EXAMINING THE FACTORS CAUSING A DRASTIC REDUCTION AND SUBSEQUENT INCREASE OF ROADWAY FATALITIES ON UNITED STATES HIGHWAYS BETWEEN 2005 AND 2016

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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May 2019

Major Subject: Civil Engineering

ABSTRACT

The substantial decline in motor-vehicle fatal crashes over the period of 2008 to 2011 has been subjected to extensive research in the last few years. Starting from the early 1970s, reduced fatalities have been associated with economic downfalls by looking into empirical historical evidence in many countries of the world. Following the perceptible reduction in fatalities in the United States (U.S.) beginning in 2008, which concurred with a major economic recession during the same period, some researchers focused on finding the relative influence of such a hypothesis using statistical modeling. This study sought to serve as an extension of the Project 17-67 by the National Cooperative Highway Research Program (NCHRP) to provide a thorough investigation of the factors influencing fatalities during and after the 2008 recession using an updated dataset. Two Poisson-gamma regression models, considering (MCS) or not considering (MNCS) a varying effect among states, and a log-change regression model were developed under the Project NCHRP 17-67. The primary research objectives were to run the existing models with a state-based dataset from 2001 to 2012 and recalibrate it with an updated dataset to 2016 to check the adequacy of the models in predicting fatalities after the recession or if any additional variable is required. The study further investigated the inconsistent effect of the recession on fatalities by land use type. The modeling results showed remarkable improvements with the updated dataset, where both the MNCS and MCS models could reflect the fluctuations in fatalities over the focus period. The Poisson-gamma models outperformed the log-change model in predicting total, rural, and urban fatalities. 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. The goal of this research was to provide a better understanding of the economic variables affecting fatalities, alongside focus on rarely addressed issues like variable effect on rural versus urban environments.

DEDICATION

Starting from grassroots, my parents have come a long way to establish themselves as individuals to stand upright in society with honor and dignity. They have given their everything to build a family from a household and do good deeds to people they come across in life. They have always cherished their children's individualities with encouragement and helped us become who we are today. Hence, I dedicate this thesis to my parents, who have always stood by my side with love and affection, and without whom none of my achievements would have been possible.

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to my committee chair, Prof. Dominique Lord, and my committee members, Prof. Yunlong Zhang, and Prof. Jeffrey D. Hart, for their guidance and support throughout the course of this research. I heartily thank Dr. Xiubin Wang, Assoc. Prof. from Zachry Department of Civil Engineering to kindly agree to substitute for Professor Yunlong Zhang during the final examination.

I would like to thankfully mention Mr. Robert Wunderlich, Dr. Srinivas Geedipally, and Dr. Lingtao Wu from Texas A&M Transportation Institute (TTI) for their valuable ideas and inputs, which made this research undertaking a successful one. Thanks to Dr. Hadiuzzaman from Bangladesh University of Engineering and Technology and Dr. Subasish Das from TTI for giving me the opportunity to work in collaborative efforts and enriching my research endowments.

Thanks to my parents for their encouragement, love, and support. I would like to take the opportunity to especially mention my dear sister, who never stops believing in me. Thanks to my brother-in-law for his constant support and encouragement.

I also want to thank all my friends, classmates, and everyone from the Fulbright Student Association and Bangladesh Student Association for always extending their love and support. I am very grateful to have such amazing people in my life, who inspire me to achieve greatness.

Finally, thanks go to the department faculty and staff for their cooperation and making my time at Texas A&M University a great experience.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a thesis committee consisting of Professor Dominique Lord and Professor Yunlong Zhang of the Department of Civil Engineering and Professor Jeffrey D. Hart of the Department of Statistics of Texas A&M University. Dr. Xiubin Wang of the Department of Civil Engineering substituted for Professor Yunlong Zhang during the final examination.

Data were partially provided by Dr. Srinivas Geedipally and Dr. Lingtao Wu of Texas A&M Transportation Institute. The statistical coding used in the analysis was originally written by Dr. Srinivas Geedipally under the Project NCHRP 17-67 by National Cooperative Highway Research Program (waiting to be published as an NCHRP research report when this thesis was submitted) and was modified later. All other work conducted for the thesis was completed by the student independently.

Funding Sources

Graduate study at Texas A&M University was fully supported by a grant under Fulbright Foreign Student Program, sponsored by the U.S. Department of State, Bureau of Educational and Cultural Affairs, and two fellowships from the University, namely the Troy Marceleno ’60 Fellowship (2017-18) and the Civil Engineering General Fellowship (2018-19). This work was also made possible in part by the Texas A&M Transportation Institute and the University of Michigan under the Project NCHRP 17-67. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the funding agency, the NCHRP.

NOMENCLATURE

AEDS	Alcohol Epidemiologic Data System
AIC	Akaike Information Criterion
ASES	Annual Social and Economic Supplements
ASIRT	Association for Safe International Road Travel
BAC	Blood Alcohol Content
BEA	U.S. Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
BTU	British Thermal Unit
CPI	Consumer Price Index
CPS	Current Population Survey
CURE	Cumulative Residual
DUI	Driving Under Influence
ESC	Electronic Stability Control
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standards
GDP	Gross Domestic Product
GES	General Estimate System
HLDI	Highway Loss Data Institute
HSS	Highway Statistics Series

HSIP	Highway Safety Improvement Program
IIHS	Insurance Institute for Highway Safety
ITF	International Transportation Forum
ITRD	International Transport Research Documentation
MAD	Mean Absolute Deviation
MAP-21	Moving Ahead for Progress in the 21st Century Act
MCS	Model Considering States
MCSAP	Motor Carrier Safety Assistance Program
MF-205	State Motor-Fuel Tax Rates [Source: Highway Statistics]
MNCS	Model Not Considering States
MSPE	Mean Squared Prediction Error
NABCA	National Alcohol Beverage Control Association
NASS	National Automotive Sampling System
NCAP	New Car Assessment Program
NBER	National Bureau of Economic Research
NCHRP	National Cooperative Highway Research Program
NCSA	National Center for Statistics and Analysis
NHTS	National Household Travel Survey
NHTSA	National Highway Traffic Safety Administration
NIAAA	National Institute on Alcohol Abuse and Alcoholism
NIH	National Institute of Health
NOPUS	National Occupant Protection Use Surveys

OECD	Organization for Economic Co-operation and Development
SAFETEA_LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users
SAIPE	Small Area Income and Poverty Estimates
SEDS	State Energy Data System
SHSP	Strategic Highway Safety Plan
SF-2	Summary File for State Disbursements for Highways
TTI	Texas A&M Transportation Institute
TxDOT	Texas Department of Transportation
U.S.	United States
VMT	Vehicle Miles Traveled

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CHAPTER 1

INTRODUCTION

The traffic fatality is 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 of 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., traffic designers, safety engineers and analysts are always concerned about fatal crashes because of the unquantifiable distress these impose on human lives. Aside from having a moderate downward trend, when 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 factors to cause this dramatic 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 fatal crashes during that period (NHTSA, 2016). Although from 2005 to 2007 showed some substantial decline, a historically marked 21 percent decrease in traffic fatalities occurred between 2007 and 2011, reaching the lowest count of the last 50 years in 2011. Data from the subsequent years show a gradual increase in traffic fatalities. Figure 1.1 presents a graphical depiction of the yearly change in fatalities from 2001 to 2016 in the U.S.

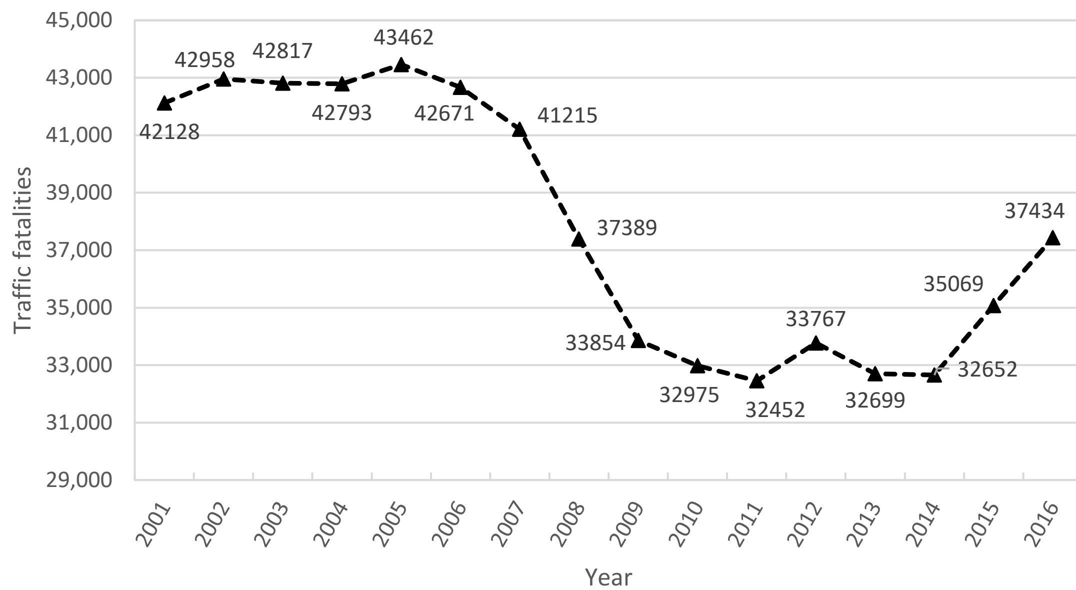


Figure 1.1 Traffic fatalities, 2001-2016.

1.1 Road Safety and Economy

An important notion in traffic safety states that traffic crashes are closely related to the amount of risk and exposure to which the travelers are subjected. If within a population roadway exposure in terms of vehicle miles traveled increases, the associated risk goes up, which in turn results in more crashes and fatalities or injuries (Hauer, 1995). During an economic crisis, it is thus reasonable to assume that the total vehicle miles traveled (VMT) reduce due to the relative consequences of increased unemployment, lower growth of gross domestic product (GDP), lesser recreational travels, and so forth. According to the above hypothesis, this means exposure to risk also reduces ultimately resulting in an improved and safer roadway condition in terms of decreased fatality rates (Antoniou et al., 2015). This improvement in safety condition due to an economic downturn is inferred to take place even if there is no countermeasure or enforcement adopted. This plausible association of traffic safety with the economy has been analyzed over and again, whenever within a country or a population a reduction in fatalities and injuries is observed in the aftermath of a recession.

While the rapid yearly decline of fatal crashes was being observed in the U.S. over the periods of 2005 to 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, called the "Great Recession" was observed in all U.S. states from 2007 to 2009 because of the considerable contraction of 5.1% in GDP growth. NBER (2010) defines a recession as "…a significant decline in economic activity spreading across the economy that can last from a few months to more than a year." 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).

1.2 Problem Statement

As design and adaptation of safety countermeasures and law enforcement depend on statistical analysis of crash data, this dramatic decline in traffic fatalities created setbacks for the policymakers and safety engineers to estimate overall road safety performance using the existing models. For example, the Strategic Highway Safety Planning (SHSP), which requires crash predictions 5 years in the future by each state to determine a course of actions to improve safety condition, was challenged (Flannagan et al., 2018). Also, researchers were curious to find out the effects which resulted in a fast-rated road safety improvement during the recession period in order to incorporate the information for implementing countermeasures. With these motivations, much research efforts were employed in the investigation of a causal relationship among the processes causing this decline in fatality counts.

Apart from identifying the complex relationship among mechanisms involved with the reduction of fatalities during a period of recession using statistical techniques, some studies have investigated the robustness of the association of economic factors with traffic safety (Elvik, 2015). As identified in multiple articles reviewed by Wijnen and Rietveld (2015), during the time of recession, the vehicle miles traveled (VMT) is reduced or shows a slower growth compared to a typical rate, which ultimately reduces the number of fatalities directly, as traffic volume is the most influencing parameter in the event of fatal crashes and the associated crash risk (Hauer, 1995). Other than the processes discussed by Wijnen and Rietveld (2015) in detail, additional significant factors have been identified in the literature (see Table 1.1).

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 causes that might have played a role in declining traffic fatalities during that period.

Table 1.1 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

The findings of the studies focusing on all 50 states are not consistent with each other and provide no definite direction towards an appropriate modeling approach to incorporate economic downturn in fatality prediction (Table 1.1). A research effort by the National Cooperation of Highway Research Program (NHCRP) under the Project 17-67 recently found that the drastic decline in fatalities is mainly caused by a change in characteristics of traffic fleet with fewer high-risk drivers (aged from 16 to 24) on the road (Blower et al., 2019). However, the models developed by the researchers were not validated using any dataset from the aftermath of the recession to examine if those models can 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. Another research gap identified based on the literature review is that although these models do separate urban from rural highways in terms of VMT, the crash risk is expected to be very different based on the type of land use and rural and urban fatalities should be analyzed separately. Therefore, a detailed investigation of rural versus urban VMT is essential to see the inconsistency in results.

1.3 Research Objectives

This study seeks to serve as an extension of the Project 17-67 by the National Cooperative Highway Research Program (NCHRP 17-67) to provide a thorough investigation of the factors influencing fatalities using an updated dataset. The objectives of this research are twofold and are stated as follows:

- The primary objectives are to run the existing models developed under the scope of the Project NCHRP 17-67 with a state-based dataset from 2001-2012 and recalibrate it with a new dataset updated to 2016 to determine if the models are adequate to predict the number of fatalities after the recession or if any additional variable is required to be considered.
- The study further seeks to investigate the inconsistent effect of the recession on fatalities in terms of land use type by separating the dataset for the rural and urban environment and developing separate prediction models.

The goal of this research is to provide a better understanding of the economic variables on fatalities for all U.S. states, alongside focus on rarely addressed issues, such as the variable effect on rural versus urban environment. The outline of this paper will follow this subsequent order:

- Chapter 2 summarizes some of the early review studies and a literature survey with the most recent articles investigating economic changes with fatalities
- Chapter 3 discusses the sources of data
- Chapter 4 describes the results and interpretations of the exploratory data analysis
- Chapter 5 explains the methodology of modeling
- Chapter 6 contains a detailed discussion on results, and finally
- Chapter 7 concludes with the limitations of the study and future directions of research.

The next chapter presents a literature review of studies that have associated traffic fatalities with economic changes.

CHAPTER 2

LITERATURE REVIEW

Numerous studies have documented the association of traffic safety with economic activities starting from the early 1970s. One of the first literature evinces the relationship between fuel crisis and the reduced speed limit on the decreased number of crashes and fatalities in the U.S. during the 1970 recession (Tihansky, 1974). This chapter describes the findings of the literature review investigating the association of economic and other factors with fatalities. The chapter is divided into four sections. Section 2.1 covers early literature that did not include the recession of 2008, Section 2.2 covers recent studies that examined the 2008 recession, Section 2.3 presents the details of the Project NCHRP 17-67, and finally, Section 2.4 ends the chapter with a summary.

2.1 Early Literature

During the period of the Great Recession of 2008, the countries with higher per capita income and higher GDP growth also experienced a dramatic short-term decline in traffic fatalities alongside the U.S. (ITF/ITRD, 2015). In a report by the International Transportation Forum (ITF), six different research studies were included, where the researchers investigated the relationship between economic activities and traffic fatalities during the 2008 recession in various member countries of the Organization for Economic Cooperation and Development (OECD). While two of these studies were, in fact, literature reviews of the previous studies that examined the association between economy and traffic safety over the years (Wijnen and Rietveld, 2015; Elvik, 2015), other studies have focused on analyzing this relationship based on data from the business cycle and crash reports (Antoniou et al., 2015; Bergel-Hayat et al., 2015; Forsman et al., 2015; Noble et al., 2015). Two separate studies by Wegman et al. (2017) and Allsop (2015) extensively reviewed the ITF report to assess the robustness of the relationship between economic downturn and road safety improvements and proposed causal mechanisms that can explain the decline in the number of fatalities during recessions.

This section presents a review of the studies by Wijnen and Rietveld (2015) and Elvik (2015), addressing the articles attempting to investigate the association of economic development with road safety from 1975 to 2011 and 1984 to 2011, respectively. Conceptual discussions and appraisals on these reviews will be included from Allsop (2015) and Wegman et al. (2017), where the author deems fit.

2.1.1 Wijnen and Rietveld (2015)

Wijnen and Rietveld (2015) included a total of 41 studies dated between 1975 and 2011 with a view to understanding the economic mechanisms involved in declining the number of fatalities and injuries. The study was based upon three previous literature reviews by Hakim et al. (1991), Scuffham (1998), and Wiklund et al. (2011). Wijnen and Rietveld (2015) argued that their work provides a more long-term analysis of studies dating from 1975 to 2011. Also, this review provides 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.

Table 2.1 summarizes the studies included in the review of Wijnen and Rietveld (2015). While most of the studies (63%) were from the U.S., a few studies from Europe, Australia, Canada, New Zealand, and China were also reviewed. Although there were 41 individual studies, some provided multiple estimates based on different analysis approaches making the total number of estimates of fatality counts to be 49 (Wegman et al., 2017).

2.1.1.1 Economic factors with fatalities vs. crash risk

To summarize the robustness of the relationship between economic development with traffic safety, Wijnen and Rietveld (2015) investigated the statistical significance of this hypothesis based on the findings of the studies listed in Table 2.1. The authors found that among 49 estimates, 34 estimates showed a statistically significant positive relationship between economy and the number of fatalities, 10 estimates provided evidence of statistically significant negative relationship and the rest 5 estimates were derived to be statistically insignificant in support of the above hypothesis. Here, a statistically significant positive relationship means that economic growth in terms of growth in GDP and employment rate is expected to be followed by an increased number of fatalities and vice versa.

Table 2.1 Studies reviewed by Wijnen and Rietveld, 2015

<table>
<tr><th colspan="3">National studies</th></tr>
<tr><th colspan="2">Country of study</th><th>Previous research studies</th></tr>
<tr><td colspan="2">United States</td><td>Peltzman (1975), Eshler (1977), Hoxie et al. (1984), Joksch (1984), Partyka (1984), Zlatoper (1984), Hoxie and Skinner (1985), Evans and Graham* (1988), Saffer and Chaloupka (1989), Wagenaar and Streff (1989), Wagenaar et al. (1990), Zlatoper (1991), Reinfurt et al.* (1991), Partyka* (1991), Keeler (1994), Ruhm (1995), Ruhm (1996), Robertson (1996), Farmer* (1997), Ruhm* (2000)</td></tr>
<tr><td colspan="2">Sweden</td><td>Johansson (1996), Wiklund et al.* (2011)</td></tr>
<tr><td colspan="2">Switzerland</td><td>Wilde and Simonet* (1996)</td></tr>
<tr><td colspan="2">Norway</td><td>Fridstrøm* (1999)</td></tr>
<tr><td colspan="2">New Zealand</td><td>Scuffham* (2003)</td></tr>
<tr><td colspan="2">Germany</td><td>Neumayer* (2004)</td></tr>
<tr><td colspan="2">Belgium</td><td>Van den Bossche et al.* (2005) Hermans et al.* (2006)</td></tr>
<tr><td colspan="2">Spain</td><td>Garcia-Ferrer et al.* (2007)</td></tr>
<tr><td colspan="2">China</td><td>Hu et al. (2008)</td></tr>
<tr><th colspan="3">Regional studies</th></tr>
<tr><th colspan="2">Region of study</th><th>Previous research studies</th></tr>
<tr><td rowspan="5">U.S.</td><td>Michigan</td><td>Wagenaar* (1984)</td></tr>
<tr><td>California</td><td>McCarthy and Ziliak (1990) McCarthy (1994)</td></tr>
<tr><td>District of Columbia</td><td>Leigh and Waldon* (1991)</td></tr>
<tr><td>Indiana Counties</td><td>McCarthy (1993)</td></tr>
<tr><td>Texas</td><td>Loeb (1995)</td></tr>
<tr><td>Canada</td><td>British Columbia</td><td>Mercer* (1987)</td></tr>
<tr><td>Australia</td><td>Victoria</td><td>Pettitt et al. (1992), Haque* (1993), Newstead et al.* (1998), Tay* (2003)</td></tr>
</table>

* Studies also reviewed in Elvik (2015)

Among the 49 estimates, the authors found 19 estimates, where the effect of the recession on the change in the rate of crashes (average number of crashes over total traveled distances) was examined. Here, changing how traffic safety improvement was measured changed the interpretation of the findings in these studies. Among the 19 estimates, eleven estimates found a statistically significant positive relationship (58%), seven estimates have shown significant negative association (37%), and only one study (6%) was inconclusive in providing a clear relationship between economic variables with the rate of crashes. Figure 2.1 demonstrates these statistics, where traffic safety improvement in terms of reduced fatality counts and reduced crash risk is associated with economic variables, such as an increase in the rate of unemployment and a contraction in the GDP.

