • Decreased proportion of young drivers in the traffic fleet aged between 17 and 24 years • Fewer licenses issued to young drivers • Reduced infant passengers aged between 0 and 5 years • Increased enforcement of laws against unlicensed drivers • Safety features, such as seat belts, air bags, helmets • Driving under influence
Forsman et al. (2015)	Sweden (2001-2012)	• Less non-work-related trips • Driving under influence • Unlicensed driving due to not being able to afford to get a license
Maheshri and Winston (2016)	Ohio, U.S. (2009-2013)	• Reduction in the number of high-risk drivers on the road
He (2016)	All U.S. states (2003-2013)	• Less drunk- driving • Fewer heavy trucks in the vehicle fleet • Safe driving practices
Noland and Zhou (2017)	All U.S. states (1984-2013)	• Rural VMT

He (2016) analyzed datasets from all 50 states of the U.S. from 2003 to 2013 to find the relationship between reduced fatalities and the recession. The findings illustrated that the drastic reduction in fatalities observed in the aftermath of the Great Recession can be attributable to a resultant reduction in fatality rates by approximately 90%. This means that the declined number of fatalities was hardly caused by simply a decline in the level of exposure in terms of VMT, rather a complex mechanism among other plausible processes needs to be taken into consideration. The author further pointed out that some of the possible causes of the sharp reduction in fatalities were i) less drunk-driving, ii) fewer heavy trucks in the vehicle fleet, and iii) safe driving practices. Maheshri and Winston (2016) analyzed a dataset for the state of Ohio between 2009 and 2013 and found that the VMT did not change during the subjected period of recession, and the most relevant contributing factor in reducing the number of fatalities in Ohio was the reduction in the number of high-risk drivers on the road.

Noland and Zhou (2017) conducted a detailed analysis taking data from all 50 states of the U.S. from 1984 to 2013. The study design was similar to that of He (2016). However, in this research, the authors decompose the variable VMT into rural vehicle miles traveled and total vehicles miles traveled, and the findings suggested that a reduction in the rural VMT contributed a considerable proportion to the reduced number of fatalities observed during the recession, which seems to be inconsistent with the results of some other studies (He, 2016; Elvik et al., 2015). It is also noted here that the authors of these studies did not consider similar variables in their models. Noland and Zhou (2017) estimated the net decline in fatalities as 1840 during the recession period (2006-2014), which only accounts for 20 percent of the actual reduction of fatalities (9,964). This can be explained by the fact that in their study, the authors considered the growth of population during the study period, which presumably contributes to an increase in the number of fatalities (Wegman et al., 2017).

It can be summarized that the studies are not consistent among each other in terms of variable selection or considered data structure and consequently presented significantly different results. A recent research effort by the National Cooperative Highway Research Program (NHCRP) Project 17-67 conducted an extensive investigation of numerous factors on traffic fatalities and found that the drastic decline in fatalities is mainly caused by a change in the characteristics of traffic fleet with fewer high-risk drivers (aged from 16 to 24) on the road (Blower et al., 2017). Although the models developed by the researchers provided reasonable fit to the data until the end of the Great Recession, the dataset used in the modeling was limited with respect to the sample size. As Blower et al. (2017) did not include data from after-recession period, it is unknown whether or not the same model can be used to estimate fatalities with reasonable accuracy after a recession. Although in Flannagan et al. (2018), new data from two states were used for verifying the goodness of estimation of those models, a thorough investigation of model performance for all 50 states needs to be conducted with new or more recent data. Although there were many research efforts found in the literature investigating the decline in the number of fatalities in the U.S. during the Great Recession, to the authors' best knowledge, no study was found that have investigated the factors influencing traffic fatalities during the economic expansion beginning in 2012. This study addresses these limitations with reasonable accuracy and shows significant improvements in modeling results. The next section presents the data used in the analysis and their respective sources.

DATA SERIES AND SOURCES

The data series were obtained from various sources as listed in **Table 2** to represent the vehicle, crash, driver, and environmental factors contributing to traffic fatalities. Under the scope of the NCHRP Project 17-67, a complete panel dataset was prepared, containing data from all 50 states between 2001 and 2012. The researchers decided to exclude the District of Columbia from the analysis as the data showed large variance and accounted for less than 0.1 percent fatalities during the analysis period. For the scope of this research, the dataset was further updated to 2016 for analyzing the factors contributing to the decline and subsequent increase in fatalities during and after the Great Recession. The sources of the data series are listed in **Table 2**:

TABLE 2 Sources of the data series (Source: Blower et al. (2017)