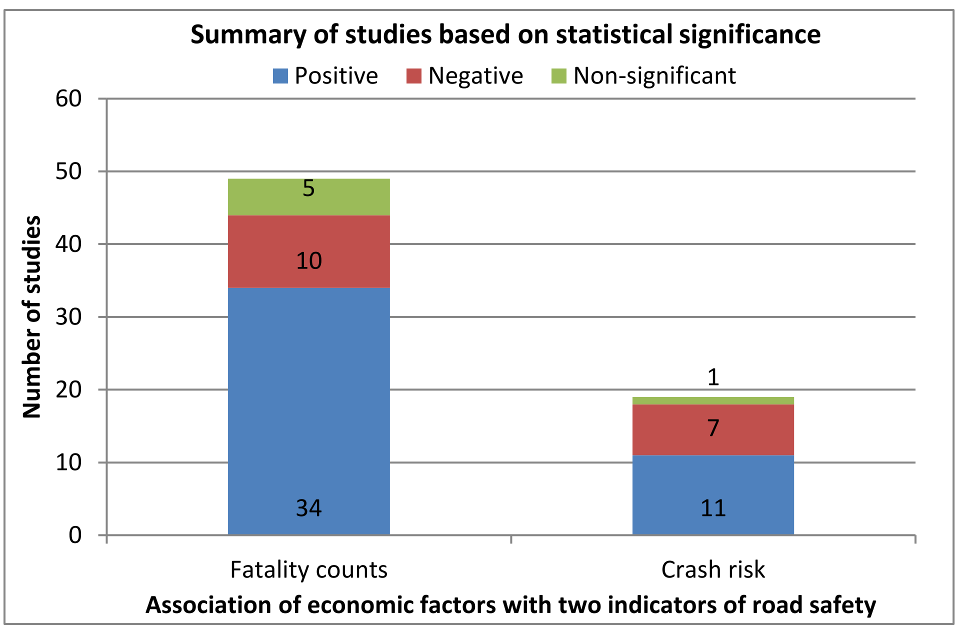


Figure 2.1 Summary of studies that found a statistically significant/insignificant relationship between economic factors and road safety.

2.1.1.2 Fatalities with unemployment versus GDP

Similar to comparing studies between two measures of traffic safety, a reduction in the number of fatalities and crash risk, the authors also listed studies that examined the effects of two different economic variables on fatalities, such as i) the rate of unemployment and ii) GDP growth. According to the definition by OECD commission, a recession is recorded when a significant increase of unemployment is observed in an economy, or when there is no growth of GDP per capita recorded between two consecutive quarters of time-period (Wegman et al., 2017).

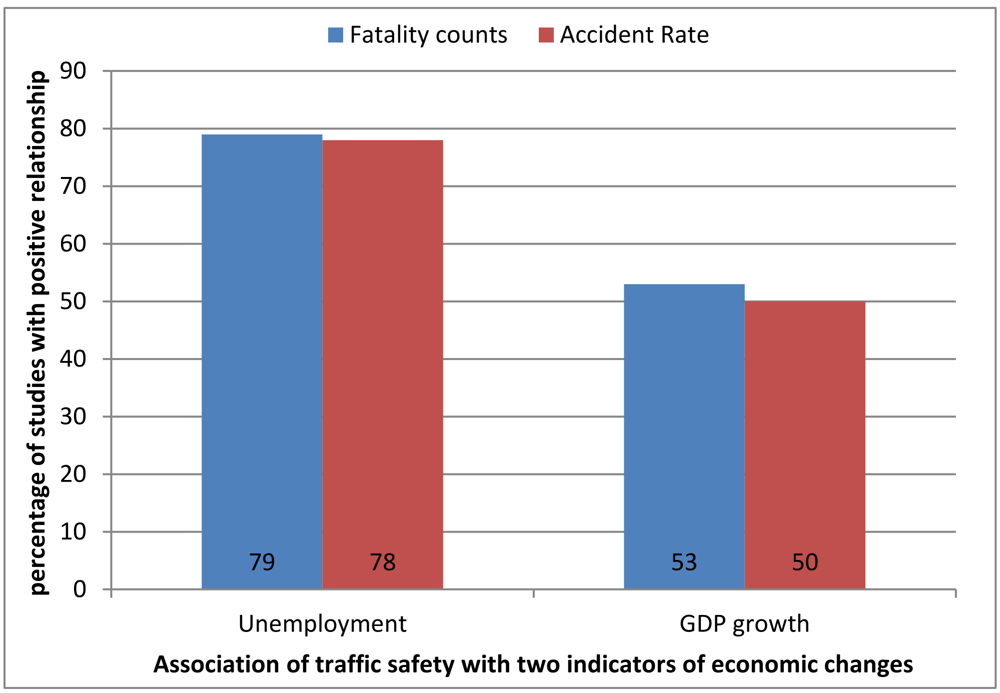


Figure 2.2 Percentage summary of studies correlating two different economic factors with roadway safety indicators.

Figure 2.2 illustrates the percentage distribution of the studies reviewed by Wijnen and Rietveld (2015) in which they found a statistical positive association of fatalities or crash rates with unemployment or GDP per capita measures. Between these two frequently used economic parameters of recession, the rate of unemployment seemed to express a more profound relationship with traffic safety in terms of reduced fatality counts and crash rates, whereas the relationship between GDP growth and the number of fatalities and crash rates showed inconclusive results. Thus, the unemployment rate is a more reliable predictor of improvement in traffic safety, and an increase in unemployment rate within an economy will likely be followed by a decline in traffic fatalities in most cases (Wijnen and Rietveld, 2015).

2.1.1.3 Other factors influencing the number of traffic fatalities during a recession

During the time of an economic downturn within a business cycle, the most commonly observed phenomena include a decrease in the 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 literature were outlined in detail by Wijnen and Rietveld (2015). These mechanisms can be grouped in the following subheadings:

Volume of traffic

The vehicle miles traveled (VMT) is reduced or shows a slower growth during recessions compared to a typical rate. This reduction in exposure reduces the number of fatalities, as traffic volume is an influencing parameter in fatal crashes (Hauer, 1995).

Modified driver class

Recession periods are commonly followed by an increased rate of unemployment. Looking into the historical evidence, it has been shown that employment-cutback in the aftermath of a recession affects the young age population more than others. Again, as listed in the literature, crash risk or crash rate among young drivers (aged between 16 and 24 years) is higher under all circumstances because of their inexperienced driving skill and error in judgments. Thus, when the proportion of young age drivers in traffic mix goes down, a consecutive improvement of traffic safety in terms of reduced crash rate is observed in most of the cases as stated by several studies (Wijnen and Rietveld 2015, Maheshri and Winston 2016, Noble et al. 2016).

Behavioral changes among users

The behavior of road users also changes due to financial constraints in terms of lower per capita household income. Different researchers, as cited in Wijnen and Rietveld (2015), have discussed this phenomenon by stating that during a recession, people may reduce alcohol consumption due to limited affordability. This may reduce the number of crashes caused by drunk-driving, ultimately reducing fatality counts. Another behavioral process associated with economic changes that might influence crash rate is the increased cautiousness among drivers. During a bad economy, people may tend to drive carefully to avoid added expenses of vehicle repairing, additional maintenance charges, and increased premiums by insurance companies.

Investments in safety countermeasures

Safety investments may be reduced due to lack of funding during a recession, which may influence the crash rate and the number of fatalities. Again, the sale of new cars may drop, and with the increased number of old cars on roads, the crash rate may increase, which is a reasonable assumption reported in previous studies (Wijnen and

Rietveld 2015, Noble et al. 2016). Overall, less public investments to install new or improved safety features in vehicles may increase the number of fatalities.

These causal mechanisms, as identified by Wijnen and Rietveld (2015), make the clear distinctions between the probable causes influencing the number of fatalities and crash rates by means of two counteractive processes. While fewer vehicle miles traveled (VMT), lower volume of traffic, decreased proportion of high-risk drivers, and safe driving practices positively influence traffic safety condition, other mechanisms induced by a bad economic condition, such as lack of public and private investments may negatively affect crash rates, ultimately resulting in fewer number of fatalities (Allsop, 2015).

Figure 2.3 illustrates these processes in association with economic and road safety parameters as identified by Wijnen and Rietveld (2015). This conceptual framework proposed by the authors surely provides a comprehensive understanding of the underlying causes of safety improvements during an economic downturn. However, assuming such a simplified interaction between these variables as shown in Figure 2.3 can underestimate the influence of other potentially influencing parameters (Wegman et al., 2017).

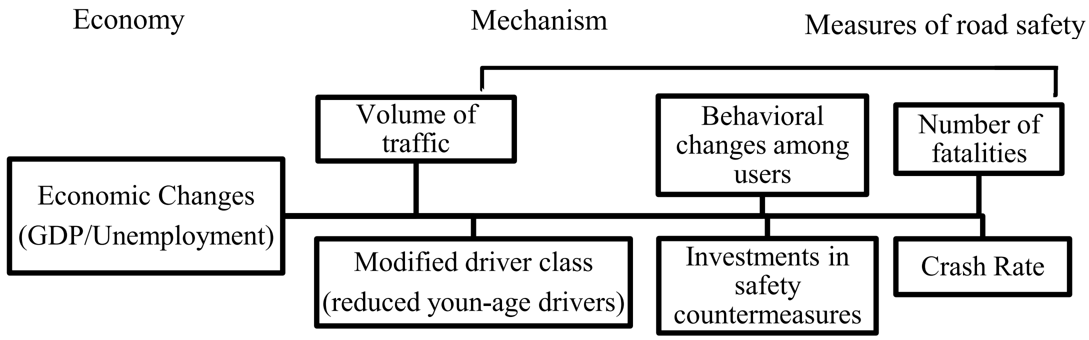


Figure 2.3 Association of road safety with economic changes through relative processes (Wijnen and Rietveld, 2015)

2.1.2 Elvik (2015)

Elvik (2015) reviewed a total of twenty-two studies between 1984 and 2011, most of which (86%) are also reviewed and discussed in Wijnen and Rietveld (2015). The remaining three studies are by Scuffham and Langley (2002), Kweon (2011) and Yannis et al. (2014). Apart from discussing the mechanisms involved with traffic safety improvements during an economic downturn, which is similar to the discussion made by Wijnen and Rietveld (2015), Elvik (2015) investigated the effects of the coefficients associated with predictors from all classes influencing the number of fatalities. A total of 127 coefficients from twenty-two studies were examined to sort information about the robustness of the association of traffic safety with the economy. Figure 2.4 illustrates the percentage of coefficients that provided either a statistically significant relationship (at 5% level) or a non-significant relationship between economic changes and safety conditions as discussed below.

According to the notations made by the author, a negative coefficient means that the parameters will contribute to improving road safety by declining the number of traffic fatalities with a consecutive decline in economic condition. From the review, the author found that among 127 coefficients, 82 (65%) coefficients had statistically significant negative effects, and 8 coefficients showed statistically significant positive effects. On the other hand, 31 coefficients had statistically non-significant negative effects and 6 coefficients showed a non-significant positive association between the predictor and the outcome (Elvik, 2015). Here, as most coefficients (65%) indicated a negative relationship between traffic safety with the prevailing condition of the economy, the assumption that an increase in the rate of unemployment is followed by a decrease in the number of fatalities is valid.

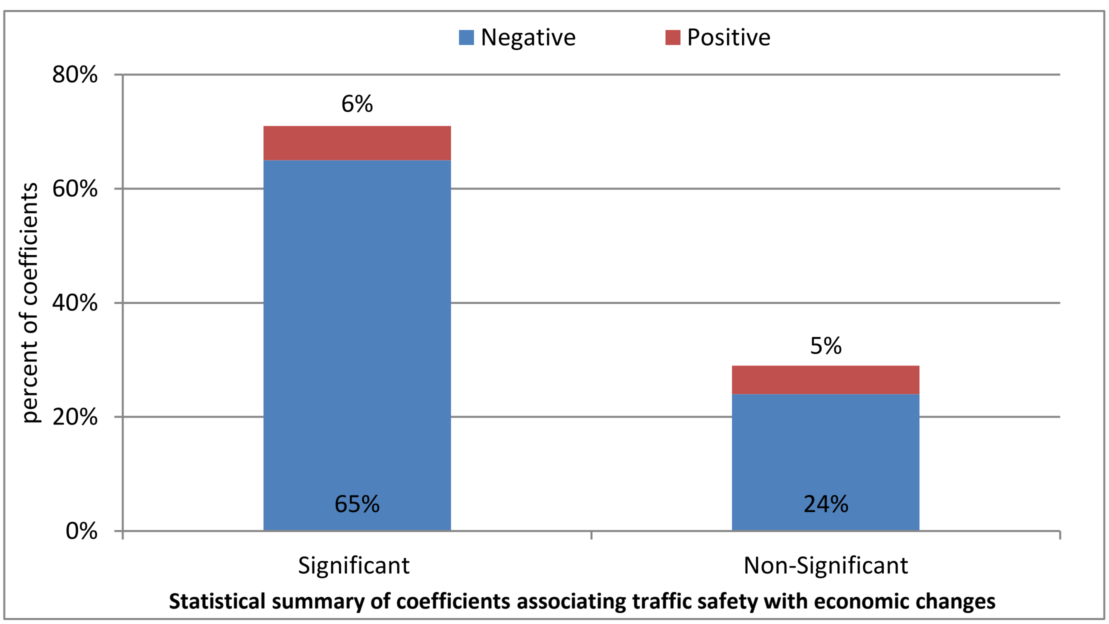


Figure 2.4 Statistical significance of variables considered in all reviewed studies.

To generate a profound interpretation from these coefficients, Elvik (2015) conducted a meta-analysis, where the elasticity of the coefficients was analyzed to investigate the association of traffic safety with a one percent increase in the unemployment rate. The weighted mean estimates from different analysis approach extracted from the meta-analysis were negative (-0.024 to -0.060) and statistically significant ($P_r < 0.001$), which gives evidence in favor of the hypothesis associating fatality counts with an economic downturn.

2.2 Recent Studies

As stated in Chapter 1, historical-statistical evidence proves that a fast improvement in road safety condition in terms of reduced fatalities is generally observed after a period of recession in countries with a moderate number of fatalities (Wijnen and Rietveld, 2015). Numerous research studies discussed in the previous sections have also investigated the robustness of this hypothesis and found a significant relationship between indicators of road safety and economic development by means of various statistical techniques. However, these previous studies investigated the hypothesis by looking into historical data before 2008 not incorporating the effect of the most current recession and focused only on finding a long-term trend of fatality estimates.

When the Great Recession occurred at the end of 2007, a majority of the developed countries that otherwise retain a stable economy have encountered a drop in the GDP growth accompanied by a sudden rise in unemployment rate, which is more profound than a long-term moderate rate. A marked decline in the number of fatalities was also observed in those countries. This similar phenomenon of a decline in fatalities, followed by an economic downturn, was historically recorded during the 1970s, 1980s and 1990-91s recessions. However, while the Great Recession was being observed in the U.S., safety policies and other relevant factors, potentially influencing the number of fatalities, have also evolved compared to the previous recession periods (Allsop, 2015). Better cars with advanced safety features were introduced, and seat-belt and helmet use, and DUI laws are made stricter. Therefore, a more extensive and careful analysis of the dramatic fatality decline taking place during the 2008 recession is warranted that can differentiate between the influence of the economy on road safety and the effect of the countermeasures. In this effort, innovative statistical techniques have been proposed in recent times, which are summarized in this section.

2.2.1 Antoniou et al. (2015)

Antoniou et al. (2015) analyzed datasets from a total of thirty European countries from 1975 to 2011 to find an association between changes in fatalities and changes in GDP per capita. Macro-panel regression was considered for the statistical analysis, where the model parameters were estimated by taking logarithms of each of the economic and road safety indicators (GDP per capita and the number of fatalities). According to the study, the relationships between per capita GDP and fatalities in terms of short-term annual fluctuations and long-term trends can be expressed in the following functional forms:

$$\log(Fat_{it}) - \log(Fat_{i(t-1)}) = \alpha_i + \beta_{oi}[\log(GDP_{it}) - \log((GDP_{i(t-1)})] + v_{it} \tag{1}$$

$$\log(Fat_{it}) = \alpha_i + \beta_{oi}\log(GDP_{it}) + v_{it} \tag{2}$$

Here, the constant term v_{it} corresponds to a fixed decline in fatalities that is observed in all countries over a long-term period. The model (1) correlating short-term changes in GDP per capita with short-term changes in fatalities is known as a 'growth rate model'. On the other hand, the model (2) estimating a long-term relationship between traffic safety and economic development is called the 'static model'. Here, the two models help to understand the distinction between a short-term and a long-term trend of fatalities associated with a change in GDP per capita across different countries over multiple years of observation, called a panel dataset. According to Antoniou et al. (2015), the motivation of choosing a macro-panel regression analysis was that this technique helps to understand the relationship between the economic variables and the number of fatalities more profoundly by aggregating regression statistics for multiple countries. Another motivation for choosing macro-panel analysis was the higher level of precision offered by grouping model estimates for a number of countries or entities as compared to that of a single model for a single country.

The short-term model (1) estimated an annual decline of fatalities in the range of 0.96% to 1.75% for three groups of countries considered in the study. The elasticity analyses were conducted to investigate the relationship of 1% increase in GDP per capita with that of an increase in fatalities and 1% decrease in GDP per capita with that of a decrease in fatalities. The results fall under the ranges of 0.42% to 0.66% and 0.15% to 0.75% respectively, where the averages of the elasticity values are statistically significantly different from 0 with opposite signs. The long-term model (2) estimated a positive mean with 0.63% elasticity of fatalities to GDP per capita. After adding more variables to the model accounting for road safety countermeasures, the results of the elasticity changed to a negative value. The authors interpreted this finding by stating that the dramatic changes in fatalities might have been the result of implementing effective countermeasures to some extent, which contradicts with the modeling assumption of expressing fatalities as a function of GDP only, and the association, in turn, yielding a negative trend. Both the models generated an estimate of the constant annual declining trend of 2.3% for a short period and 4.8% for a long period for most of the countries considered in the study.

Yannis et al. (2014) previously provided a similar short-term panel-regression model as shown below:

$$\ln(Fat_{it}) - \ln(Fat_{i(t-1)}) = \alpha + \beta_1[\ln(GDP_{it}) - \ln((GDP_{i(t-1)})] + \beta_2 CountryGroup_{it} + \varepsilon_{it} \quad (3)$$

According to the model (3), the estimates were obtained based on changes in the number of fatalities for different groups of countries. Here, the coefficients were considered to be constant values estimated for either increase or decrease in GDP for each country group assuming a linear relationship between the changes in fatalities and the changes in GDP.

2.2.2 Elvik et al. (2015)

Elvik et al. (2015) analyzed datasets from 14 OECD countries from 1970 to 2010 in order to investigate the relationship between roadway safety and economy. The authors employed one additional dataset that contained age of the driver population from 1995 to 2010, which allowed them to analyze if young age drivers were particularly affected by the recession leading to a reduced number of fatalities. In addition to GDP per capita, they incorporated the rate of unemployment as an indicator of economic activities in the model. Three types of models were considered for the analysis as shown below:

$$Fatalities = e^{\alpha+\beta_1(Year)+\beta_2\ln(GDPpercapita)+\beta_3 ln(UnemploymentRate)} \tag{4}$$

$$\Delta Fatalities = \alpha + \beta_1(Year) + \beta_2(\Delta GDPpercapita) + \beta_3(\Delta UnemploymentRate) \tag{5}$$

$$\begin{gathered} \ln(Fat_{t+1}) - \ln(Fat_t) = \alpha + \beta_1(Year) + \beta_2[\ln(GDP_{t+1}) - \ln((GDP_t)] + \\ \beta_3[\ln(Unemployment_{t+1}) - \ln((Unemployment_t)] \end{gathered} \tag{6}$$

The first model (4) was based on a negative-binomial regression, which estimates the number of fatalities with the basic assumption of a crash prediction model that the distributions of the number of fatalities from year to year for each nation follow a Poisson process whereas, the mean fatalities over all nations observed each year are gamma distributed. This model contains a major issue in fitting any dataset because of the correlation of GDP with a common time-trend (years), both of which are considered as independent variables in the model (Wegman et al., 2017). In order to address this issue model (5) was proposed as a ‘change model’, where annual changes were considered for each variable influenced by a time-trend rather than using raw counts. The model (6) was formulated based on the change model proposed by Antoniou et al. (2015) incorporating natural logarithmic difference of rate of unemployment as an independent variable for predicting the annual changes in fatalities. The authors made a comparative assessment of the models based on five criteria: i) goodness of fit, ii) prediction bias, iii) distribution of the standard error of estimates or residuals, iv) homogeneous short-term elasticity, v) autocorrelation. According to the test, none of the models seemed perfect, however, the model (6) provided the best estimates compared to the other two models (Wegman et al., 2017).

2.2.3 Bergel-Hayat et al. (2015)

Two separate models were proposed by Bergel-Hayat et al. (2015) to examine the association of economic variables with road safety parameters. The functional forms of the models are presented below:

$$Fat_t = a(GPD/h)^2 + b(GDP/h) + c + \varepsilon_t \tag{7}$$

$$\begin{aligned}
\log(Fat_t) &= \mu_t + \gamma_t + \beta x_t + \sum_{k=1}^{K} \lambda_k w_{kt} + \varepsilon_t \\
\mu_t &= \mu_{t-1} + \sum_{l=1}^{L} \lambda_l w_{lt} + \eta_t \\
b_t &= b_{t-1} + \zeta_t \\
\gamma_t &= \sum_{j=1}^{s-1} \gamma_{t-j}
\end{aligned} \tag{8}$$

Where,

Fat_t = number of fatalities observed each month;

x_t = monthly unemployment rate;

w_{kt} and w_{lt} = variables associated with K and L countermeasures, respectively;

μ_t and b_t = representing the trend parameters (means and slopes) of the model; and,

γ_t = structured variation parameter.

The first model (7) corresponds to a quadratic relationship between the GDP per capita and the annual fatality rates in a nation. The model (7) was applied to generate estimates for five European countries based on time-series data from 1970 to 2012. As, the model (7) did not correspond to a change of GDP in the change of fatalities, detailed discussion on this model is considered out of scope for this paper.

The next model (8) is a local linear trend-model integrated with a structural model or, a state-fixed model to investigate the relationship between the monthly rate of unemployment and the number of fatalities observed each month. The model also includes variables representing the effects of safety countermeasures. The dataset contained monthly time-series data from 1983 to 2012 from three European countries: France, Spain, and Greece. The model was initially developed by Harvey and Durbin (1986) to estimate the number of fatalities in the United Kingdom (U.K.) between 1969 and 1984. According to the authors, this type of time series analysis provides better estimations of variance by considering a stochastic linear trend between the dependent and independent variables in the model. Also, by incorporating the countermeasure variables in a prior analysis, the effect of these measures can be scaled down from the model estimates. The analysis results found an elasticity of 0.3% between the number of fatalities and 0.1% change in the monthly unemployment rate, which is consistent with other studies described above.

2.2.4 Other studies

Aside from the studies discussed so far, Wegman et al. (2017) reviewed a few other studies that conducted statistical analyses on datasets from the most current recession to investigate the relationship between economic changes with traffic fatalities. Some of these studies are discussed in this subsection.

Noble et al. (2015) studied the mechanisms behind a decline in the road traffic crashes from 2007 to 2010 in Great Britain. Other than the processes discussed by Wijnen and Rietveld (2015) in detail, the authors identified factors, such as decreased VMT by heavy-good vehicles, decreased proportion of young drivers in the traffic fleet aged between 17 and 24 years, and fewer licenses issued to young drivers, which are found to be significant in reducing the number of fatalities during recession. The factors not directly influenced by the changes of economic conditions, such as reduced infant passengers aged between 0 and 5 years, increased law enforcement to control unlicensed drivers, seat belt and helmet use, drunk-driving etc. are also found to be contributing to the drastic decline of fatalities during the 2008 recession.

Forsman et al. (2015) studied the trend of fatalities before and during the period of the Great Recession in Sweden. The major findings included fewer night-time crashes, which can be interpreted as fewer non-work trips during the recession, fewer drunk-driving fatalities as compared to overall fatalities, more fatalities involving unlicensed drivers, which are interpreted as non-affordability of drivers to get a license. 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.

He (2016) analyzed datasets from all fifty states of the U.S. from 2003 to 2013 to find the relationship between reduced fatalities and the recession. For the purpose of analysis, the author equated the number of fatalities with the change in vehicle miles traveled (VMT) and recorded the changes in the predicted fatality rates. 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 some of the possible causes of sharp reduction in fatalities, which are listed as 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 fifty states of the U.S. from 1984 to 2013. The study design was similar to He (2016). However, in this research, the authors decomposed the variable VMT into rural vehicles miles traveled and total vehicles miles traveled, and the findings of the analysis made a nonpareil revelation. Here, 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 to be 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 this 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).

2.3 Project NCHRP 17-67

The primary focus of the NCHRP Project 17-67 was to "…provide a multidisciplinary analysis of the relative influence of the types of factors that contributed to the recent national decline in the number of highway fatalities and rates in the U.S. (Blower et al., 2019)." Two research papers from this project were presented in the 97th Transportation Research Board Annual Meeting in 2018, which are discussed briefly in this subsection below.

Flanngan et al. (2018) proposed two separate models, namely the 'count model' and the 'change model', to predict the state-level fatalities based on the independent variables from economic, demographic, expenditure, and intervention records from 2001 to 2012 for all U.S. states. The models primarily focused on forecasting the state-level fatalities for designing countermeasures and policy planning under the SHSP target setting. The count model (9) predicts the raw counts of the number of fatalities based on the parameters independently for each year, whereas the change model (10), which is similar to the model (6) proposed by Elvik et al. (2015) estimates the changes of fatalities from year to year. The change model has an advantage over the count model in the fact that it predicts the annual changes of fatality counts based on the changes in GDP and unemployment rates, and hence, without prior knowledge of the base level economic or demographic condition of the state, prediction can be made. The disadvantage of the model is that to obtain a fatality count from this model, the predicted change for the target year has to be added to a base count from one of the previous years, which if contains anomalies in the estimation, the prediction becomes anomalous too. The count model, on the other hand, provides direct predictions of fatality counts for the target year, hence retains no issue of 'anomalous base year' effect. However, the state-specific parameter γ_s can be estimated only once from the base model and thus, requires reevaluation so that it does not get biased over time. Later in the analysis, two models were employed to predict state-level fatalities for Michigan and Texas from 2013 to 2016, where both the predictions were reasonable and could capture the trend of changes in fatalities with that of the expected changes in VMT for that state. The functional forms of the models are presented below:

Count model:
$$\mu = VMT \times e^{[(\beta_0+\gamma_s)+\sum_i(\beta_i x_i)]} \tag{9}$$

Change model:
$$\ln(Fat_t) - \ln(Fat_{t-1}) = \beta_0 + \sum_{j=1}^{k}\beta_j z_t = \beta_0 + \sum_{j=1}^{k}\beta_j(\ln(x_t) - \ln(x_{t-1}))$$
$$z_t = \frac{x_t}{x_{t-1}} \tag{10}$$

Here, x 's and z_t 's correspond to independent variables considered in the study and their transformed change variables from one year to the following year, respectively, γ_s 's are the state-specific parameters, and β 's are the parameter coefficients.

Geedipally et al. (2018) investigated the probable mechanisms that led to the sharp decline in fatalities during the Great Recession in the U.S. The study employed similar two models as per Flannagan et al. (2018), where the count model was used to estimate fatality counts based on the parameters relative to each contributing mechanism. The change model was employed to validate the results of the count model to check if the changes in fatalities could be captured by the model, and what factors were significant in the prediction. The findings of the study revealed that the increased rate of unemployment among young age population (aged between 16 and 24 years), less alcohol consumption, and a reduction in the GDP per capita were the most significant factors in explaining the dramatic drop in fatalities during the period of recession. Other significant factors in the model were the implementation of strict DUI laws, reduced rural VMTs, and an increased number of safer cars in the traffic fleet.

However, the research undertaking by NCHRP 17-67 only included data from 2001 to 2012, although the research results were finally ready to be published in 2018. As the researchers could only include data from the recession period, they were unable to affirm the causes of the substantial increase in fatalities the next couple of years after the recession. Another shortcoming in their research findings was that the researchers primarily focused on finding one combined model for all fatalities, although the crash risks on rural and urban roads are very different from each other and need to have separate prediction models. Therefore, a detailed investigation of rural versus urban fatalities needs to be conducted to see the differences in findings.

2.4 Chapter Summary

Before initiating a scientific investigation, it is customary to review the existing literature to find the research gap and a direction to the future research scope. This chapter summarizes the research studies that statistically analyzed the association of traffic fatalities with the condition of the business cycle on a national scale. The detailed review of the existing literature on road safety associating with economic changes has unfolded the following key points:

- The studies mostly considered a linear or log-linear relationship to represent a longitudinal association of road safety improvement with economic downturn for a nation, or a transverse relationship across multiple nations, over a single year or a period of multiple years (Allsop, 2015).
- Numerous studies employed their research efforts in statistical modeling of the relationship between economic development and road safety in terms of varying indicators with differing definitions, which ultimately propagated different statistically significant or insignificant, positive or negative results.
- Most studies showed evidence of an existing relationship between the economy and road safety. Therefore, it is reasonable to believe that the number of fatalities in a nation is significantly influenced by the business cycle activities of that nation, which means if the economy improves, fatalities will rise, and vice versa.
- Various studies have identified a variety of factors associated with the decline in fatalities which can be attributed to their differing modeling assumptions, geographical considerations, and data availability. A more generalized modeling approach including data from both before and after the recession would provide a more appropriate solution to the problem in hand.

The next chapter discusses the overall data collection process listing out the vast array of data sources.

CHAPTER 3

DATA COLLECTION

Numerous studies have provided statistical evidence in favor of the hypothesis that a change in economy pertaining to a nation consequentially influences the trend in traffic fatalities. The first step to conduct a study with a generalized approach to investigate the change in fatalities in the U.S. over the last decade was to identify the processes that were involved in influencing the number of fatalities each year. This chapter presents a detailed discussion on the reasoning behind the choice of the factors, types of data collected and assembled for this study, and their relative sources. The chapter is divided into four sections. Section 3.1 lists the key processes involved in fatality fluctuations. Section 3.2 describes the factors influencing risk and exposure. Section 3.3 presents the details on the types of data collected and their respective sources. Finally, Section 2.4 provides a summary of the chapter.

3.1 Key Processes Involved with Traffic Fatalities

A standard analytical approach is presented in the NCHRP 17-67 research report that expresses fatality in terms of risk and exposure as the product of the two, where risk is simply defined by taking the rate of fatalities over a unit of exposure, i.e., vehicle miles traveled (VMT), and exposure is the overall subjectivity of the population to crashes (Blower et al., 2019). The authors argue that although the risk is expressed as a rate of exposure, these measures of safety need to be accounted for separately in order to explain the sharp decline and subsequent increase in fatalities. The plausible explanations for the change in the number of fatalities measured within a fixed population over a certain period of time can be summarized in terms of risk and exposure in the following ways:

- Change in travel pattern in terms of reduced VMT influencing overall risk
- Change in driver class in terms of fewer high-risk drivers on the road
- Change in the effectiveness of safety countermeasures in terms of laws, infrastructures, investments, and technologies
- Change in the behavior of the drivers in terms of more cautious driving, and strict licensing, and
- Change in the distribution of exposure from high to low crash-prone roads.

These complex processes involved in changing the number of fatalities from year to year can be distinguished as short-term and long-term factors considering the period of influence. The factors having a long-term or fixed effect on influencing traffic fatalities can be categorized as long-term factors. Some examples may include the use of safety belts or helmets, DUI laws, driver licensing, consumption of alcohol, development of the infrastructure and vehicular technology. The time series data over the past 20 years reveal that these long-term factors show a moderate trend from year to year and cannot explain the dramatic decline in fatalities that occurred during the Great Recession. In contrast, the short-term factors that are considerably affected by the changes in the prevailing economic conditions seem to have substantial effects on changing the number of fatalities during the recession. Some examples of short-term factors include vehicle miles traveled, unemployment rate, GDP per capita, median income per household, the price of gasoline, government spending on safety countermeasures, etc. The next section describes a process of structurally distinguishing these factors related to the changes in fatalities over the period from 2001 to 2016 using the Haddon Matrix.

3.2 Identifying Factors Influencing Risk and Exposure

The researchers of the NCHRP 17-67 (Blower et al., 2019) employed a Haddon matrix to structurally organize the factors influencing fatal crashes over the period of the Great Recession and its aftermath. A similar Haddon matrix as depicted in Table 3.1 serves as a structural framework for identifying factors related to crash risk and exposure. William Haddon, Jr., in the attempt to conceptualize and quantify the complex interactions between human, vehicle, roadway, and the surrounding environment, before, during, and after a collision, proposed the 'Haddon matrix' in 1970 (Haddon, 1970). In the event of a traffic collision or injury, different rows of the Haddon matrix categorize the timeline of the overall event under pre-crash, crash, and post-crash phases, and the columns of this matrix classify the influencing factors of different crash phases under the human or host, vehicle or agent, physical environment (such as the roadway) and socio-economic factors (such as available policies and services) (Baker and Haddon, 1974).

Table 3.1 Factors influencing crash risk and fatalities using a Haddon Matrix

Phases \ Factors	Human	Vehicle	Physical/Socio-Economic Environment
Pre-crash	Driver characteristics, such as licensing, experience, age, gender	Safety features on vehicles, such as model year, electronic stability control, antilock braking systems	Aspects of road design incorporating safety countermeasures, such as rumble strips, median barriers, retroreflective signs
Crash	Actions of drivers and occupants leading to crash or avoiding it, such as driving under influence, restraint use, maneuvering	Safety devices protecting occupants from severe outcomes, such as airbags, seat belts, crash sensors	Features of roadside design to reduce crash severity, such as guard rail, clear zones
Post-crash	Occupant characteristics determining crash severity and outcome, such as physical condition, age	Technologies increasing post-crash survivability, such as automatic collision notification, post-crash braking	Emergency medical services, fast and immediate crisis response, recovery services

3.3 Data Series and Sources

Based on a similar framework as illustrated in Table 3.1, the researchers of Project NCHRP 17-67 collected and assembled numerous data series from various sources to investigate the relative influence of the factors on the national decline of traffic fatalities in the U.S. This subsection provides a brief discussion on the types of data collected and their respective sources.

The data series were obtained from various sources as listed in Table 3.2 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 3.2:

Table 3.2 Sources of the data series*

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/
Crash data on injury severity	NHTSA's National Center for Statistics and Analysis (NCSA). Accessed from: https://cdan.nhtsa.gov/tsftables/tsfar.htm
Rural vs. Urban Crash Statistics and Comparisons	Traffic Safety Facts Sheets from NHTSA's Crash Stats database for each year, 2001-2016. Accessed from: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812181
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
Labor force, by state, month & year	Bureau of Labor Statistics, Current Population Survey
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, Regional Economic Accounts: Download
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

Table 3.2 Sources of data series* (contd.)

Data	Source
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

*Blower, D., C. Flannagan, S. Geedipally, D. Lord, and R. Wunderlich. Identification of factors contributing to the decline of traffic fatalities in the United States from 2008 to 2012. Final Report NCHRP Project 17-67. Transportation Research Board, Washington, D.C., 2019.Reprinted with permission from the National Academy of Sciences, Courtesy of the National Academies Press, Washington, D.C.

3.3.1 Crash data series

The crash data on fatalities were obtained from the National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System (FARS), which is a publicly available nationwide census, storing accident, person, and vehicle level information regarding fatal injuries in motor vehicle crashes in the U.S. The FARS database contains information on crashes that took place on highways that are open to the public use, and in which at least one person (either occupant or non-occupant) died within 30 days of the crash. FARS data are collected through the state or local analysts, who compile all fatal crash data from police reports, state vehicle registration files, driver licensing files, state highway department data, vital records department data, death certificates, medical examiner reports, and the emergency medical service reports (FARS Brochure, 2014). For analysis purposes, fatal crash data were obtained from the FARS FTP website (ftp://ftp.nhtsa.dot.gov/fars/) in a raw form from 2001 to 2016. For the trend analysis reported in Chapter 4 later in this thesis, national and state-level data tables were obtained from the FARS Encyclopedia (www-fars.nhtsa.dot.gov/Main/index.aspx).

Crash data on the non-fatal or injury crashes were obtained from the National Automotive Sampling System's (NASS) General Estimates System (GES). GES data are gathered from nationally representative police accident reports (PAR), where at least one motor vehicle was involved traveling on a public roadway, and in which the crash outcome is at least one of the following: property damage, injury, and/or death. Annually, the NHTSA publishes a summary report based on the GES data in combination with the data from the FARS database, called the 'Traffic Safety Facts', which are open to the public in the NHTSA's website as NCSA publications, and were consulted for this analysis when it was informative to use data from nonfatal crashes.

For comparing the trends based on land use (rural/urban), which are reported in Chapter 4 later in this thesis, information on the rural and urban traffic fatalities were obtained. The data series was obtained and compiled from the NHTSA's NCSA publications under the 'Traffic Safety Facts' on Rural/Urban Comparison of Traffic Fatalities from 2001 to 2016. These fact sheets are published annually for public view in the NHTSA's website containing information from the FARS database. For preparing these reports, information on rural and urban boundaries are obtained from the State highway departments approved by the FHWA, where the State highway departments gather their information on these boundaries from the U.S. Census Bureau.

3.3.2 Exposure data series

In traffic safety, exposure means any factor that directly or indirectly poses an imminent risk of danger of causing a crash (Chapman, 1973). The overall probability of an individual, a population, or a nation being subjected to crashes is determined by the amount of exposure within a certain period. The size of the population in an area and the number of vehicle miles driven by that population are the most basic measures of exposure for motor vehicle crash investigations in the area of traffic safety.

For this study, the population data were obtained from the U.S. Bureau of the Census. The U.S. Bureau conducts national surveys to gather data on population by state, age, sex, ethnicity, etc. and the reports are published every 10 years on their website for public view. It also publishes the state-based population data estimates for non-census years as the ‘Intercensal Estimates of the Resident Population’, which are also available on their website and were consulted for obtaining population data for this study for each state by gender and age. For normalizing the population data, information on the land area by state was obtained from the state area measurements provided by the U.S. Bureau of Census.

The national and state-based data series on the vehicle-miles traveled were obtained from the FHWA’s Highway Statistics and for normalizing the VMT data, information on road miles by roadway function class was obtained from the FHWA’s Highway Statistics website (Table hm10).

3.3.3 Economic data series

To analyze the effect of economic change on fatality trends, the data series on the labor force statistics by state and year were obtained from the U.S. Bureau of Labor Statistics’ Current Population Survey (CPS). The BLS defines unemployment as a jobless state of an individual, where the person is 16 years or older, is currently without a job, and has made active efforts within the past three months to find employment. The BLS publishes national and local area based (county and state) data on the existing labor force in tabulated format to provide information regarding employment and unemployment counts and rates, by age, race, ethnicity, gender, occupation, industry, and many other parameters for each month, season, and year.

Gross domestic product (GDP) is a comprehensive measure of the economy. It considers the prices of goods and services produced in each state from the breakdown of industries to provide the state-based GDP estimates. The Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce publishes annual GDP estimates for each state, which are publicly available on its website (https://www.bea.gov/data/gdp/gdp-state). To obtain yearly estimates of the GDP per capita, the estimates obtained from the BEA were divided by the overall population of the year.

The data on the median household income were gathered from the CPS of the U.S. Census Bureau recorded under two separate programs. Prior to 2005, the CPS's Annual Social and Economic Supplements (ASES) provided the national and state-based median income estimates based on a representative survey of 75,000 households. The ASES household income data were obtained from 2001 to 2004 for this research undertaking. Starting from 2005, Small Area Income and Poverty Estimates (SAIPE) program of the U.S. Census Bureau provides yearly estimates of the poverty level in the U.S., median household income for each state, county, and school districts, from which the data on median household incomes were obtained from 2005 to 2016 for the study.

The data on the state motor fuel (gasoline/gasohol/diesel) tax rates in terms of cents per gallon were obtained from the FHWA's Policy and Governmental Affairs' Office of Highway Policy Information: Table MF-205. Two separate versions of the data series were needed to assemble data for the entire focus period of analysis (2001-2016) for this study. The Table MF-205, Highway Statistics 2015 (published on August 2016) contained the state tax rates from the year 2000 to 2015 and the Table MF-205, Highway Statistics 2016 (published on June 2017) contained the tax rates from the year 2003 to 2016. The tax rates include inspection fees and environmental cleanup fees if directed towards highway fuel use. The rates also include local taxes if the rates are uniform for all counties in the state.

The data series on the costs of fuel were obtained from the U.S. Energy Information Administration's State Energy Data System (SEDS). The SEDS has been providing comprehensive state-based time-series statistics since 1970 on energy production, consumption, prices, and expenditures by state for research, analysis, and forecasting purposes. The prices of regular-grade gasoline were selected for the analysis as this is the most commonly used fuel type in the U.S. Finally, fuel prices were converted to dollars per gallon from dollars per million BTUs (British Thermal Unit) and added with fuel tax rates in terms of dollars per gallon to represent the overall expenditure or the price at the pump by state from 2001 to 2016.