Crash data series	
Data	**Source**
Crash data on fatal accidents	Fatality Analysis Reporting System (FARS) of the National Highway Traffic Safety Administration (NHTSA). Accessed from: ftp://ftp.nhtsa.dot.gov/fars/
Exposure data series	
Population by state & age	Bureau of the Census, Table 2. Intercensal Estimates of the Resident Population by Sex and Age
Square miles by state	Bureau of the Census, Geography. Accessed from https://www.census.gov/geo/reference/state-area.html
Road miles by roadway function class and year	Highway Statistics, Federal Highway Administration (FHWA), Table hm10 for each year, 2001-2016
VMT by roadway function class, vehicle type, urban/rural, national	Highway Statistics, FHWA, Table VM-1 for each year, 2001-2016
VMT by roadway function class, urban/rural, by state	Highway Statistics, FHWA, Table VM202 for each year, 2001-2016
Economic data series	
Employment rate, total counts of employed by state, month, & year	Bureau of Labor Statistics, Current Population Survey, Local Area Unemployment Statistics
Unemployment rate, by state, month, & year	Bureau of Labor Statistics, Current Population Survey
State GDP by year	US Department of Commerce, Bureau of Economic Analysis
State median household income by year	US Census Bureau, Current Population Survey, Annual Social and Economic Supplements. for data from 2001-2004, and Small Area Income and Poverty Estimates (SAIPE) Program for data from 2005-2016
Fuel tax by state by year	Highway Statistics, FHWA. Table MF-205
Fuel costs	US Energy Information, State Energy Data System, prices for regular gasoline, data are converted from prices per million BTUs
Driver- and vehicle-related data series	
Seat belt, primary vs secondary, by state and year	Compiled from Insurance Institute for Highway Safety, Digests of state laws, available at http://www.iihs.org/iihs/topics/laws/safetybeltuse
Belt use rates	Compiled from NHTSA's NOPUS program, reported in Chen and Ye, 2009; Chen, 2014, and NCSA, 2018
Alcohol-related laws and penalties, by state by year	Compiled from state laws, the index was developed from Klinich, 2016
Motorcycle helmet by state by year	Digest of motorcycle helmet laws from IIHS website. Accessed from http://www.iihs.org/iihs/topics/laws/helmetuse/helmethistory?topicName=Motorcycles#tableData
Alcohol consumption	Compiled from National Institute of Alcohol Abuse and Alcoholism (Haughwout and Slater, 2018)
ESC-penetration	Compiled from Loss Bulletin, Vol. 31 by Highway Loss Data Institute, (Highway Loss Data Institute, 2014a, 2014b)
Post-1991 model year	Estimated from GES, using a quasi-induced exposure technique
Highway expenditures	
Capital expenditures	Compiled from Highway Statistics, FHWA, Table SF-2, includes construction, relocation, resurfacing, restoration, rehabilitation and reconstruction, widening, capacity improvements, restoration of failed components, additions and betterments of roads and bridges. See Federal Highway Administration N.D.

Maintenance	Compiled from Highway Statistics, FHWA, Table SF-2, includes preserving the entire highway, including surface, shoulders, roadsides, structures, and traffic control devices, as close as possible to the original condition as designed and constructed
Administration, Research, Planning	Compiled from Highway Statistics, FHWA, Table SF-2, including all general and miscellaneous expenditures not related to a specific project, expenditures for highway planning, research, and planning
Law enforcement and safety	Compiled from Highway Statistics, FHWA, Table SF-2, including all relevant Federal Safety programs, sections 402, 403, 405,406, 407, 408, 410, and 411 of Title 23 of the United States Code, as well as MCSAP. Also includes capital expenditures designated by states as safety-related
Highway Safety Improvement Program	Compiled from FHWA funding tables under SAFETEA-LU and MAP-21. Available from https://www.fhwa.dot.gov/safetealu/fundtables.htm and https://www.fhwa.dot.gov/map21/funding.cfm

STATISTICAL MODELING

This study considers the methodology proposed in Blower et al. (2017), one of the most recent studies offering a comprehensive investigation of traffic fatalities on all 50 states of the U.S. Blower et al. (2017) developed a Poisson-gamma count model, also known as the negative-binomial model (NB), for the statistical analysis of the number of fatalities. The technique was discussed in the review by Elvik (2015). The NB model focuses on capturing the long-term trend of the fatalities by using raw fatality counts as the response variable and the VMT or population as the exposure. Here, all other factors are linked together by an exponential function, and the coefficients of these factors are interpretable as influencing parameters to the rate of fatalities per VMT or per capita population. In other words, the statistical inference of the predictors is related to the risk of crashes by incorporating the exposure. The mathematical expression of the Poisson-gamma model in highway safety can be presented as stated below:

$$Y_{it} \mid \theta_{it} \sim Po(\theta_{it}) \text{ for } i = 1, 2, \ldots, N \text{ and } t = 1, 2, \ldots, T \qquad (1)$$

Where,
$\theta_{it} = \mu_{it} \exp(\varepsilon_{it})$
Y_{it} = number of crashes for i-th entity (state) and t-th time period (year);
θ_{it} = mean number of crashes;
μ_{it} = a function of the covariates (for example: $\mu_{it} = \exp(\beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + ... + \beta_k X_{kit}$ where k is the total number of covariates);
β = vector of unknown coefficients; and
ε_{it} = model residuals.

According to **Equation 1**, the number of crashes for the i-th entity (state) and the t-th time period (year), Y_{it}, conditional on its mean θ_{it}, is expected to follow a Poisson distribution. The underlying assumption is that the number of crashes is independent over all entities and time periods, and the term exp (ε_{it}) is independent and gamma distributed (Miaou and Lord, 2003). The mean of exp (ε_{it}) is expected to be equal to 1.0 and have a variance equal to $1/\phi$ for all the *i*'s and *t*'s (here, ϕ is called the inverse dispersion parameter, which is assumed to be greater than 0). The reason behind using a NB model instead of a Poisson model is that a Poisson model assumes the mean is equal to the variance, which is not always true for count data. A known observation regarding count data is that the data is generally over-dispersed or under-dispersed (rarely), which makes the variance much different than the mean (Lord et al., 2005). Hence, as a viable alternative to the Poisson distribution, an NB model is an appropriate model that allows capturing over-dispersion in the data (Hilbe, 2011).