In order to account for inflation from year to year, all monetary values in the economic data series discussed in this subsection were converted to constant 2013 dollars using the consumer price index (CPI) calculator available in the BLS website (https://www.bls.gov/cpi/).

3.3.4 Driver and vehicle-related data series

Data on traffic safety-related aspects regulated by state laws were obtained from the Insurance Institute for Highway Safety (IIHS), which is an independent, nonprofit organization, funded by U.S. auto insurers. The yearly data series on seat belt laws and motorcycle helmet laws by state were obtained from the IIHS's Highway Loss Data Institute (HLDI). These data were used to develop indexes on the strength of laws on wearing seat belts and motorcycle helmets for each state. The data series on the rates of seat belt use was obtained from the NHTSA's National Occupant Protection Use Surveys (NOPUS) program. The data on alcohol consumption was obtained from the National Institute of Alcohol Abuse and Alcoholism (NIAAA). The indexes on DUI laws were developed following the methodology stated in Klinich (2016).

The annual per capita consumptions of beer, wine, and other alcoholic spirits by state are available in the NIAAA's website (https://pubs.niaaa.nih.gov/). The NIAAA publishes the state alcohol consumption rates as the Surveillance Report annually. The NIAAA's data on alcohol consumption are based on the sales data collected from the states or the National Alcohol Beverage Control Association's (NABCA) Alcohol Epidemiologic Data System (AEDS) and the reports from various sources of the alcoholic beverage industry. Finally, the population data from the U.S. Census Bureau was used to obtain per capita consumptions for each state from 2001 to 2016.

The penetration data of Electronic Stability Control (ESC) were obtained from the Loss Bulletin, Vol. 31 (2014a and 2014b) from the HLDI. This data series represents the percentage of cars manufactured with either of the standard or optional ESC technology by model year. Another data series was obtained to represent the improvement and insertion of vehicular safety technology in car manufacturing, which is the penetration rate of the post-1991 model year. This data series was compiled from the NHTSA's GES data using quasi-induced exposure method (Blower et al., 2019). This data series containing penetration rates of the post-1991 model year cars into the vehicular fleet is used as a surrogate measure of the NHTSA's New Car Assessment

Program (NCAP) and the federal regulations under the Federal Motor Vehicle Safety Standards (FMVSS).

3.3.5 Highway expenditure data series

The data series on highway expenditures were compiled from the FHWA's Highway Statistics Series (HSS). The HSS provides annual reports in forms of tables and charts containing statistical information on fuel, vehicle registration, driver licensing, taxation, mileage, and highway finance. The state expenditure data on infrastructure, maintenance, administration, research, planning, law enforcement, and safety programs were obtained from the HSS's summary file for the state disbursements for highways (Table SF-2). The funding data under the Highway Safety Improvement Program (HSIP) were collected and assembled from the FHWA's extensions: the SAFETEA-LU and MAP-21 programs. The data series on highway expenditures were incorporated in the analysis as a surrogate for the new safety countermeasures in road design through the various state programs. It is to be noted here that different projects have their own cost-benefit ratio and not all countermeasures are effective at the same level. Some may have immediate results (i.e., design improvements, fixing horizontal curves, installing guardrails), while other safety interventions, such as enforcing regulatory laws may not show immediate effects, however, may prove to be successful and essential in the long run. Hence, taking funding data as the surrogate of the effectiveness of all safety measures is not a perfect assumption, although, under current data availability, this is a reasonable surrogate.

3.4 Chapter Summary

This chapter discusses the characteristics of the data collected for this study and lists their respective sources. Some of the key points of this chapter are presented below:

- In traffic safety, fatalities are commonly expressed as a product of risk and exposure, where a change in fatalities within a population can be caused by a change in the amount of exposure or a change in the cumulative effect of risk or a combination of both.
- A structural framework, called the Haddon matrix, helps safety analysts dissect a system's components in terms of human, vehicle, and environmental factors related to the pre-crash, crash, and post-crash events. In this study, the Haddon matrix was used to correctly identify factors that affect the trend of fatalities by looking at the complex interaction among a number of processes in action.
- A number of data series were prepared and compiled from various government and/or independent, publicly accessible sources, which are categorized under the crash, exposure, economic, driver and vehicle related, and highway spending frameworks. The variables under these data series fall under different cells of the Haddon matrix.
- Surrogate measures were adopted to represent some variables, where data were not readily available. These include the penetration of the post-1991 model year cars in the vehicular fleet adopted as a surrogate measure of motor vehicle advancement in terms of more crash-worthiness and crash-avoidance capabilities. State expenditures in terms of capital, safety, and law-enforcements were used as

surrogates of safety countermeasures. Although these surrogate measures do not exactly replicate the influence of their parent parameters in the system, under current circumstances, the assumptions can be considered reasonable.

The next chapter presents a discussion on trends of different variables, which are used in the analysis.

CHAPTER 4

EXPLORATORY DATA ANALYSIS

As discussed in the previous chapter, traffic fatalities are influenced by a system of complex processes related to the exposure to crashes and the risk of fatalities or a combination of both. Based on the results of the literature review, it is observed that the exposure to crashes (usually measured as vehicle miles traveled or VMT) has not changed much since 2005 to cause a drastic decline in fatalities that occurred in the aftermath of the 2008 recession. The studies further described some plausible factors that may help explain the change in the amount of risk related to traffic deaths, which ultimately led to a reduction in the number of fatalities nationwide. Before conducting any statistical modeling, it is customary to examine the descriptive statistics of different variables to understand the trends over the period of analysis.

This chapter presents the results of a detailed exploratory data analysis conducted from the data collected for this project as described in Chapter 3. Section 4.1 describes the observed national trends related to the characteristics of drivers, vehicle and person types, roadway classification, vehicle design and model year, seat belt use, state regulatory laws, economic factors, and infrastructure. Section 4.2 describes the trends of the variables related to the land use type (rural/urban), as a part of the analysis will be focusing on rural and urban fatalities separately. Section 4.3 concludes the chapter and provides a brief summary of the exploratory data analyses.

4.1 National Trend

Figure 4.1 illustrates the national trend of fatality rates based on the population, registered vehicles, and licensed drivers. From this figure, it is ascertained that fatality rates measured as a ratio of licensed drivers provide the largest estimates among the three units. The fatality rates based on the population and licensed drivers remained constant until 2005, after which the rates started to decline. Over the period of the recession, this decline accelerated, finally becoming stable in 2010. For the fatality rates based on registered vehicles, the only exception observed is that the estimates were slowly coming down even before the recession. The measures used in computing the fatality rates usually show a gradual growth over the years following a long-term trend. Hence, a steeper slope for fatality rates per 1000,000 registered vehicles indicates that the growth of the registered vehicles was faster than the growths of the population and licensed drivers. All three estimates of the fatality rates started increasing from 2014.

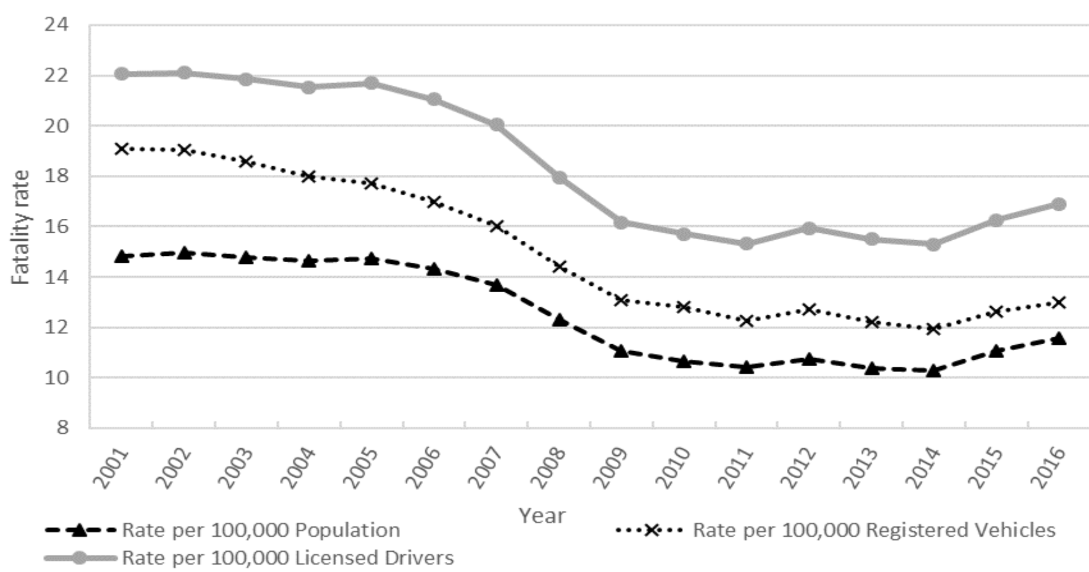


Figure 4.1 Trends of fatality rates by population, registered vehicles, and licensed drivers, 2001-2016

This section discusses more on some important national trends of factors influencing the risk of fatalities. The first subsection focuses on the age of drivers and occupants killed in fatal crashes.

4.1.1 Age distribution

In order to interpret the distribution of age of both the drivers and occupants in fatal crashes, at first, the overall age-range of drivers and occupants were divided into four groups: i) less than 16 years, which qualifies for the graduated driver licensing program (drivers mostly aged between 15 to 17 years), ii) 16-24 years, which is considered to be the most vulnerable group of drivers with a higher crash-risk, iii) 25-64 years, this group is taken to be the most experienced driver group, also having the largest percentage of drivers with lower crash rates, and finally, iv) over 65 years, which usually shows an increased crash rate compared to other age groups. Figure 4.2 presents a timeline of the percentage distribution of the four age groups from 2001 to 2016.

Based on Figure 4.2, the age-group consisting of 15 to 24-year-old drivers first maintains a constant trend before the recession period. However, this age group shows a sharp decline beginning in 2008, where the percentage of drivers falls from an average of 25% (2001 to 2007) to 20% in 2011. The percentage continues to drop in the subsequent years reaching its lowest at 18% in 2016. The age-group representing drivers of 25 to 64 years of age shows a slightly increasing trend prior to the recession reaching up to 66% from a stable 63%. However, this percentage stars to drop in 2009 bringing it back at 63% in 2011 and kept a constant trend ever since up until 2016. Lastly, the elderly driver group aged over 65 years kept a constant trend at around 11% up to 2008, and suddenly increased during the period of recession up to 16% and finally reaching 18% at the end of the year 2016.

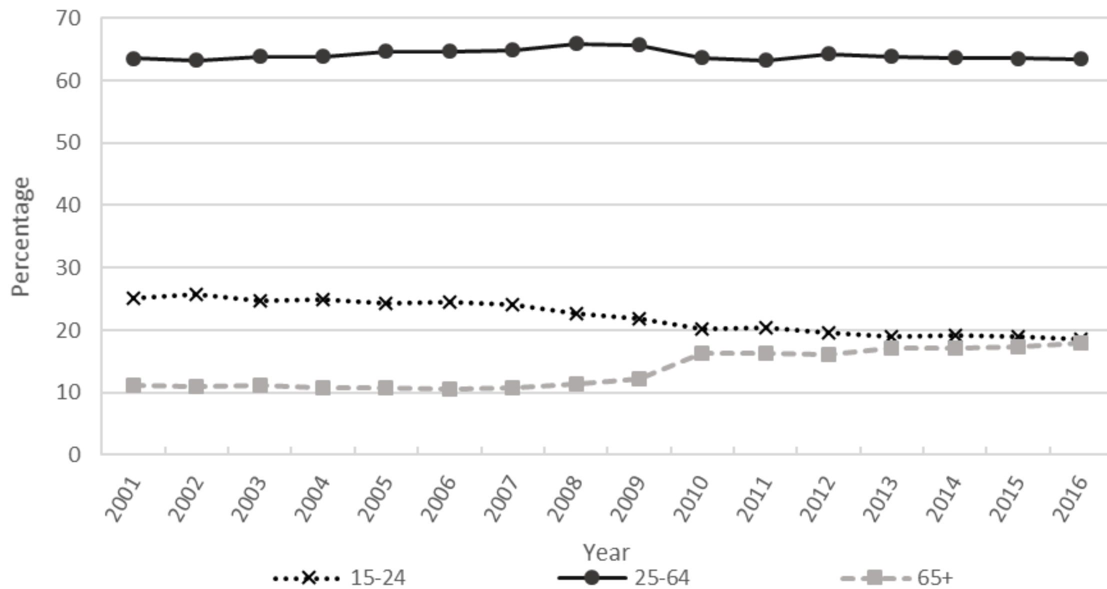


Figure 4.2 Percentage trends of drivers involved in fatal crashes by age group, 2001-2016

In the NCHRP report (Blower et al., 2019), the authors argue that there might be an actual decrease in the number of drivers aged between 16 and 24 years old, bringing the crash risk down for the age-group, which ultimately resulted in a lower number of fatalities. In support of their claim, the researchers refer to a survey report published by the National Household Travel Survey (NHTS). According to this report, which contains the most recent survey results from the years of 1990, 1995, 2001, and 2009, it is found that the average travel percentage by all age groups were reported to be reduced in 2009, which coincides with the period of recession. The only age group that reported no change in their average annual traveling is the elderly driver group aged over 65 years. Drivers, aged between 16 to 19 years, reported a maximum of 14.8% decline in travel, while drivers, aged between 20 to 34 years, reported a 12.4% decline. The smallest decline in average travel of only 3.3% was reported by the drivers aged between 33 and 54, and finally, drivers aged between 55 and 64 years reported a 4.9% less average travel in 2009 compared to 2001 survey (Blower et al., 2019). As the travel estimates by driver age group are not tracked by any available government or private data collection agencies, hence under the current circumstances, this survey provides the best possible illustration of the distribution of travelers by age group during the analysis period. Also, as the findings of the NHTS survey are consistent with other research articles and surveys (He et al., 2016), it would be reasonable to believe that the number of young age drivers, which represents the most crash-risk prone age cohort was reduced due to the effect of recession, which ultimately resulted in a sharp drop in the overall traffic fatality counts.

To better understand the distribution of age in the overall traffic fatalities from 2001 to 2016, Figure 4.3 is plotted, where the numbers of deaths under each age group are normalized to the numbers of fatalities in 2001. Normalizing traffic deaths to a base year fatality counts allows for understanding the change from year to year. Looking at Figure 4.3, it can be clearly observed that all four age groups maintained a constant rate up to 2005, after which fatalities started to drop. Beginning in 2008, the number of traffic deaths for all age group dropped drastically until 2011, which marks the ending of the recession. Starting in 2012, the fatality counts started coming up again in a consistent pattern for all age groups. It is to be noted here that although traffic deaths dropped for all age groups during the recession, the largest decline was observed for the age group of 16 to 24 years.

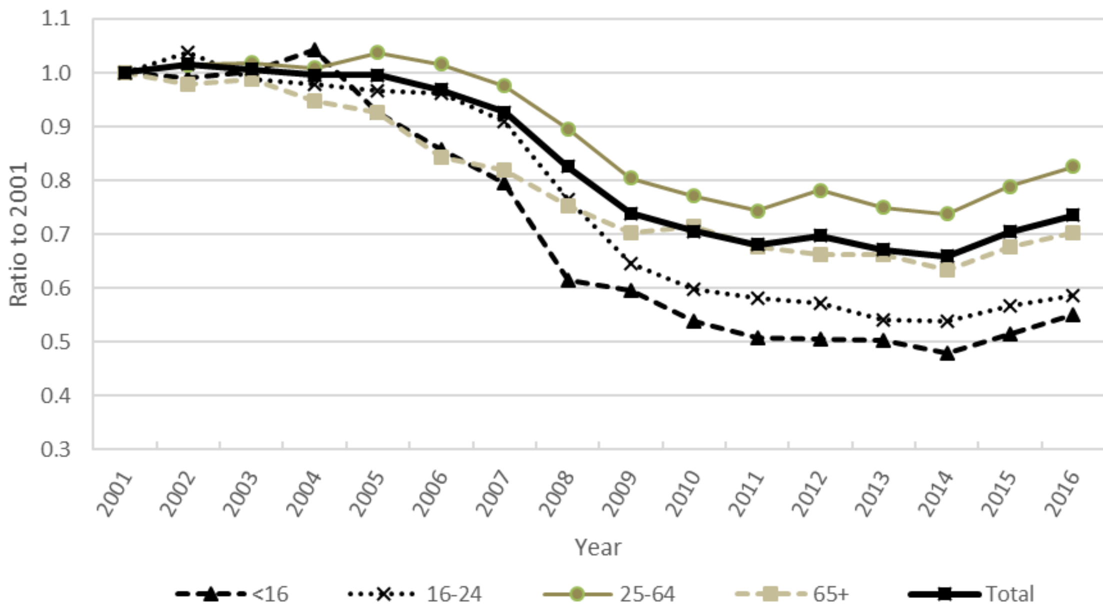


Figure 4.3 Traffic fatality rates by age group, 2001-2016

Figure 4.4 provides a graphical illustration of the percentage distribution in the change in fatalities attributable to the three major age-groups representing more than 99% of the overall traffic deaths each year from 2008 to 2016. The 2007 columns represent the percentages of traffic deaths under each age group, where it shows that the 25-64 age group accounted for the largest number of deaths with 56.4%, while the other two age groups (less than 16 years and over 65 years) accounted for 29.1% and 14.5%, respectively. The next groups of columns represent the percent changes attributable to each age group. For example, from 2007 to 2008, the age group of 16 to 24 years contributed 48.6%, the age-group of 25 to 64 years contributed 40.7%, and finally, the age group of over 65 years contributed only 10.7% to the reduction. Hence, this figure serves in identifying the age group that was more accountable for the changes brought to the total number of fatalities each year from 2007 to 2016.

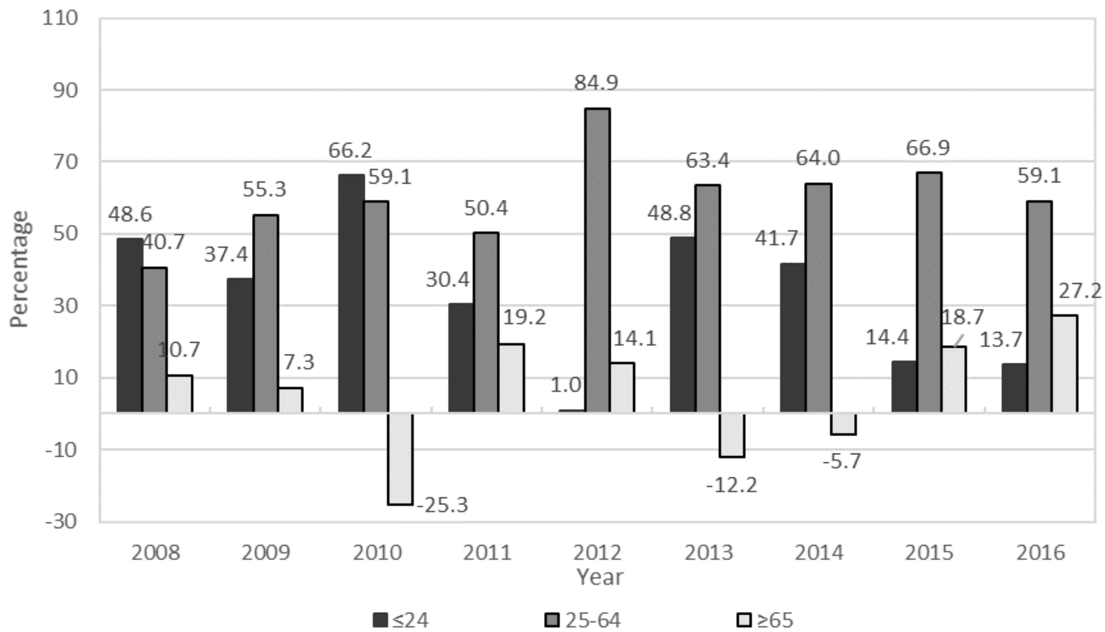


Figure 4.4 Percentage distribution in the change in fatalities attributable to the age groups, 2008-2016

Some key remarks from Figure 4.4 are discussed below. In 2008 and 2010, the age group of 16 to 24 years accounted for the largest amount (48.6% and 66.2%), whereas in 2009 and 2011, the 25-64 years age-group contributed the most to the observed reduction in fatalities. Starting from 2012, the 25-64 years age-group contributed the most to the observed changes (increase in the number of fatalities) each year up to 2016. The age-group of over 65 years contributed negatively to fatality changes in some years, which means that when the total number of fatalities declined, this age group showed an increase, and vice-versa. Hence, the substantial change in fatalities during the recession and its aftermath may not be related to the age group of 65 years and over, as its trend is not consistent with the overall trend.