According to the exploratory data analysis conducted before undertaking the statistical modeling, two different trends were observed in the variables: i) the spatial effects across different states, which are related to the size of the state, its population, environment, socio-economic, and traffic safety conditions, and ii) the temporal effects from year to year (Blower et al. 2017). In order to address these trends separately, Blower et al. (2017) proposed two different NB models, considering or not considering the effect of the states. The model not considering the varying effect of the states (called the Model Not Controlling State or MNCS model) assumes a state-fixed effect among variables, ignoring the variations between states, and thus focusing more on the time-trend of the dataset. The model considering the varying effect of the states (called the Model Controlling State or MCS model) allows variations to be captured in the effects of all variables and thus focusing more on the spatial trend of the dataset. According to Blower et al. (2017), considering two types of NB modeling is informative in deciphering the true effects of the variables. For example, if any variable shows similar trends in both models, this would mean that the effect of that variable in predicting fatalities is more general than being constrained by any local factors. On the other hand, if the effects of any variable are different for the two models, this would mean that the variable is more restrictive under the influence of states or yearly change. In other words, that variable has a different response to the change in location (states) than to the change in time (years). The functional forms of these models are presented in **Equation 2** and **3** below:

MNCS model $$\mu = VMT \times e^{\beta_0 + \sum_i (\beta_i x_i)} \tag{2}$$

MCS model $$\mu = VMT \times e^{(\beta_0 + \gamma_s) + \sum_i (\beta_i x_i)} \tag{3}$$

Where,
μ = the estimated mean of the response variable;
x_t = independent variables considered in the study for year *t;*
z_t = transformed change variables from year to year;
γ_s = state specific parameter; and
β 's = parameter coefficients.

The variable selection process was based on a detailed exploratory data analysis and factor analysis outside the scope of this paper. The variables considered in the statistical modeling are listed below:

1. Rural VMT as a percentage of total VMT
2. Capital expenditures per highway mile, in constant 2013 dollars

3. Safety Expenditures per highway mile, in constant 2013 dollars
4. State GDP per capita.
5. Unemployment rate for 16-24-year age-group
6. Total price at the pump, in constant 2013 dollars
7. Beer consumption per capita
8. DUI law rating
9. Motorcycle helmet law rating
10. Safety Belt law rating
11. Median income, in constant 2013 dollars
12. Penetration of the post-1991 model year in the traffic fleet

RESULTS AND DISCUSSION

The models were assessed based on their goodness of fit using three criteria: i) Akaike information criteria (AIC), ii) Mean absolute deviation (MAD), and iii) Mean squared prediction error (MSPE) (Oh et al., 2003). The general characteristics of the modeling results are as follows: parameter estimates, standard errors of the coefficients, associated *p*-values, and exponentiated terms of the estimates are presented in this section. The effects of the variables (i.e., parameter estimates) were examined to determine their statistical significance under the assumption of $\alpha=0.10$, which means that a *p*-value of greater than 0.10 would mean that there is not enough evidence to believe the coefficient to be significantly greater than zero, hence statistically not significant.

Table 3 presents the modeling results of the MNCS model. A total of 9 variables, such as the rural VMT proportion, capital spending, safety spending, GDP per capita, percent unemployment for ages 16 to 24, pump price, beer consumption, median income, and post-1991 model year, were found to be statistically significant at 10% level. The variables related to occupant protection, DUI rating, belt rating, and motorcycle helmet rating were not statistically significant in this model at the 10% level.

Table 4 presents the modeling results from the MCS model with the VMT as exposure. The statistically significant variables (at $\alpha=0.10$) for this model are the GDP per capita, percent unemployment for age 16 to 24, pump price, beer consumption, DUI rating, belt rating, motorcycle helmet rating, and the post-1991 model year. The other four variables, the rural VMT proportion, capital spending, safety spending, and median income were not statistically significant in this model, even at the 10% level.

TABLE 3 Parameter estimates for the MNCS model

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-2.3155	0.2279	<.0001	-
Rural VMT proportion	0.2729	0.0566	<.0001	1.314
Capital spending (in $1000)	0.0007	0.0002	0.0009	1.001
Safety spending (in $1000)	-0.0018	0.0011	0.0941	0.998
GDP per capita (in $10,000)	0.023	0.0089	0.0097	1.023
Unemployment for age 16 to 24 (%)	-0.0087	0.002	<.0001	0.991
Pump price ($ per gallon)	-0.0672	0.0159	<.0001	0.935
Beer (gallons)	0.263	0.0356	<.0001	1.301
DUI rating	-0.0024	0.0022	<u>0.2866</u>	0.998
Belt rating	-0.0022	0.0058	<u>0.7006</u>	0.998
Motorcycle Helmet rating	0.0009	0.0061	<u>0.8819</u>	1.001
Median Income (in $10,000)	-0.1999	0.0121	<.0001	0.819
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	-0.0124	0.0024	<.0001	0.988
Dispersion parameter	0.0288	0.0016	-	-
AIC*	9487.57			
MAD*	513.93			
MSPE*	1122646.54			

Underlined values denote p-values > 0.1 (corresponding to statistically non-significant variables)
*Smaller values are preferred

TABLE 4 Parameter estimates for the MCS model

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-4.1587	0.2059	<.0001	-
Rural VMT proportion	0.1502	0.1127	<u>0.1826</u>	1.162
Capital spending (in $1000)	0.0002	0.0001	<u>0.1159</u>	1.000
Safety spending (in $1000)	0.0011	0.0008	<u>0.1657</u>	1.001
GDP per capita (in $10,000)	0.0596	0.0097	<.0001	1.061
Unemployment for age 16 to 24 (%)	-0.0105	0.0011	<.0001	0.990
Pump price ($ per gallon)	-0.0311	0.0080	<.0001	0.969
Beer (gallons)	0.5209	0.0577	<.0001	1.684
DUI rating	-0.0093	0.0025	0.0002	0.991
Belt rating	-0.0152	0.0066	0.0220	0.985
Motorcycle Helmet rating	-0.0347	0.0152	0.0218	0.966
Median Income (in $10,000)	-0.0156	0.0137	<u>0.2536</u>	0.985
Post-1991 model year	-0.0077	0.0015	<.0001	0.992
Dispersion parameter	0.0038	0.0003	-	-
AIC*	8319.25			
MAD*	516.55			
MSPE*	1171622.47			

Model Comparison

The predicted fatalities by the MNCS and MCS models are plotted against the observed number of fatalities in **Figure 2** and **3**, respectively. It shows that the MCS model predicts the total fatalities very closely throughout the entire analysis period from 2001 to 2016 (**Figure 2**). In fact, the 95% prediction interval of the MCS model captures the observed fatalities every year except for some minor deviations occurring in 2001, 2005, 2009, and 2014 (**Figure 3**). Although the MNCS model could capture the trend of fatalities over the years, it failed to reflect all the variations in fatalities. The model under-predicted the fatalities prior to the recession and over-predicted afterward, indicating missing effects by one or more parameters in the model. The deviation of the MNCS model clearly depicts that the integrated effects of the predictors failed to capture the variations properly and that some influential factor might not have been accounted for in the model (**Figure 3**). However, this model is still valuable in interpreting national trend of some predictors, which are transient in any local (state) effect.

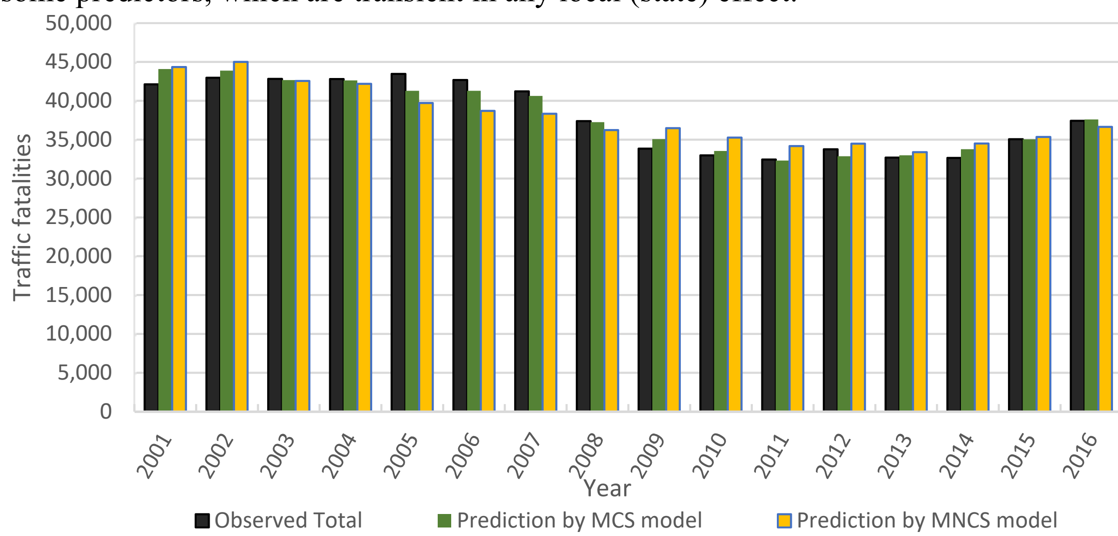


Figure 2 Observed versus predicted total fatalities by the MNCS and MCS model, 2001-2016

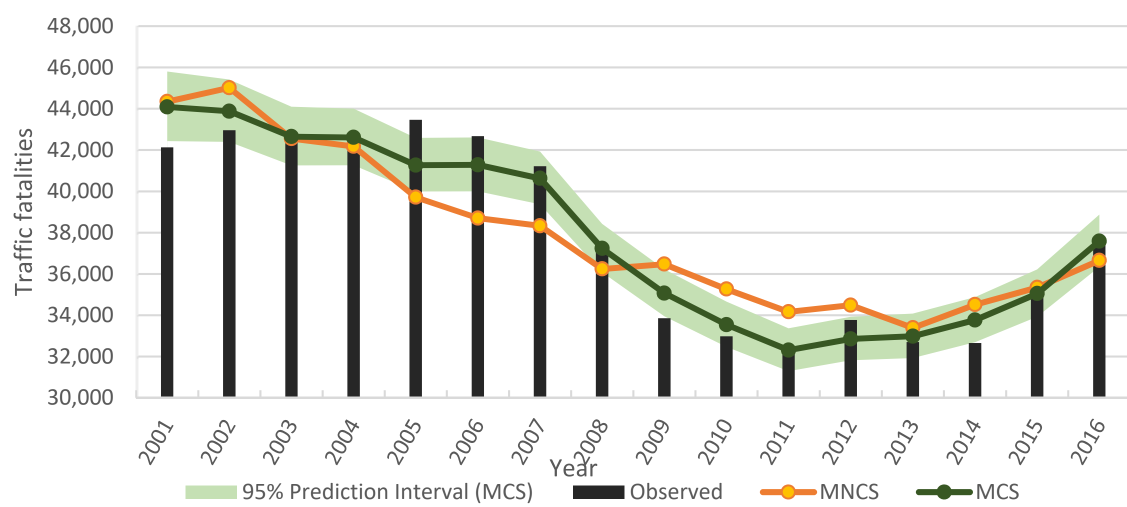


Figure 3 Comparison of predicted fatalities for MNCS and MCS model with observed fatalities on all U.S. highways, 2001-2016