Figure 4.5 presents a graphical depiction of the percentage of fatalities to understand the effect of each age group in the observed reduction from 2008 to 2012 and the substantial rise in fatalities from 2012 to 2016. The first set of columns represent the percentage distribution of fatalities by age group in 2007. The second set of columns represent the accountability of each age group in the average reduction of fatalities from 2007 to 2012. The columns show that the age groups of less than 25 years and 25 to 64 years together contribute about 93% to the overall decline. Although the young age group (<25) only accounted for less than one-third of the total number of fatalities in 2007, it was responsible for 46.6% of the reduction during the period of recession. Similarly looking at the two sets of columns on the right, it can be deduced that the age group containing 25 to 64-year-old drivers and occupants contributed almost 79% (more than three fourth) to the overall rise observed between 2012 and 2016. The young age group fatalities continued to decline even when the economy was fully recovered.

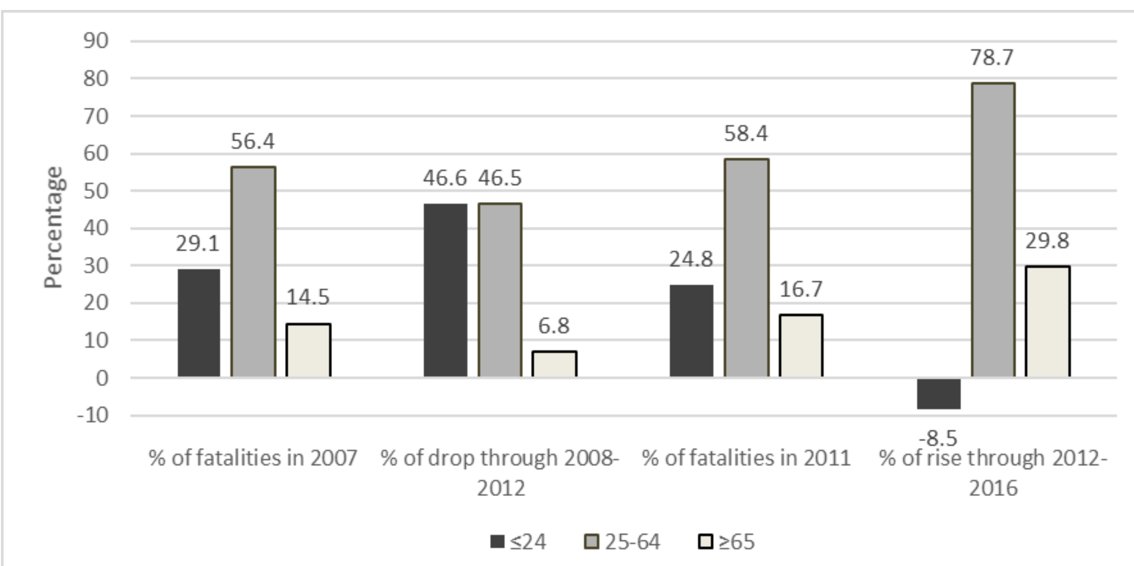


Figure 4.5 Estimated reduction and subsequent rise in fatalities by age group through 2008-2012 and 2012-2016

4.1.2 Vehicle and person type

This section describes the trends of fatalities during and after the recession by looking at the distribution based on vehicle and person type. Although neither parameter was highly significant in causing the dramatic decline and substantial increase in fatalities, it still helps to understand some long-term trends associated with vehicle types and persons involved in the fatal crashes.

Figure 4.6 represents the number of fatal crashes from 2001 to 2016 by vehicle type. It is seen that before the recession, the number of fatal crashes associated with the passenger cars was dropping at a constant rate between 2001 and 2007. This moderate trend could be attributed to the implementation of effective countermeasures, restraint use, strict DUI laws and advanced technologies with more crash-worthy cars on the vehicular fleet. However, the numbers dropped drastically during the recession reaching its lowest of 17,508 in 2011 from 22,856 in 2007 and afterward started increasing.

The number of crashes involving light trucks was increasing before the recession reaching its peak at 22,411 in 2006, dropped during the recession period to its all-time low at 16,806, and rose again in the aftermath. This trend can be associated with the business cycle activities under the assumption that during a recession, small businesses transporting goods in light trucks were not getting enough trade, hence the vehicle miles driven by land transport vehicles or LTVs (including light trucks, and sports utility vehicles) were reduced, which ultimately reduced the crash-risk and fewer fatal crashes occurred during that period (He et al., 2016). The heavy trucks also demonstrated a sharp decline during the recession, which aligns with the findings by He et al. (2016). The number of motorcycle crashes was steadily increasing before the recession reaching 5,409 in 2008, declined slightly in 2009 and 2010 reaching 4,625 crashes and then started increasing again. The fatal crashes involving motorcycles surpassed the numbers by heavy trucks in 2006, and it has still remained the same.

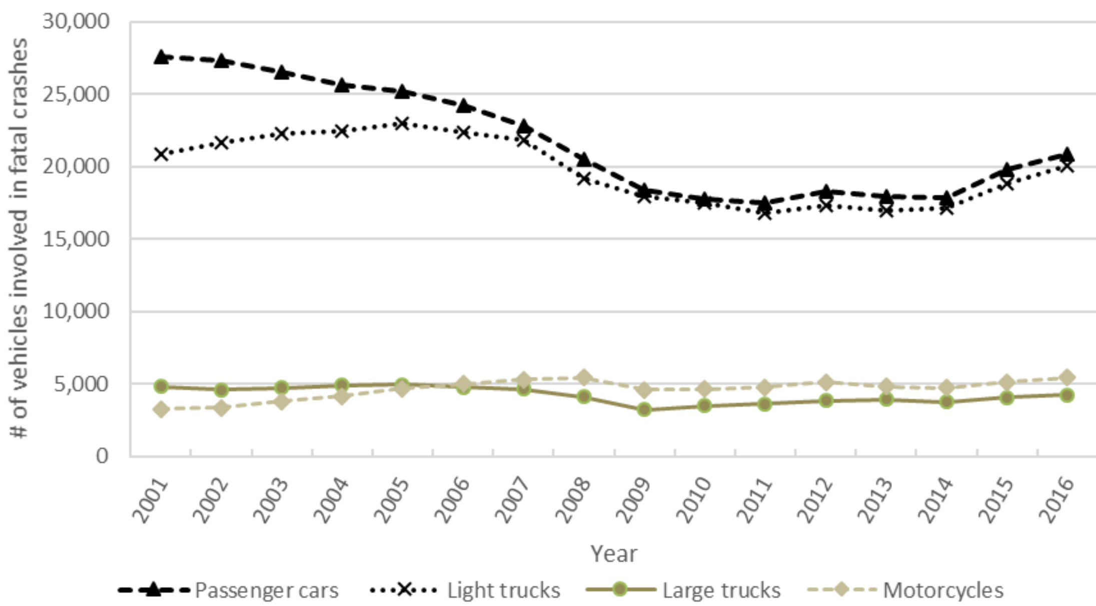


Figure 4.6 Motor vehicles involved in fatal crashes by vehicle type, 2001-2016

In order to fully understand the involvement of various types of vehicles in fatalities, Figure 4.7 is plotted. In this figure, the data points represent the ratio of each years' number of fatalities to 2001 fatalities for each vehicle type. Normalizing the numbers this way allows for a better understanding of the yearly trend. Here, it is seen that the percentage of fatalities involving passenger cars steadily decreased a total of 20% from 2001 through 2007. However, over the period of the recession, the percentage of passenger cars dropped another 20%. Between 2012 and 2016, the percentage of passenger cars did not change much (ratio remained constant at about 60%), but then finally started increasing from 2014.

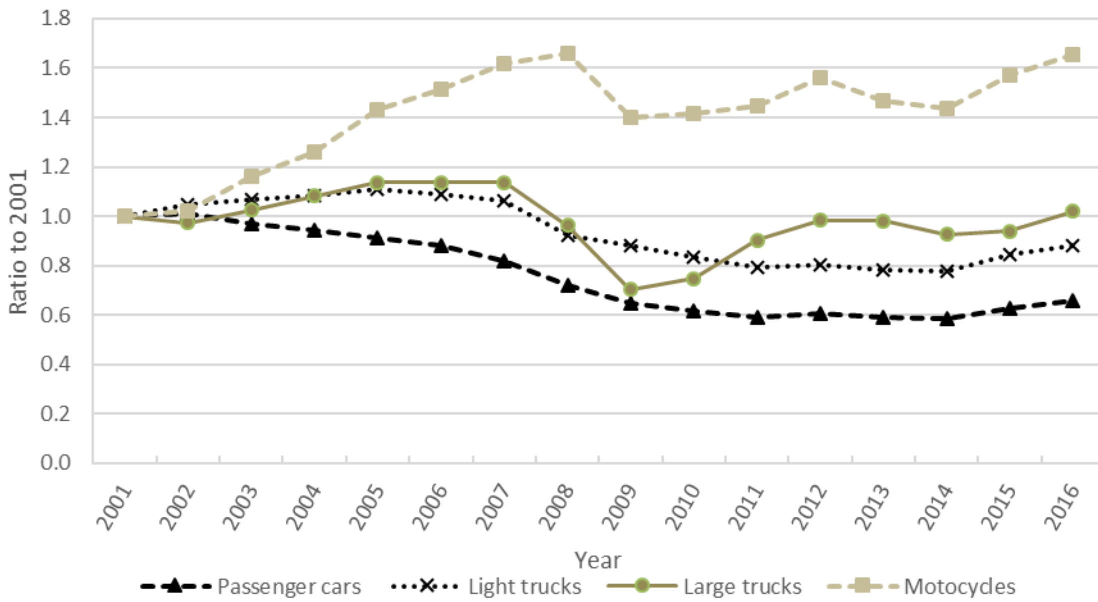


Figure 4.7 Persons killed in fatal crashes by vehicle type, 2001-2016

For the LTVs, the pattern followed a somewhat similar trend as for the number of crashes shown in Figure 4.6. At first, the fatalities involving the LTVs increased up to at most 11% through 2007 from 2001, declined 31% during the recession (2008-2010) dropping to a ratio of 0.8 to the 2001 fatalities, and finally started increasing steadily from 2012. The fatalities involving large trucks increased up to a maximum of 14% in 2007 compared to 2001, sharply declined during the recession dropping 44% from its 2007 ratio, started increasing steadily from 2010, and finally being stable in 2012 (at 0.98).

Although the fatalities involving motorcyclists only account for an average of 12% to overall fatalities, it showed an interesting yearly trend mimicking the highs and lows of the economic activities during the analysis period. From 2001 through 2007, the fatalities involving motorcyclists increased sharply reaching a maximum of 5,312 fatalities in 2008 from 3,197 in 2001 (i.e., around 60% increase). This number dropped sharply in 2009 to 4,469, after which a steady increase was observed that continued up to 2016, with an exception occurring in 2012 when it increased slightly compared to the previous year.

Figure 4.8 shows that the drivers account for more than half of the total number of fatalities throughout the entire period of analysis (2001-2016), which is true for most motor vehicle fatal crashes irrespective of the types of vehicles. The fatality percentage of drivers dropped marginally from 55% in 2001 to 49% in 2016, and the trend was also not affected by the recession period. This subtle decline in fatalities can be attributable to the long-term constant trend of fatalities, which is not associated with economic cycle activities. The percentage of fatalities for passengers dropped in a similar way from 24% to 17% between 2001 and 2016. The percentage of pedestrians showed a stable increase throughout the entire period. On the other hand, the percentage of motorcyclists showed a stable increase from 2001 to 2008, sharply dropping in 2009, and finally maintaining a stable percentage till the end of the analysis period. The percentage of fatalities for bicyclists maintained a constant low throughout the entire period.

To better understand the trend over time for each person type, the ratios of fatalities normalized to 2001 are presented in Figure 4.9. The plot demonstrates that the fatalities for drivers and passengers remained stable over the whole period. The pedestrian fatalities remained constant up to 2007, increasing steadily afterward. For motorcyclists, the fatalities increased markedly (87%) between 2001 and 2007, and again between 2010 and 2012, only declining (15%) from 2008 to 2009. After 2012, fatalities involving motorcyclists maintained a constant trend at a rate of 90% higher than the fatalities occurred in 2001.

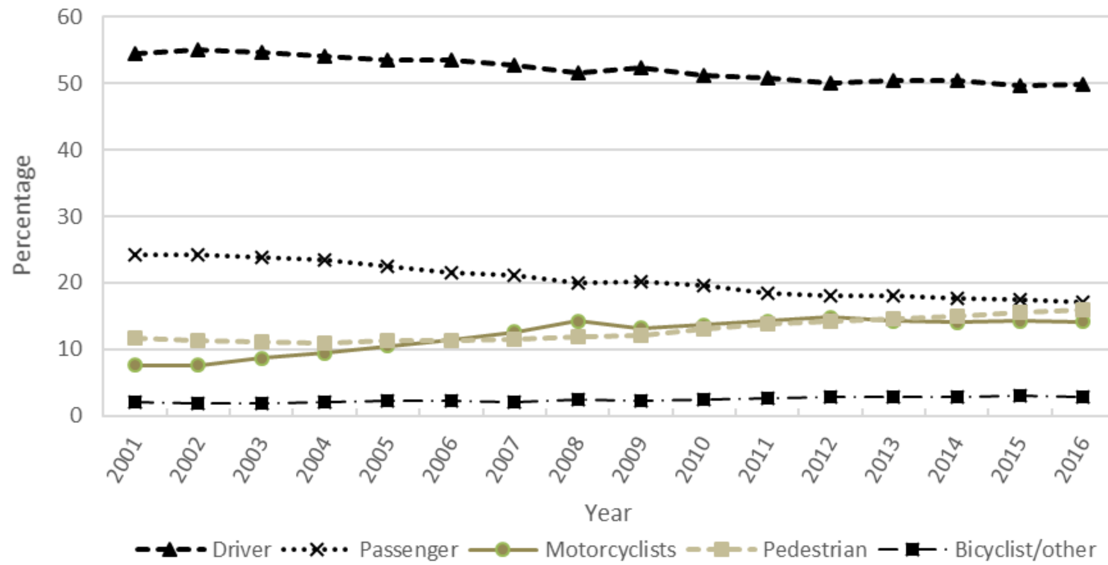


Figure 4.8 Persons killed in fatal crashes by person type, 2001-2016

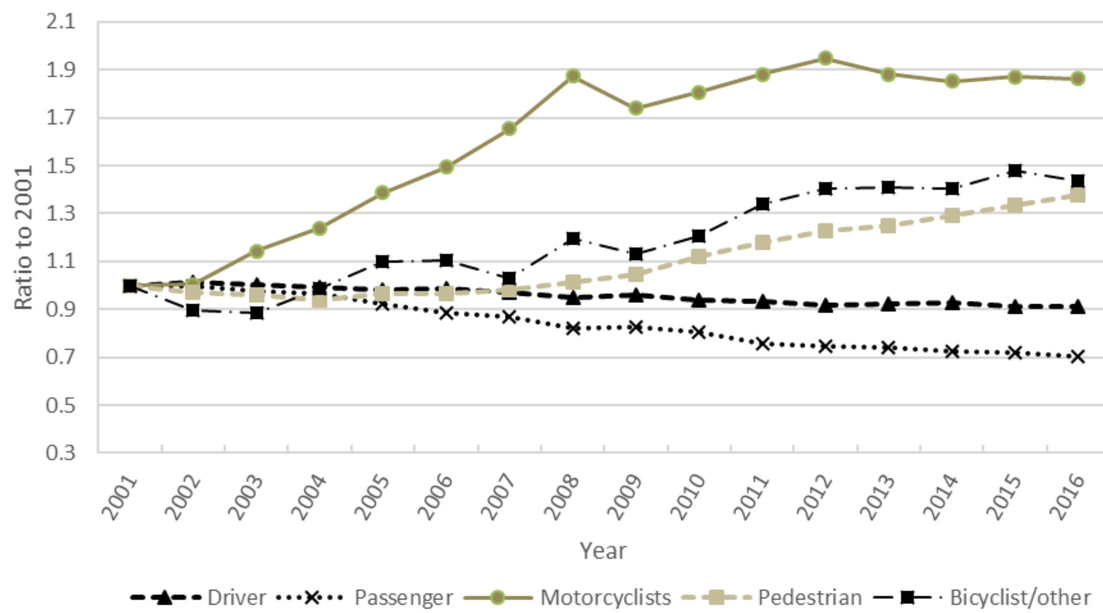


Figure 4.9 Fatalities by person type normalized to 2001, 2001-2016

For bicyclists, the trend over time constantly changed every other year, which makes it difficult to interpret. However, as bicyclists only account for an average of 2% of the total fatalities, their contribution to the substantial decline and increase in fatalities during and after the recession can be considered minuscule and out of scope for this study.

4.1.3 Roadway function class

In highway safety, the most common measure of exposure is the total miles driven on public roadways (Hauer, 1995). Here, the underlying assumption is that the likelihood of crashes directly depends on how much people drive. As the VMT is an indicator of the crash probability, the functional classification of roadways can also regulate the chances of crash occurrence as the average traffic speed, volume, surface-condition, and other roadway design parameters influencing crashes also vary for each road type. Figure 4.10 provides an illustration of the VMT by roadway function class to understand the trend of the combined effect of exposure on different road types. The VMTs are normalized to 2001 to better contemplate the yearly effect of a change on the trend.

Here, in Figure 4.10 it is seen that over the years, the VMT tended to increase for the urban roads, whereas for the rural roads, it showed a gradually decreasing trend. During the period of recession, the consistent growth of the urban VMT somewhat subsided, whereas the VMT on the rural roads continued to decline. Once the recession was over, the VMT on all urban roads started to increase at an even faster rate compared to the prior-recession period. Increasing VMT in urban areas might be explained by the faster growth of urbanization, referred to as urban sprawl, where city areas tend to spread out over a large amount of land, generating longer trips on urban roads. This contrasting trend also indicates that each year, a portion of the trips might have been shifted to the urban roads from the rural roads. This is an important observation for this study as the crash risk of fatalities on the rural roads tend to be much higher than on the urban roads. More discussion on the trends of VMT by land use type will be covered in later part of this chapter in Section 4.2.