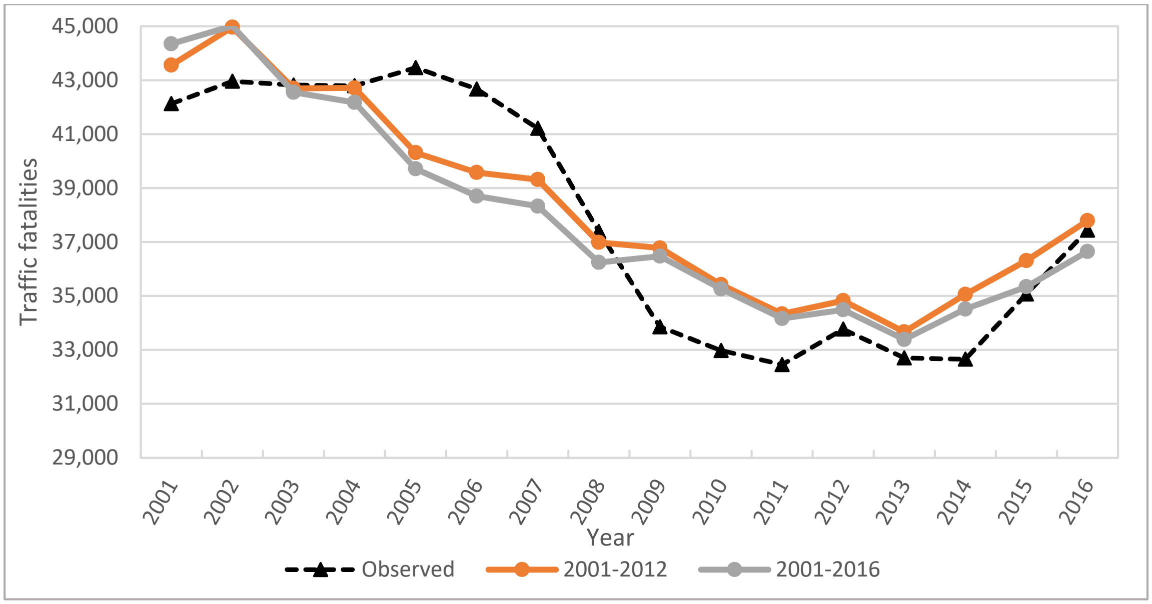
Improvement in Results by using an Updated Dataset

Based on the relative quality of the models, the results obtained from calibrating the models with the updated dataset show drawbacks in terms of all three estimations of the goodness of fit: AIC, MAD, and MSPE. According to the NCHRP report (Blower et al., 2019), in the previous analysis, the AIC values ranged between 5,643 and 6,537, MAD values ranged between 35.8 and 93.1, and MSPE estimation ranged between 3,165 and 21,186 for the MCS and MNCS models, respectively. Based on the results with the updated dataset, the AIC values show an increase on an average of 46%, ranging between 8,319 and 9,488; MAD values increased by a factor of 5 to 13, ranging from 514 to 517; and MSPE values increased a substantial amount by a factor of 54 to 354, ranging between 1,122,646 and 1,171,622 for the MNCS and MCS models with VMT, respectively.

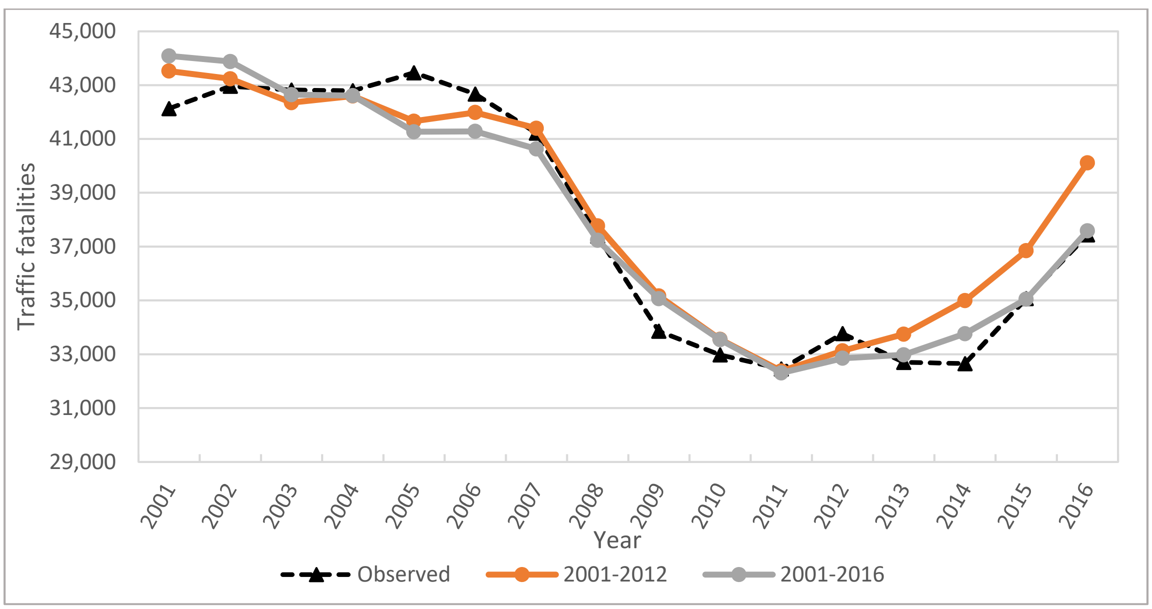
The increased AIC values indicate the increased amount of information lost while predicting fatalities with the updated dataset. The increased MAD values indicate that the predictions are now more spread-out, and the variability in the model has increased by a factor of 5 to 13. The increase in the values of the MSPE indicates missing predictors in the model, the effect of which could not be captured by the existing dataset. It is important to note here that the updated dataset contains 2,800 more data points compared to the previous dataset (data on 14 variables from an additional 4 years for 50 states), which are likely to increase any estimation of prediction errors (technically, the goodness-of-fit measures should be compared with the same dataset in order to provide an accurate comparison). Also, some predictors might have worked well in the previous models, however, failed in the updated analysis. For example, the penetration rate of post-1991 model year vehicles, which was used as a surrogate measure to represent the advancements in vehicle technology and occupant protection systems to improve safety, reached 99% in 2013 and remained unchanged until the end of the analysis period. Although this predictor shows no change from 2013 to 2016, the vehicle protection system continued to grow, making the predictor invalid as a surrogate. However, based on the available information, this was still a reasonable assumption.

To provide a better inference on the goodness-of-fit (GOF) of the models, graphical representations of the predicted and observed values for each model are presented in **Figure 4a-b**. The predictions by the MNCS model provides a poor fit to the observed fatality values over the entire period of analysis for both datasets (**Figure 4a-b**).

The MCS model does not fit well for the earlier years of the data from 2001 to 2006, however, starting from 2007, the model captures the fatality trend very well (**Figure 4b**). In fact, the MCS model using updated dataset tracks the observed trend perfectly between 2007 and 2016, except for some minor deviations. Hence, based on these graphical depictions, it can be said that using the updated dataset, the relative prediction quality of the models has improved significantly.



(a) MNCS model

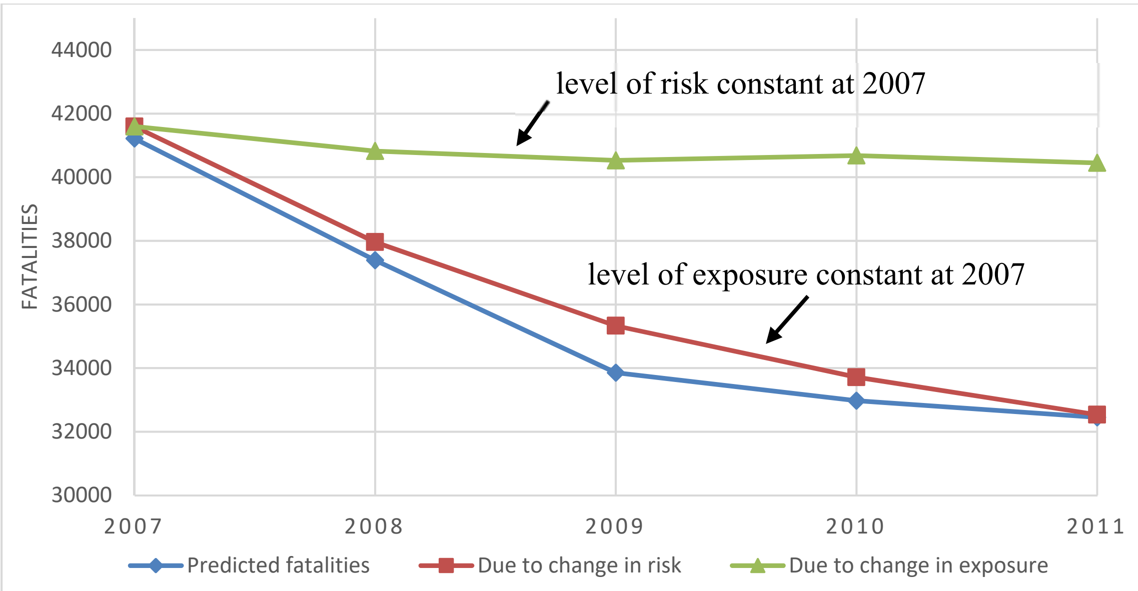


(b) MCS model

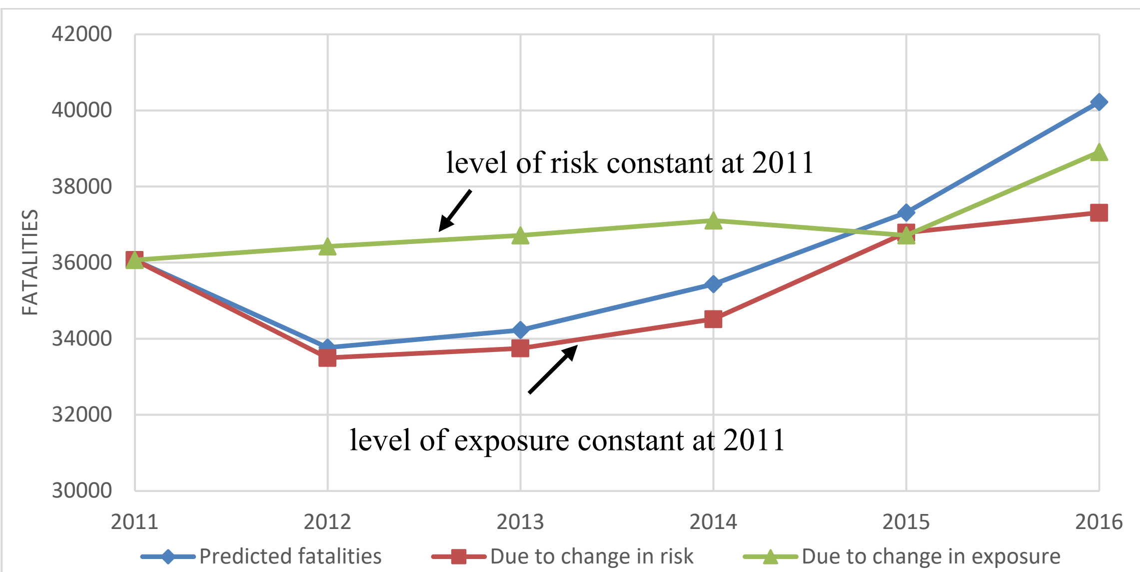
Figure 4 a-b Comparison of predicted fatalities for the MNCS model and MCS model, 2001-2016