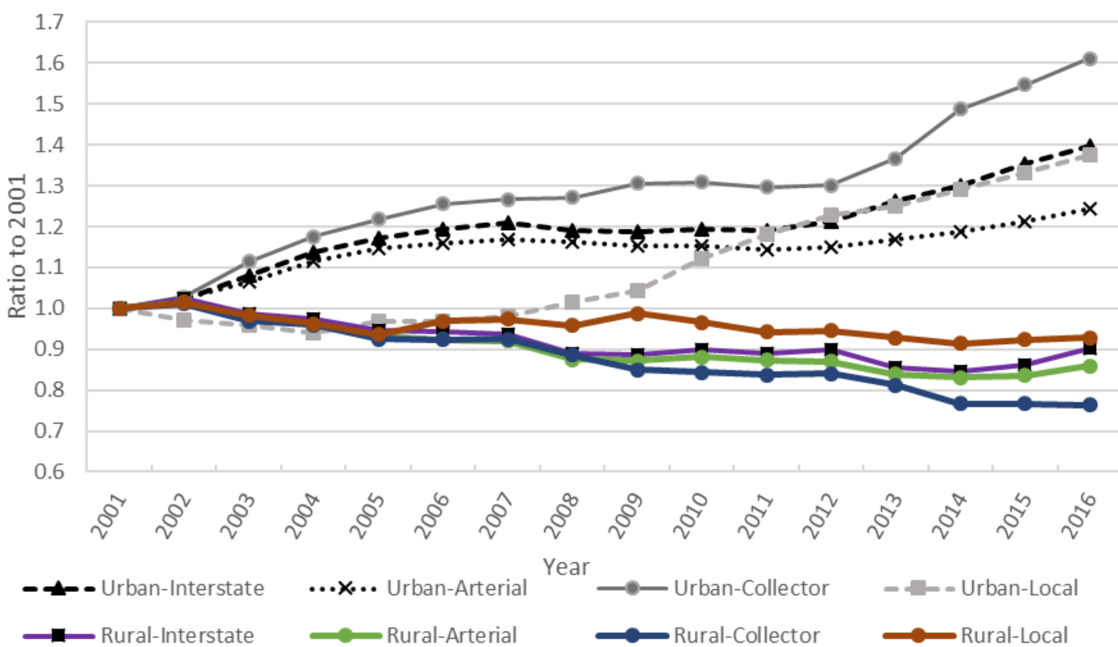
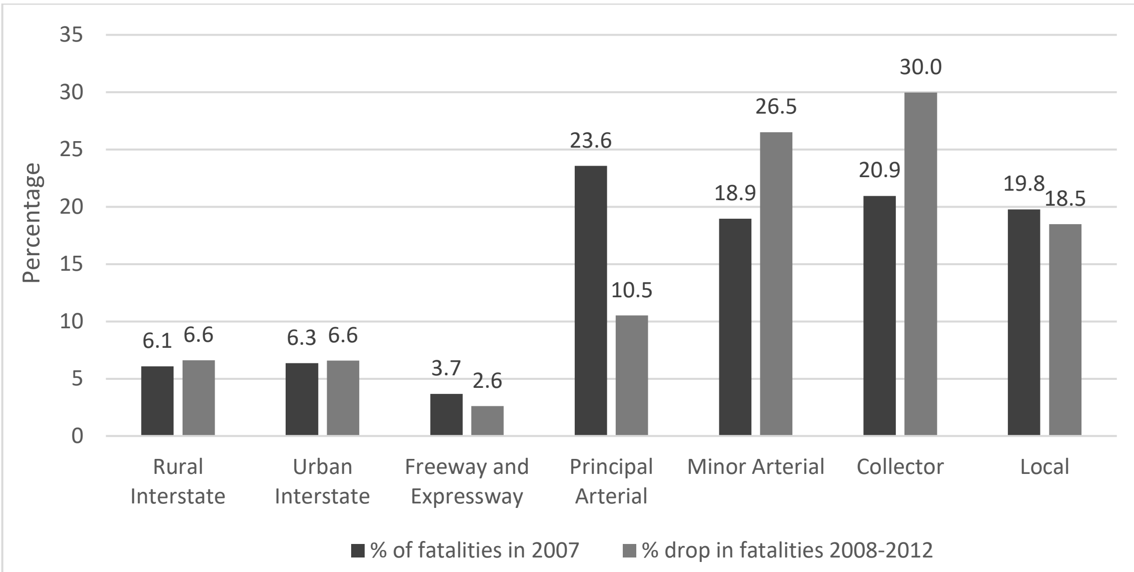


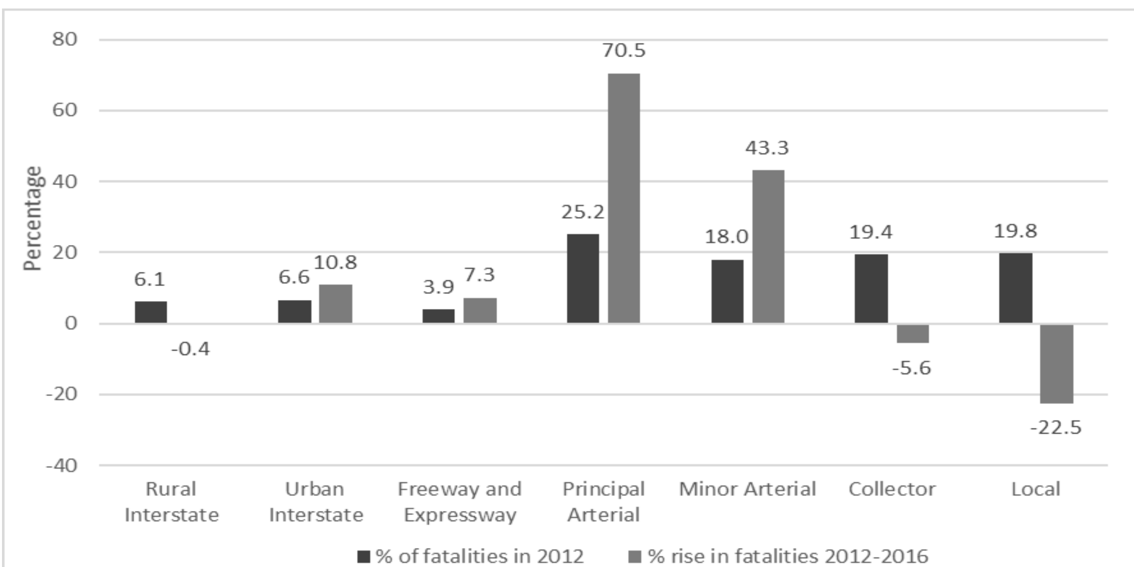
Figure 4.10 Vehicle miles traveled by roadway function class, 2001-2016

Figure 4.11 presents the percentage distribution of fatalities by functional classification of roadways. The darker columns in Figure 4.11a represent the percentage of fatalities observed on each road type during 2007. The lighter columns project the percentage of reduction in fatalities from 2008 to 2012 accountable to each road class.

Similarly, Figure 4.11b shows the disaggregation of fatalities by road classes in 2011 and the contribution of each road type to the observed increase in fatalities from 2012 to 2016.



(a)



(b)

Figure 4.11 (a-b) Estimated reduction and subsequent rise in fatalities by roadway function class through 2008-2012 and 2012-2016

Figure 4.11a depicts that the arterial, collector, and local roads accounted for more than 85% of the total fatalities observed during and after the recession. The reduction in fatalities observed on the minor arterials and collector roads contributed more than 55% to the overall reduction. The fatalities on these road classes continued to decrease even after the economy was recovered. From 2007 to 2012, the fatalities on the principal arterials increased only 2%. However, this slight increase was responsible for 70% of the total rise in fatalities observed between 2012 to 2016 (Figure 4.11b). Figure 4.11b also reveals that the major and minor arterial roads alone are accountable for the overall increasing fatalities from 2012 to 2016, which is in line with the findings observed in Figure 4.10.

4.1.4 Vehicle design and model year

As discussed in Chapter 2, multiple studies found an association between improved vehicle technologies and declining crash risk and fatalities (Farmer 2004, Farmer and Lund 2014, Kahane 2015). By analyzing data from 1970 to 2012, Kahane (2015) found that this declining crash risk is largely explainable by the changes made in the Federal Motor Vehicle Safety Standards (FMVSS), which required a strict regulation of occupant protection as well as advanced crashworthy and crash-avoidance technologies be introduced in the new vehicle designs. Two of the changes made to the FMVSS for target years 2001-2016 were requiring all passenger cars and LTVs be equipped with electronic stability control (ESC) and tire pressure monitoring system (TPMS). While the direct safety effect of the TPMS has still not been documented by any study, the ESC has been proven to be a significant factor in reducing single-vehicle crashes by multiple studies (Kahane 2014, Farmer and Lund 2006). The New Car Assessment Program (NCAP) by the NHTSA is another government safety program encouraging auto-manufacturers to build safer cars by testing and rating the crashworthiness of the passenger cars and LTVs (Farmer 1997). This study includes two surrogate measures to represent the overall safety factor brought about by these advanced technologies being incorporated in the modified and improved government standards in the form of the FMVSS and NCAP.

One of the surrogate measures to represent improvements in vehicle technologies is the penetration of the post-1991 model year vehicles into the traffic fleet. This surrogate measure represents the percentage of the registered vehicles that were the model year 1991 or later. 1991 model year was chosen to provide a reasonable 10 years span for penetration of new cars in the fleet. The actual percentage of the post-1991 model year vehicles in the total registered vehicle lot, which should be a part of the vehicle registration data were not obtainable by the researchers of the NCHRP 17-67 (Blower et al., 2019). Hence, the researchers chose to implement a quasi-induced exposure (QIE) method to get estimates for the data series. The NASS GES data from the NHTSA were used to extract the number of vehicles not directly involved in crashes (such as the cars that were rear-ended) that were of the model year 1991 or later from 2001 to 2016. Under the assumptions of the QIE method, these vehicles were taken to be a representative of the vehicles that were present on the roadway and used as a measure of exposure. Although this representation of the vehicle fleet is not a perfect one and contains anomalies in most cases (think about roads with higher volumes of traffic, such as urban arterials), this is a reasonable surrogate under the circumstances of data unavailability.

Figure 4.12 represents the percentage of the post-1991 model year into the vehicle fleet as a measure of improvements in crashworthiness and occupant protection system over the years from 2001 to 2016. The data followed a similar trend as reported by Kahane (2015) for a surrogate measure of the vehicle-based risk index in his study (Blower et al., 2019). From the figure, it is observed that vehicles with better technologies were increasing at a decreasing rate from 2001 to 2012, becoming constant afterward. Over the years from 2012 to 2016, the rate of penetration remained constant at 98%, which makes this surrogate measure a questionable one to be incorporated in this study. However, as no other data was obtainable to replace this surrogate measure in the dataset, hence it was included in the analysis regardless.

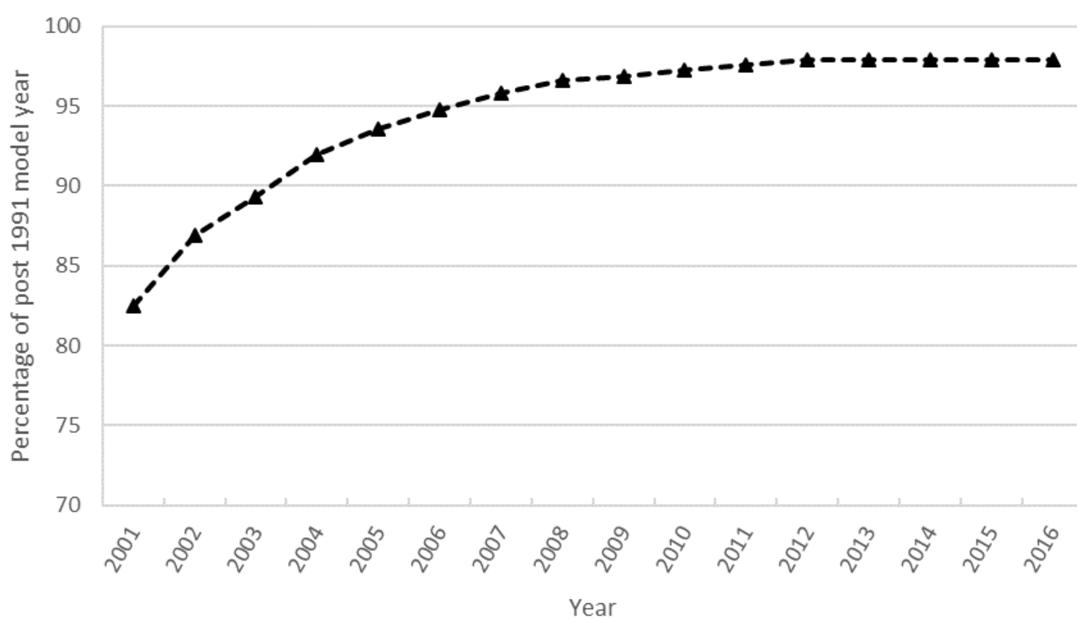


Figure 4.12 Penetration of the post-1991 model year in the vehicular fleet

Another data series that was included in the analysis to project the safety effect of programs, such as FMVSS and NCAP, was the penetration of the ESC (Figure 4.13). Data on the percentage of vehicles equipped with the ESC were obtained from the HLDI from 2001 to 2016. Figure 4.13 shows that the penetration of the ESC equipped vehicles was increasing at an exponential rate before the recession from 2001 to 2008. During the recession, this rate somewhat died down and could be explained by the impact of the economic condition of households to not being able to afford new cars, resulting in fewer ESC equipped cars being registered over the period. However, the increasing penetration of the ESC-equipped cars continued even during the recession, although at a slower rate, and finally reached 99% in 2013. As this dataset also illustrates a constant rate of change over certain years, this also becomes an arguable surrogate measure to represent safety effects of the vehicle crashworthiness and occupant protection system.

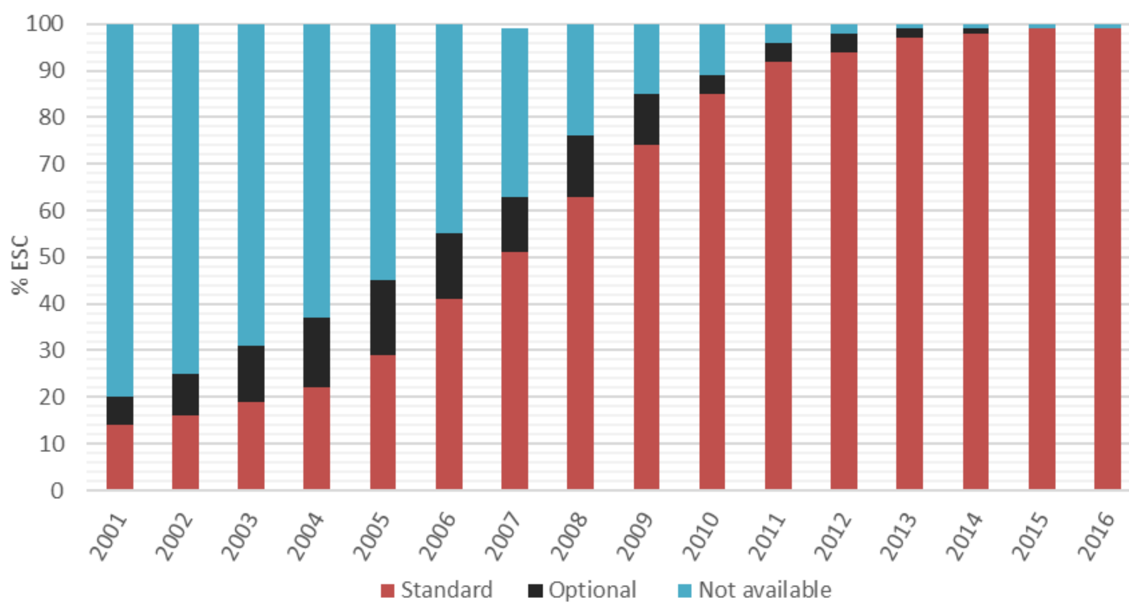


Figure 4.13 Fleet penetration of ESC in registered vehicles, 2001-2016.

4.1.5 Seat belt use

Among all the regulatory safety standards implemented by the FMVSS, occupant restraints have been shown to be the most effective one in reducing crash severities by multiple studies (Evans 1984, Kahane 2004). According to Kahane (2015), almost 56% of lives were saved by wearing seat belts in the events of severe crashes in 2015. As of 2018, all 50 states have mandatory seat belt laws in place, the only exception being the state of New Hampshire (IIHS, 2014). Figure 4.14 represents the percentage of drivers and occupants killed in fatal crashes based on restraint use. It shows that both the percentage of drivers and occupants for those wearing seatbelts showed a gradually decreasing trend over the period. It is noted here that this increasing trend of fatalities wearing seat belts do not indicate that over years more and more people were getting killed by wearing seat belts. In fact, it means that the rate of restraint use among the overall population was increasing over time, hence more people were found getting killed wearing seat belts. On the other hand, the drivers and occupants not wearing seat belts showed a gradually decreasing trend. Again, this means that there were fewer people not using restraints each year, hence the percentage of people killed not using seat belts consequently decreased over the years. This gradual trend of fatalities related to seat belts is expected, as the use of seat belts, which is a primary occupant protection device, could not be implemented to the whole population overnight. This is a customized safety practice, which had to be introduced gradually as a habit to the users, and for which regulatory laws have to be implemented to ensure usage among the vehicle occupants. Hence, it is reasonable to consider seat belt laws in each state as a factor influencing fatalities over the years.

Among the 49 states that have seatbelt laws, 34 states impose primary enforcement, meaning that a law enforcement officer can stop a vehicle solely for the violation and penalize the drivers and occupants for not wearing seatbelts. Secondary enforcement means that if a vehicle is stopped by a law enforcement officer due to some other offense (such as speeding) and finds them not wearing seatbelts, only then penalty can be issued in terms of a monetary sentence. In 15 states, not wearing a seatbelt is considered to be a secondary offense.

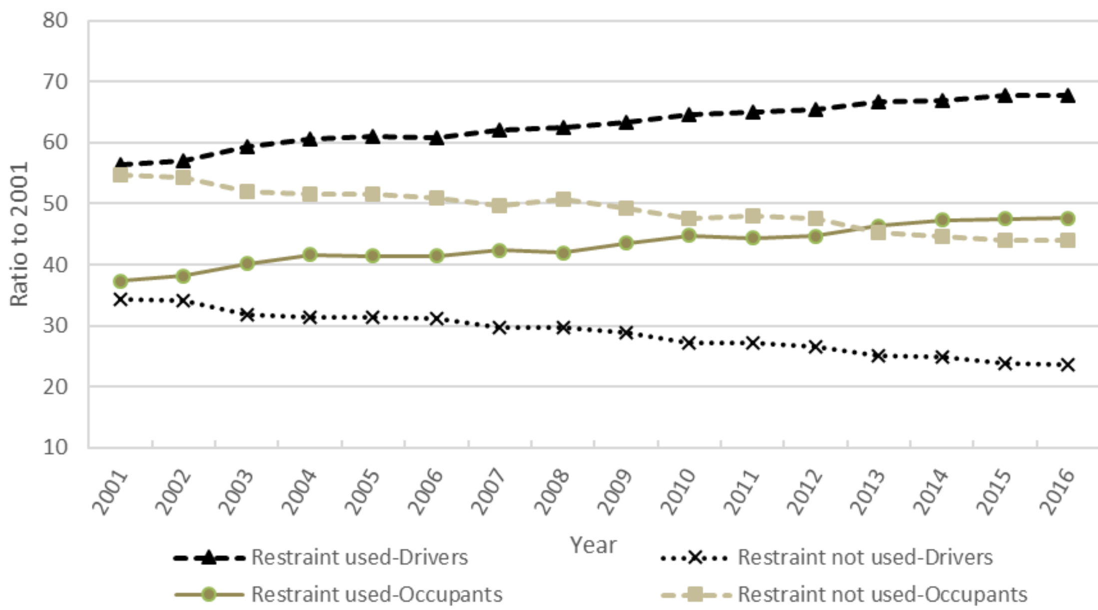


Figure 4.14 Drivers and occupants killed in fatal crashes by restraint use normalized to 2001, 2001-2016

Figure 4.15 shows the trends of states on seatbelt laws over the period of 2001 to 2016. In order to use the belt use laws as a time-series factor in predicting change in fatalities, it was ideal to use a rating system based on which the enforcement of laws will be ranked. The researchers of the NCHRP 17-67 implemented a belt use rating based on the strictness of laws from 1 (most restrictive) to 0 (no requirement) (Blower et al., 2019). The existing laws of each state were rated from 2001 to 2016 based on the type of enforcement (i.e., primary or secondary) while considering if the law was enforced either on the front seat occupants or all occupants. The vertical lines with positive slopes represent a change in the law, where it was made stricter from one year to the next. Hence, it is inferred that the seatbelt law was made stricter in some states every year prior to and during the period of recession, except for 2008, and since 2012, no state implemented a change in seatbelt laws. 15 states made the laws stricter during the whole period of analysis, and one state (Arizona) even made it flexible in 2010 compared to the 2009 law.

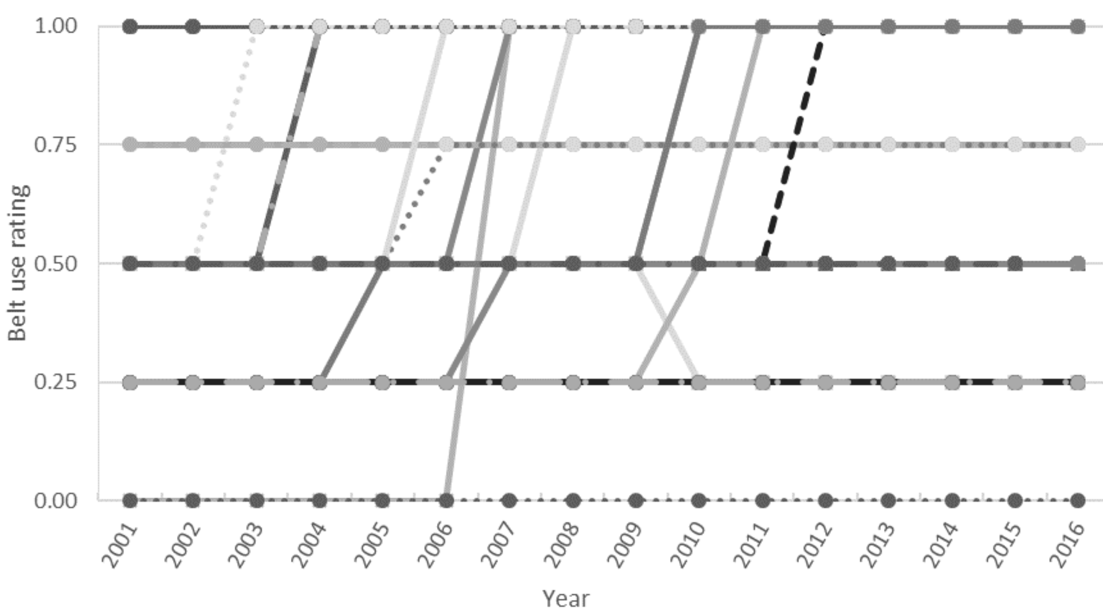


Figure 4.15 Restraint law indices for 50 states indicating most restrictive (1) to no requirement (0), 2001-2016

4.1.6 Other state regulatory laws

Among other regulatory laws, the legislative measures by the states to prevent driving under influence (DUI) is considered to be a significant factor in reducing fatal crashes. Figure 4.16 shows the trends of states on implementing the DUI laws over the period of 2001 to 2016. Similar to rating the seatbelt laws, the DUI laws for each state were rates (from 1 being most strict to 0 being no regulation) by considering multiple factors, such as allowable blood alcohol content (BAC), jail terms and monetary fines for violation and multiple offense, license revoking, third time offense being considered a felony, treatment programs, victim rights, and increasing penalty for operating under intoxication (OWI) with a much higher BAC. Here, the vertical lines with positive slopes mean that there has been a change made to the existing law in a state, where the law was made stricter. One state (Hawaii) was found to change its DUI law three times, twice in 2006 and 2007 making it stricter, and once in 2010 making it a little flexible.