Statistical Inference

The very first step to draw statistical inference on the effects of the predictors to fatalities was to identify the relative effect of risk and exposure influencing the number of fatalities (Blower et al., 2017). Changes in fatalities can be attributable to the changes in the level of risk or exposure or a combination of these two mechanisms. In order to distinguish the variable effects of risk and exposure on changing the number of fatalities, hypothetical fatality values were estimated by considering the level of risk or exposure being constant at their initial level. For drawing separate statistical inference on the causes of reduction and increase in fatalities, two time periods, the peak recession period (2007 to 2011) and the post-recession period (2012-2016), will be addressed separately in this discussion. **Figure 5 a-b** present graphical representations of the hypothetical numbers of fatalities with constant risk or constant exposure over observed fatalities.



(a) 2007-2011



(b) 2011-2016

Figure 5 a-b Predicted fatalities versus fatalities with constant risk or exposure, 2007- 2011 and 2011-2016, respectively

It is evident that during the 2008 Great Recession, the effects of the change in the level risk on fatalities was quite higher than the effect of the change in exposure (VMT) (**Figure 5a**). For this reason, even though the VMT did not change much during the Great Recession, the fatalities dropped drastically due to a considerable change in the level of risk. During this period, the change in VMT contributed positively to accelerate the sharp reduction in fatalities (**Figure 5a**). On the other hand, after the recession, the relationship between risk and exposure to fatalities is not so straightforward (**Figure 5b**). At the beginning of the period between 2012 and 2014, the increase in fatalities is largely caused by the increase in the level of risk. During this period, the increase in VMT also contributed positively to accelerate the increment of fatalities. In 2015, while the VMT slightly dropped from its 2014 level, the rate of increase in the number of fatalities remained constant, driven more by the increase in risk. However, in 2016 the VMT suddenly increased keeping the growth of the number of fatalities constant, although the rate of increase in risk declined from 2015 to 2016 as compared to previous years.

To further specify the effect of the change in the level of risk on fatalities, the predictors were divided into five variable groups as shown in **Table 5** (Blower et al., 2017). The economic variable was further divided into two groups considering the closeness of their association to crash risk. For example, based on previous studies (Wijnen and Rietveld, 2015), the influence of unemployment rate of young-age drivers and rural VMT on crash risk is directly assumable, i.e., if unemployment rate of young-age drivers increases, the level of crash risk decreases as this age group is considered to be high-risk prone. The same causal association can be made between rural VMT proportion and crash risk. On the other hand, GDP per capita, median household income, and beer consumption are considered indirect factors because their association with crash risk cannot be directly deductible by a probable causal relationship. Also, these factors include the overall population, some of whom may not be primary drivers or directly exposed to crash risk.

TABLE 5 Groupings of variables for individual effect quantification

Variable Groupings					
	Economic	**Safety Expenditures**	**Roadway Capital Expenditures**	**Regulatory**	**Vehicle Safety**
Variables	**Direct** • Unemployment % for 16-24-year age-group • Rural VMT proportion	• Safety Expenditure per highway mile	• Capital Expenditure per highway mile	• DUI rating • Helmet rating • Safety Belts rating	• Penetration of post- 1991 model year
	Indirect • GDP per Capita • Median Income • Beer consumption				

Table 6 presents the percentage contribution of each variables group in the predicted reduction or increase in traffic fatalities during and after the recession. Here, a positive sign before the proportions indicates a positive association between a change in the variable group and a change in fatalities, and a negative sign indicates a contrasting association between the two. **Table 6** shows that changes in the economic variables account for 83% (MCS) to 87.9% (MNCS) to the predicted reduction in fatalities during the recession between 2007 and 2011. The same group of variables also contribute 81.5% (MCS) to 90.9% (MNCS) to the increase in the predicted fatalities after the recession between 2012 and 2016. Following the economic variables, vehicle safety technology contributed 12% to 13% to the reduction and 3.0% to 3.2%

to the increase in fatalities during and after the recession, respectively. The changes in fatalities due to the changes in capital and safety expenditures and regulatory measures were minor during both focus periods for both the MNCS and MCS models.

TABLE 6 Percent Reduction in Fatalities Accounted for by Variable Groupings

MCS model	Percent Reduction in Fatalities Accountable to the Variable Group from 2007-2011		Percent Increase in Fatalities Accountable to the Variable Group from 2011-2016	
Model / Variable Group	MNCS	MCS	MNCS	MCS
All Variables	100.0	100.0	100.0	100.0
Direct Economic Measures	**-43.1**	**-40.2**	**-44.6**	**-69.5**
Indirect Economic Measures	**+44.8**	**+41.8**	**+46.3**	**+12.0**
Safety Expenditures	-2.0	0.0	+0.3	+0.3
Roadway Capital Expenditures	+4.0	-1.0	+2.5	+1.2
Regulatory	-2.0	-3.0	+0.6	+4.4
Vehicle Safety	**-12.0**	**-13.0**	**+3.0**	**+3.2**

*Bold numbers represent the largest proportion contributed to the change in fatalities during the observed period

CONCLUSIONS

A dramatic decline in the number of fatalities across nations during a period of economic downturn has been observed multiple times around the world. The probable association of economic changes influencing road safety and the investigation of the associative mechanisms behind this process is the motivation of this research undertaking. There are numerous studies of different statistical approaches that attempted to model this relationship, the most recent being Blower et al. (2017). This study is an extension of the work conducted by Blower et al. (2017), where two separate Poisson-gamma models were developed to evaluate the effects of different variables on the fatalities.