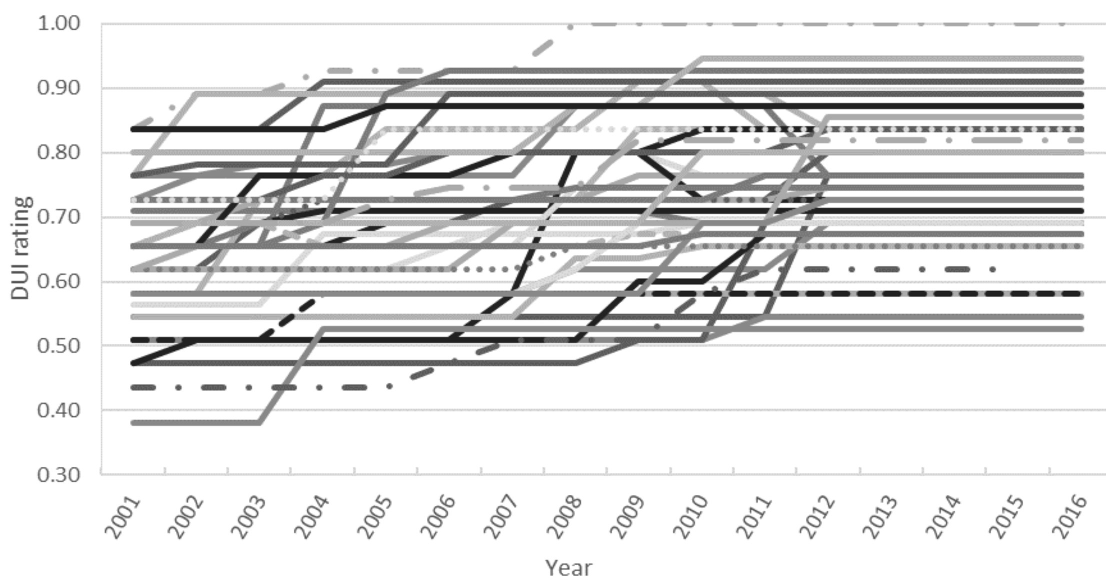


Figure 4.16 DUI law ratings for 50 states indicating most restrictive (1) to no requirement (0), 2001-2016

The motorcycle helmet laws were similarly rated based on the coverage from 0, meaning no requirement, to 4, meaning universal coverage. The indexing was done based on the requirements of who needs to wear helmets depending on age. The age limit of being considered as an adult motorcyclist (not required to wear helmets) ranges from 14 to 21 years, depending upon the state. Among all fifty states, three states did not have a motorcycle helmet law (Illinois, Iowa, and New Hampshire) during the period of 2001 to 2016, twenty-five states covered only youths with a wide range of age limit, two states only implemented the law on passengers, and finally, nineteen states had universal coverage. Only two states (Pennsylvania and Louisiana) changed their coverage during the period of 2001 to 2016 (Figure 4.17) when Pennsylvania limited their coverage and Louisiana implemented a universal coverage for the helmet law in 2003.

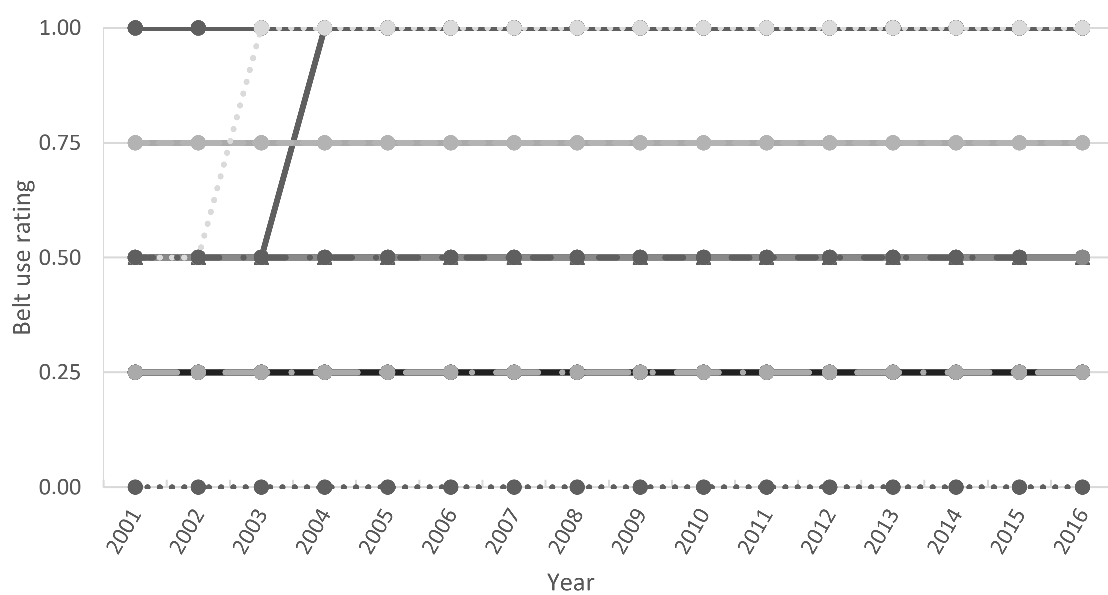


Figure 4.17 Motorcycle helmet law ratings for 50 states indicating most restrictive (1) to no requirement (0), 2001-2016

Besides using the existing DUI laws as a factor influencing the number of fatalities, another measure related to alcohol was adopted by the researchers of the NCHRP 17-67, where the rates of consumption of different alcoholic beverages were incorporated in the modeling (Blower et al., 2019). Figure 4.18 represents the national rate of consumption in terms of gallons per capita of beer, wine, and other alcoholic spirits from 2001 to 2016. The figure shows that over the period of 2001 to 2016, the consumption of beer has dropped a total of 8.5% from 1.28 gallons to 1.19 gallons. The beer was the predominant types of alcohol over the entire period of analysis, which seemed to be affected by the recession as consumption dropped rapidly during those years (2008 to 2011). Consumption of wine and other liquors have shown an increasing trend over the years, where wine consumption has increased a marked 40% and spirit consumption has increased 30% from 2001 to 2016. Both wine and liquor consumptions were unaffected by the period of recession, however, both showed a rather slower growth from 2008 to 2009. The data for Figure 4.18 on national consumption of beer, wine, and other spirits were obtained from the NIAAA of NIH, where the records were based on sales reports collected from different alcohol beverage industries. It is to be noted here that these measures of consumption do not represent the driver population only, rather it includes the overall population of the nation. However, it still perpetuates a relatively valid measure of a critical element in driver behavior.

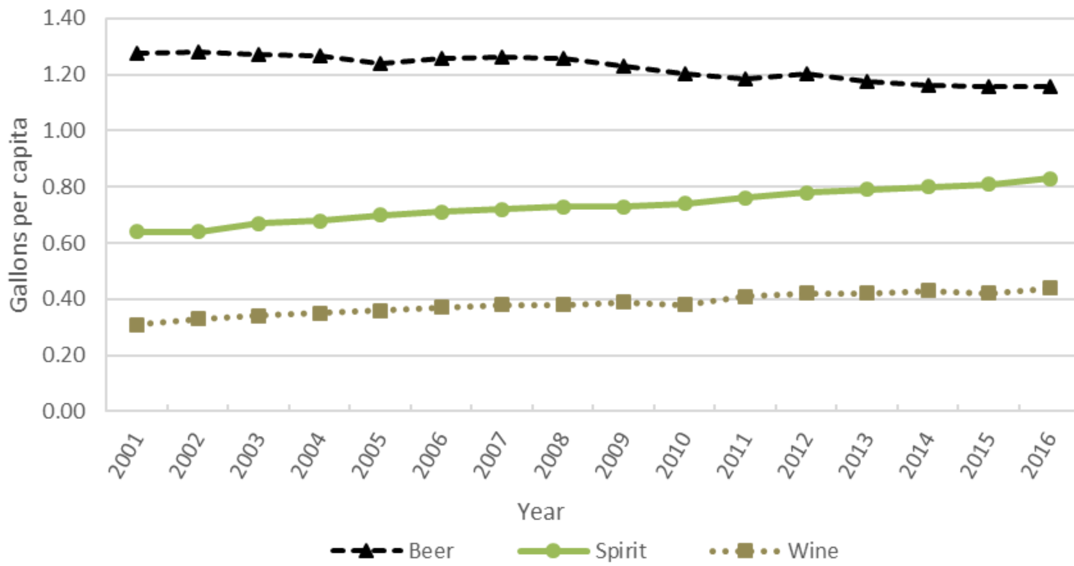


Figure 4.18 Alcohol consumption from beer, wine, and spirits in gallons of ethanol

4.1.7 Economic factors

As discussed in Chapter 2, many studies exist, where a change in the number of fatalities has been associated with a change in the prevailing economic conditions of the nation (Wijnen and Rietveld 2015, Elvik 2015, Wegman et al. 2016). These studies have incorporated varying measures of economic activities in their analysis to represent the overall effect of the economy on traffic fatalities. The researchers of the NCHRP 17-67 have established five data series (discussed in Chapter 3) in their analysis to examine the influence of the recession for the decline in the number of fatalities during the period of 2008 to 2011 and found positive results (Blower et al., 2019). This study also uses these data series to investigate the effect of the economic activities in changing the number of fatalities during the recession and afterward.

The underlying hypotheses to investigate the association of economic conditions on traffic fatalities are: 1) recession affecting travel demand, resulting in a reduced exposure, 2) recession affecting certain groups of people more so than the rest of the population, bringing a shift in driver-class, where fewer high-risk drivers (young drivers) were on the road, 3) recession affecting drivers' behaviors, resulting in reduced risky or discretional driving. To test these hypotheses, data series on the median household income, GDP per capita, unemployment rate, and fuel costs were incorporated in the analysis. It is to be noted that all these measures are surrogates of the data that could not be obtained or are abstract in nature to be expressed numerically. All the monetary values discussed in this subsection are expressed in constant 2013 dollars using the CPI.

To test the effect of economic conditions on driver behavior, median income and GDP per capita were used in the analysis. Median income captures the infinitesimal effect of the economic activities within a population by focusing on the household income. On the other hand, GDP captures the effect of the overall economic activities, normalized to the state populations. Figure 4.19 presents the national trend observed in the median household income and GDP per capita during the period of analysis from 2001 to 2016. The figure depicts that GDP per capita was gradually increasing prior to the recession reaching from $37,273 to $48,401 from 2001 to 2008. It showed a sharp decline decreasing 3% to $47,000 in 2009, after which it regained its previous consistent growth throughout the rest of the study period.

Prior to the recession period, the median income fluctuated within ±1% from 2001 to 2008 (Figure 4.19). During the period of recession, the median income dropped a marked 4.5% from $54,665 to $52,214, afterward coming back up again. It was interesting to see that the median income measured out to be 50% more than the GDP per capita in 2001, however, by the year 2014, the GDP per capita surpassed the median income, and now both are increasing at a consistent rate. Median income, being greater than the GDP per capita amount, can be explained by the increasing multiple earnings in every household. On the other hand, GDP per capita, being greater than the median income in households, indicate that in a capitalist society, the average income of a household can at times be far different from the profits made by some large corporations during economic boom, resulting in an increased level of GDP for the whole population.

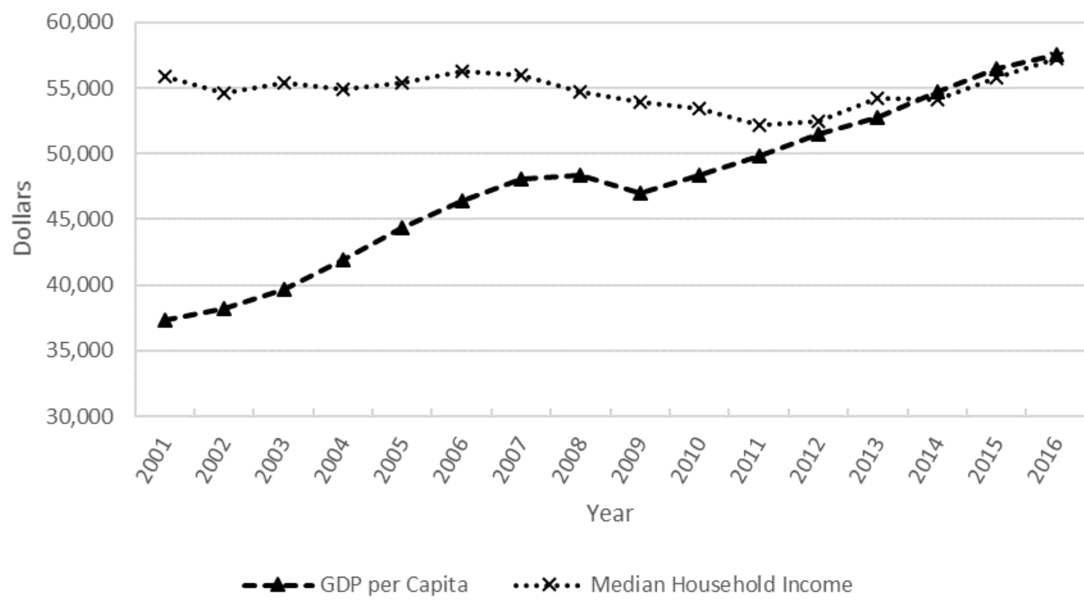


Figure 4.19 Trends in Median Income and GDP per capita, 2001-2016

Prior to the recession period, the annual unemployment rate was relatively stable from 2001 to 2007. During the recession that started in 2008, the unemployment rate increased significantly reaching an all-time low of 9% in 2010, after which it gradually started to drop (Figure 4.20). Figure 4.20 illustrates the distribution of the rate of unemployment between two age groups: young (aged between 16 and 24) and adult (aged 25 and over). The reason for aggregating the unemployment rates for the age groups in this manner is to test the hypothesis regarding the modified driver class, which states that the reduction of young age drivers (aged between 16 and 24 years), who have a much higher crash risk than the other age groups was one of the critical factors in changing the number of fatalities during and after the 2008 recession. During the recession, the young age population had a 75% increase in the unemployment rate from 10% to 17.5%, whereas, for the adult population, the rate increased a marked 100% from 4.5 to 9 percent from 2007 to 2010.

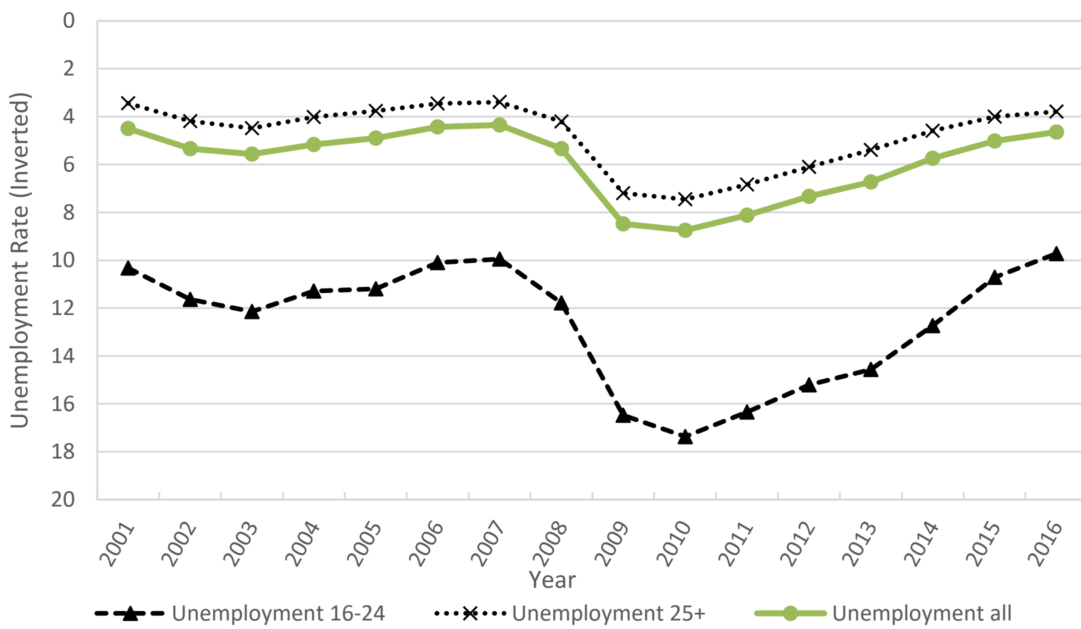


Figure 4.20 Unemployment rate by age

Figure 4.21 illustrates the trend in prices of fuels over the period of analysis. As discussed in Chapter 3, the data on fuel costs included the price of the regular-grade gasoline, which is the most commonly used fuel type and the fuel tax rate, expressed in constant 2013 dollars. The figure depicts that from 2001 to 2008, the price of fuel maintained a constant growth each year from $2 dollars/gallon in 2001 to $3.5/gallon in 2008. According to a U.S. Energy Information Administration's (EIA) report on gasoline price fluctuations (2018), this long-term increase observed each year in the U.S. is caused by a combined effect of a significant growth in demand in some countries, such as China, the Middle East, Latin America and uncertainty in the world supply, resulting in the highest ever recorded gasoline price in 2008. Once the recession started in 2008, the fuel prices dropped a marked 25% to $2.6/gallon in 2009. Afterward, the prices started to increase again beginning in 2010, finally reaching a stable point in 2011 at $3.7/gallon. Fuel prices were included in the analysis to test the hypothesis that with increasing fuel costs travel demand declines, which means less exposure to crash risk resulting in a fewer number of fatalities.

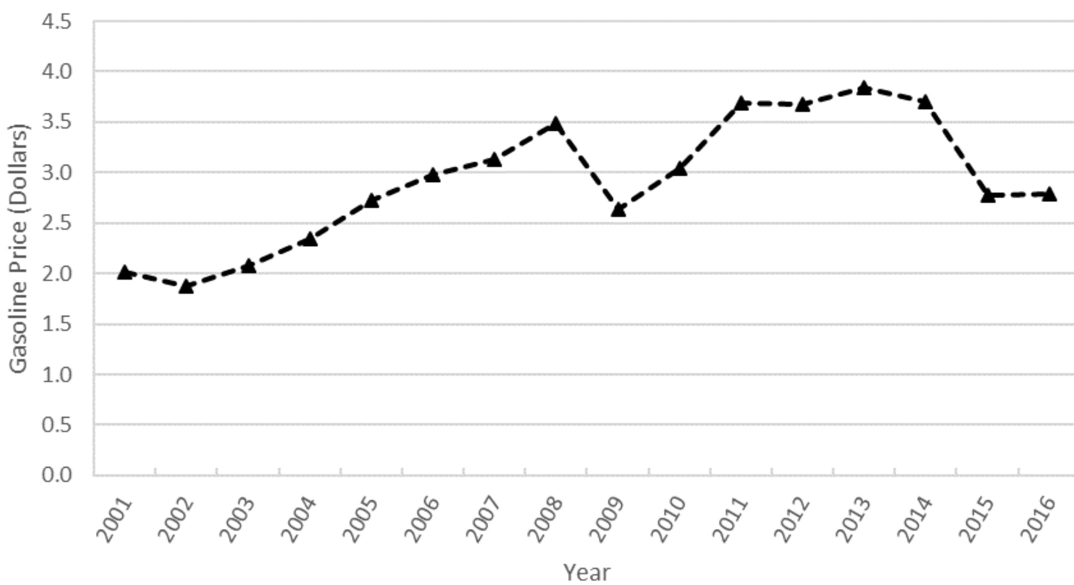


Figure 4.21 Fuel prices, constant 2013 dollars, 2001-2016

Government investment related to highway design, improvements, and safety issues is critical economic factor that might influence traffic fatalities. For this study, the data series on the government funding in terms of capital spending (includes funding for construction, relocation, resurfacing, rehabilitation, and reconstruction, capacity improvement etc.), maintenance and services (includes funding for preservation, preventative maintenance etc.), expenditures allocated to administration, research, and planning purposes, and finally, law enforcement and safety (includes expenditures by police, state safety agencies, safety improvement programs etc.). The annual state disbursements for highways under these categories of expenditures are available in the FHWA's Highway Statistics website. From Figure 4.22, it is clear that the capital expenditures accounted for the major share of the overall state expenditure in any given year, remaining unchanged from 2007 to 2008 during the beginning of the recession, otherwise showing a gradual increase over the entire period. The total state disbursements for maintenance and services showed an increasing trend prior to the recession, dropping slightly in 2008, then coming back up again starting from 2009. The funds allocated to administration, research, and planning was increasing moderately prior to the recession, even increased during 2008 surpassing the safety spending, decreasing gradually afterward from 2009. The expenditures allocated to law enforcement and safety increased very slightly from 2001 to 2016, not being affected by the recession. In this study, two separate data series related to the state expenditures were used, one of which contained the disbursements for capital, maintenance, services, administration, research and planning, and the other contained the disbursements for law enforcement and safety under the FHWA's SAFETEA-LU and MAP-21 programs, which were the surrogates of the safety effects of the built infrastructure and related safety programs.