First, this study recalibrated the models developed by Blower et al. (2017) with an updated dataset from 2001 to 2016 to examine the adequacy of the models to predict fatalities after the recession. The modeling results showed remarkable improvements in predicting fatalities with the updated dataset from 2001 to 2016. Both the MNCS and MCS models could reflect the trends in fluctuations in fatalities over the focus period. In fact, the MCS model tracked the observed fatality trend very well, even after the recession. The effects analysis reveal that the economic factors contributed as much as 84% to 86% in the reduction and subsequent increase in fatalities observed in the prior and after recession periods. The unemployment rate of the young age group (aged between 16 and 24), median household income, and the price of gasoline were found to be statistically significant (at the 10% level) and the most effective parameters influencing the number of fatalities in both the MNCS and MCS models. Other factors that were found statistically significant with minor effects on changes in fatalities were beer consumption, GDP per capita, the proportion of rural VMT (only for the MNCS model), ratings on regulatory laws (only for the MCS model), the penetration of post-1991 model year in the vehicular fleet. The effects of state expenditures were found to be not statistically significant for the MCS model and contributed very little to the reduction and increase in fatalities during and after the recession.

Limitations of the Study

Although the findings of this study provided opportunities to better understand and interpret the effects of different factors in the reduction and subsequent increase in the number of fatalities during and after the recession, there are some limitations associated with the assumptions regarding modeling and data are summarized below:

- The findings of the study suggested a strong association between some input variables with fatalities. However, the causal mechanisms involved with the change in fatalities cannot be established based on the current modeling approach.
- The data series of this study used some surrogate measures for factors on which data were not readily available. Some of the surrogate measures used in this study are capital and safety expenditure, and the penetration of 1991 model-year as surrogate measures of improvements in vehicle safety, strictness of DUI, motorcycle helmet, and seat belt laws as surrogate measure of effect of regulatory countermeasures.
- The study uses the penetration of 1991 model year vehicles into the traffic fleet as a surrogate measure for vehicle safety technology. This surrogate measure reaches a constant 99% in 2013 and remains unchanged throughout the rest of the analysis period, practically becoming invalid to have any influence on the .
- Although the modeling assumption considered a negative binomial distribution, the dispersion parameters observed in the modeling results were very small suggesting a rather Poisson process with little heterogeneity. This indicates that a Poisson process might be more appropriate for the data and the sample size and might have generated the same results with less computational and modeling effort.
- Another issue related to the modeling approach adopted in this study was that the predictions were made with the same set of data that were used to recalibrate the model parameters. Hence, the predictions were very close to the observed values, which is unusual to obtain from forecasting.

Direction for Future Research

Following are some potential research ideas to improve the applicability of this study.

- Better surrogate measures can significantly improve the prediction performance of the models.
- The models can be used in developing future SHSP targets with minimal inputs, which will increase the practical applicability of the model over moving averages or linear trends.
- Estimating elasticity range of the association between fatalities and economic factors (e.g., unemployment rates) will enable understanding the influence of changes in economic conditions on crash risk more clearly.
- Using data with more temporal granularity, i.e., monthly or quarterly data, for forecasting will enhance the effect of the economy on short-term fluctuations of fatalities during the recession.

- There are various ways to evaluate the safety effects of countermeasures including before-after analysis. However, no database is available to systematically track or estimate the safety performances of various countermeasures on U.S. highways. Research effort should be employed to develop concepts for a comprehensive framework containing data on these safety initiatives.
- The findings of this study suggested close associations between the median income and young age drivers and the changes in fatalities. A detailed investigation should be conducted to further investigate the relationship of median income by age group with the trends in fatalities.
- The effect of the recession on vulnerable road users also needs to be investigated under the plausible assumption that during a recession, people tend to limit their driving to avoid additional costs by shifting to low-cost non-motorized vehicles or walking. This modal shift might positively increase the level of risk or exposure for the vulnerable road users, resulting in an increased number of bicycle and pedestrian fatalities. To investigate the factors influencing pedestrian or bicycle fatalities, these should be modelled separately from the motor-vehicle crashes as their crash-risk and exposure differ from that of motor-vehicle crashes.

Data Needs

One of the major limitations of this study is using surrogate measures for data that were not readily available. In order to provide improvements in the results, more granular data need to be collected in the following areas:

- Safety infrastructure
- Inventory on roadway features
- VMT by age-group or VMT by household income.
- Estimates of licensed drivers based on age-groups
- The income level of drivers involved in crashes
- Behavioral characteristics of drivers involved in crashes
- Estimates of safety effects of various vehicle safety technologies and safety improvement programs
- Estimates of the effects of overall vehicle design in traffic safety

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: H. Shimu, D. Lord, S. R. Geedipally, R. Wunderlich; data collection: L. Wu, T. H. Shimu; analysis and interpretation of results: T. H. Shimu; draft manuscript preparation: T. H. Shimu, D. Lord, S. R. Geedipally, L. Wu, R. Wunderlich.
All authors reviewed the results and approved the final version of the manuscript.

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