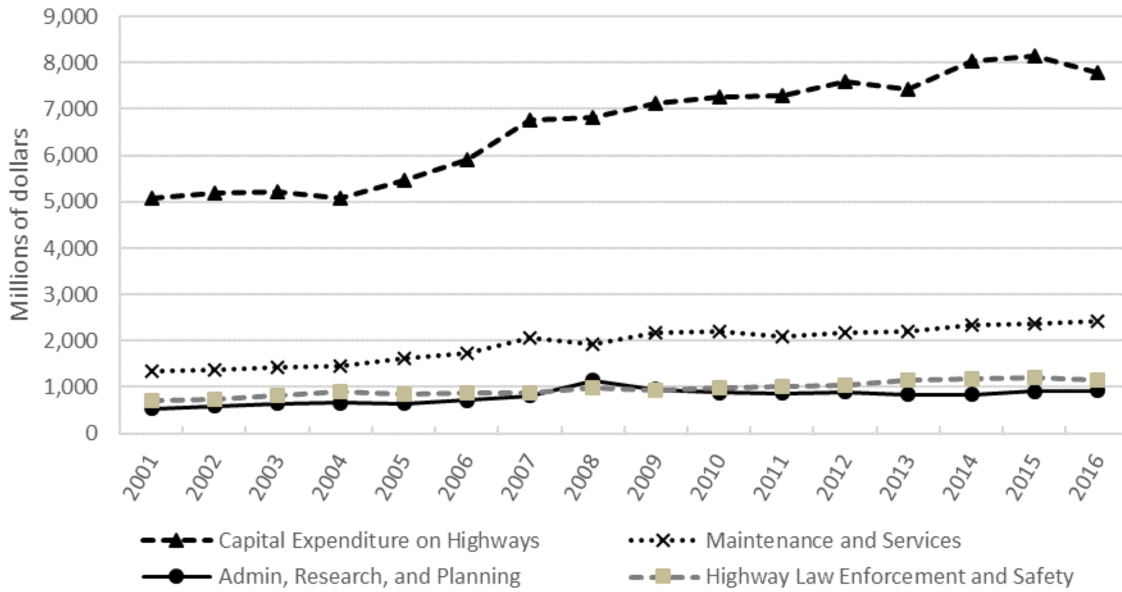


Figure 4.22 Highway expenditures for all states, 2001-2016

4.2 Trends Based on Land Use: Rural versus Urban

According to the American Community Survey from the U.S. Census Bureau, only an estimated 19 percent people lived in the rural areas in the year of 2016, still accounting for more than fifty percent of the traffic fatalities during that year (NCSA, 2018). According to the yearly statistics from the NHTSA, the crash-risk in rural areas have always been around 2.5 times higher than the crash-risk in urban areas over the years (Figure 4.23). Figure 4.23 depicts that the crash-risk in terms of fatality rates per 100 million miles traveled decreased 19% in rural areas and 17% in urban areas.

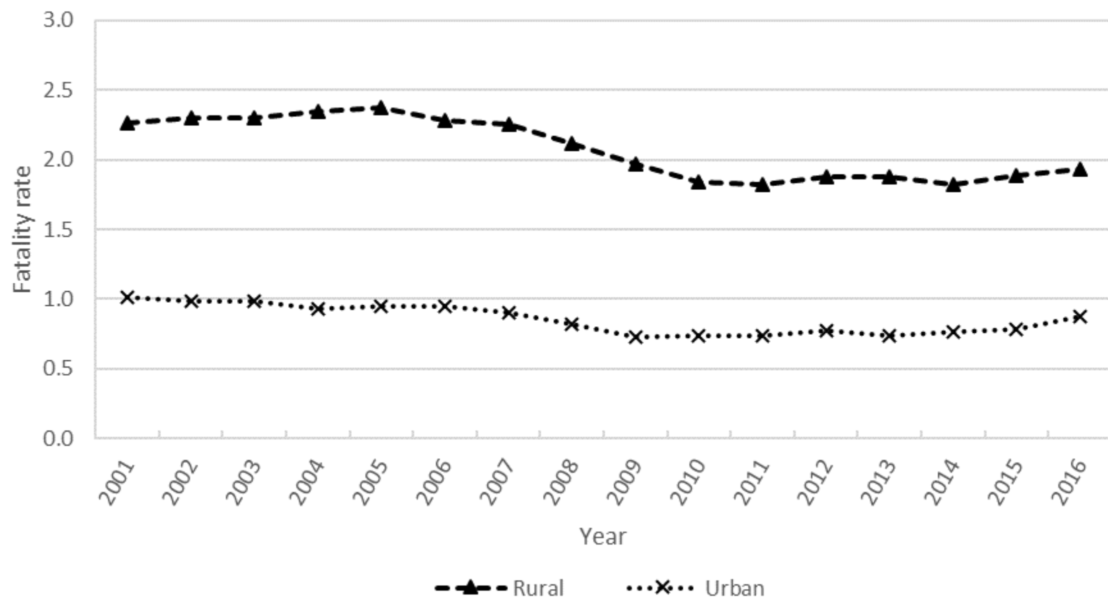


Figure 4.23 Rate of fatalities per 100 million miles traveled by land use, 2001-2016

Figure 4.24 presents a graphical illustration of the yearly change in fatalities by land use type by expressing the fatalities for each year normalized to the year 2001. The figure shows that fatalities were stable in both the rural and urban areas from 2001 to 2004, after which started to show a contrasting trend. In rural areas, fatalities started to drop from 2005, accelerated the decline during the period of recession, finally being stable between 2010 and 2014, after which it started increasing. In urban areas, the trend somewhat follows a similar pattern except for the prior recession period, when urban fatalities were, in fact, increasing between 2003 and 2006. Overall, rural fatalities dropped 20 percent from 23,524 to 18,590 in contrast to urban fatalities, which dropped only 1% from 17,908 to 17,656 from 2007 to 2011.

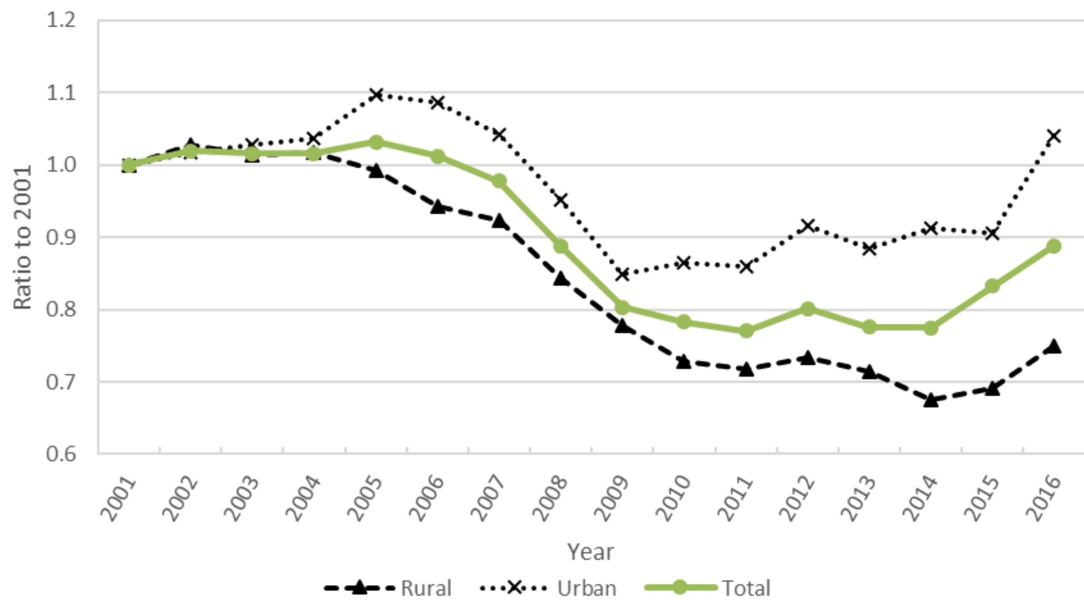


Figure 4.24 Ratio to 2001 of traffic fatalities in urban and rural areas, 2001-2016

To see the variable effects of the regulatory laws based on land use, the following figures are generated. In cases of the alcohol-impaired driving, rural fatalities decreased by 31%, from 7,346 to 5,093, in contrast to urban fatalities, which dropped only 13%, from 5,663 to 4,944 between 2007 and 2016 (Figure 4.25).

As discussed in Section 4.1.6 of this chapter, the percentage of drivers and occupants wearing seat-belts were gradually increasing over the years, whereas unrestrained driver and occupant fatalities were decreasing (Figure 4.26). This pattern is related to the increase in seat belt use among everyone within the population. It does not indicate that seat belt use was becoming ineffective in saving lives. In cases of fatalities related to restraint use, 49% unrestrained occupants were killed on rural areas, whereas

47% were killed on urban roads in 2016, whereas in 2001 these percentages differed by 45% with 55% in rural and 38% in urban.

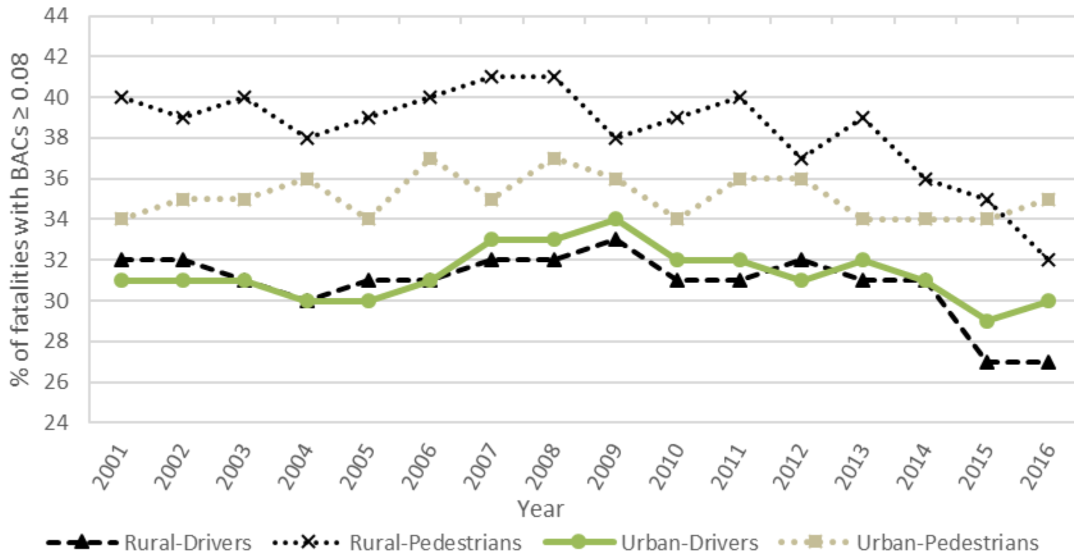


Figure 4.25 Percentages of fatally injured people with BACs ≥ 0.08% by land use type, 2001-2016

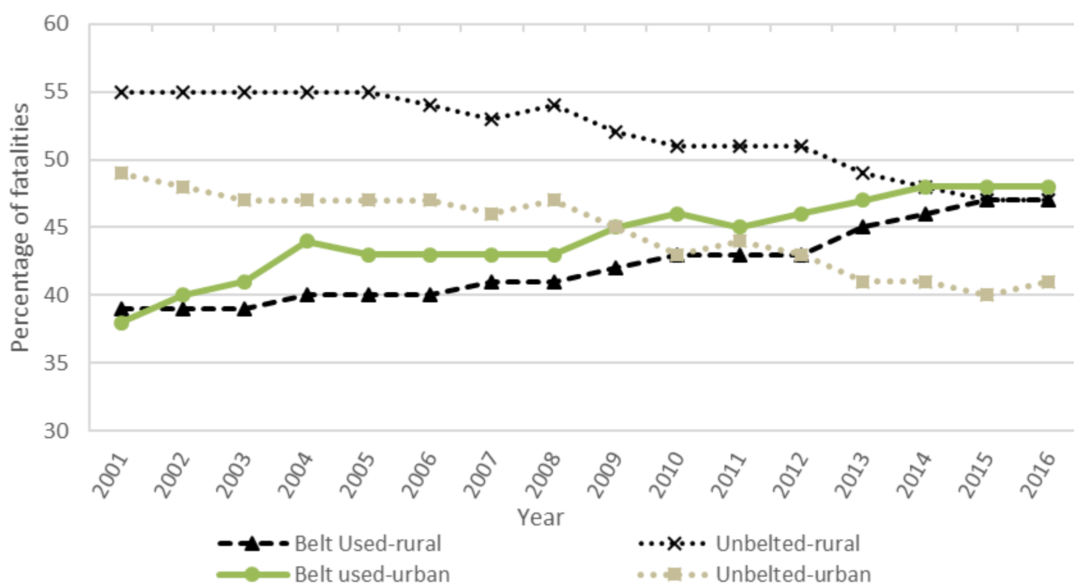


Figure 4.26 Percentages of fatally injured people based on safety belt use on rural and urban roads, 2001-2016

4.3 Chapter Summary

This section presents the results of the trend analysis of factors considered in the modeling documented in the chapter. The key points of this chapter are listed as follows:

- The purpose of this section was to identify the important trends in factors that affected fatalities between 2008 and 2011, again between 2012 and 2016.
- The areas considered were age, vehicle and person types, functional classification of roadways, vehicle design and model year, restraint use, motorcycle helmet use, DUI laws, and economic factors.
- National trends, as well as trends based on the land use in terms of fatalities in rural and urban areas, were discussed separately to understand the overall effect of factors nationally and by land use type.

The next chapter describes the methodology of the statistical modeling effort used for the analyses.

CHAPTER 5

MODELING AND ANALYSIS

This chapter documents the characteristics of the statistical modeling technique employed in this study to capture the effects of some critical factors impacting the number of traffic fatalities during the recession and afterward. As opposed to the efforts documented in the NCHRP 17-67, this study included more recent data up to 2016. Section 5.1 briefly reviews available methodologies that have been used in previous studies to investigate the relationship between the changes in fatalities and socio-economic variables. Section 5.2 discusses the theoretical background of statistical modeling approaches. Section 5.3 and Section 5.4 present the results of the factor analysis and statistical modeling, respectively. Finally, Section 5.5 concludes with a summary of the chapter.

5.1 Existing Modeling Techniques

The statistical techniques that have been historically employed to analyze the association of economic changes with a change in the number of fatalities can be broadly classified under the following three groups: i) time-series analysis ii) cross-sectional analysis and iii) panel studies (Wijnen and Rietveld, 2015; Elvik et al., 2015). The time series technique was exclusively chosen for the analysis of a single entity, such as a country or a region, over a longer span of time. There are multiple time series analysis techniques documented in the literature, some of which can be listed as ARIMA (autoregressive integrated moving average) studies, econometric studies, and stochastic studies (Wijnen and Rietveld, 2015).

The ARIMA models are specifically suited for predicting values based on a short-term trend, whereas the econometric and stochastic models are mostly employed to capture a long-term trend of the dataset. These time series analyses are generally conducted on univariate time series data and can be used for future forecasting. If the ARIMA models are used with multiple time series inputs and added transfer function for modeling and forecasting, the procedure is called the ARIMAX, details of which can be found in Box et al. (2008).

The cross-section techniques are suited for analyzing the effects of multiple variables, such as the economic, demographic, environmental, and traffic for multiple entities (countries or regions), on road safety at a single point in time. This type of procedure has the advantage of employing multiple input variables, which allows for a more comprehensive effect of the independent variables on forecasting. However, these types of techniques cannot be used for capturing the trends over time.

The panel studies take into consideration a combination of the time series and the cross-section analyses for investigating the response trend for several entities over a longer period. In this study, the problem statement addresses fifty states over a given period. Mostly, the investigation is based upon finding the critical factors causing a drastic reduction in traffic fatalities during the recession of 2008 to 2011, and the subsequent increase afterward from 2012 to 2016. Hence, the most appropriate modeling technique well-suited to the issue is the panel study where both long-term and short-term trends are investigated, and both their effects are accounted for within the modeling assumptions.

5.2 Modeling Methodology

Some statistical models as proposed by multiple studies have already been discussed in detail in Chapter 2. This study considers two types of modeling approaches as proposed by the researchers of the NCHRP 17-67 (Blower et al., 2019): one is a Poisson-gamma count model, which can also be referred to as a negative binomial (NB) model, and the other one is a log-change regression model. These techniques were 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:

$$Y_{it} \mid \theta_{it} \sim Po(\theta_{it}) \text{ for } i = 1, 2, \ldots, \text{N and } t = 1, 2, \ldots, \text{T} \tag{11}$$

$$\text{Where, } \theta_{it} = \mu_{it} \exp(\varepsilon_{it}) \tag{12}$$

Here,

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: $\mu_{it} = \exp(\beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots. + \beta_k X_{kit}$ where k is the total number of covariates);

β = vector of unknown coefficients; and

ε_{it} = model residuals.

According to the Equation (11), 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/ϕ for all *i*'s and *t*'s (here, ϕ is called the inversed dispersion parameter, which is assumed to be greater than 0). The reason behind using an 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).

On the other hand, the log-change model considers the yearly change of covariates and considers a generalized regression model between the change of fatalities and the changes of each covariate. The dataset for the analysis is prepared to represent the percent change of each predictor, as well as the percent change of fatalities. Transforming the raw counts of fatalities and other variables like this removes the state fixed effect that might play a significant role in delineating the inferences associated with the factors (Blower et al., 2019). Here, the factors can influence either the risk or the exposure or both. Before the statistical modeling was conducted, an exploratory data analysis (as discussed in Chapter 4) and a factor analysis were undertaken to see the effects of the variables influencing the trend of fatalities during and after the Great Recession and to examine the existing correlation among variables.

5.3 Factor Analysis

The factor analysis is a technique that helps to make inferences easier on statistical results (Cattell, 1966). The identification of correlations between variables helps reduce the number of parameters to include in the model so that it does not confound the interpretation of the inferences. An existing correlation between two or multiple variables is one of the major issues in dealing with panel datasets and needs to be addressed properly. For example, the researchers of the NCHRP 17-67 found that the population and VMT are closely correlated to each other with a correlation coefficient of r=0.98 (Blower et al., 2019). Here, between these two highly correlated variables, either VMT or population can be included in the model to make the associated effect with the exposure interpretable. It is to be noted here that r=1.0 or -1.0 indicates a maximum positive or negative linear correlation, whereas r close to zero indicates no linear correlation existing between the variables (Montgomery and Runger, 2003).

Based on the findings of a series of factor analyses by the researchers of the NCHRP 17-67, the predictors that were chosen for the analysis are listed in Table 5.1 (Blower et al. 2019). In their analysis, the researchers chose seven categories of variables and the variable(s) that best represented these categories were chosen, whereas the rest of the correlated parameters were excluded from the analysis.

According to Table 5.1, the total VMT was chosen as the representative variable of the overall size of each state. The proportions of rural VMT were chosen to represent the risk associated with the 'ruralness'. The economic conditions were chosen to be represented by the GDP per capita, median household income, and unemployment of 16 to 24-year age group. The rate of belt use, laws associated with belt use and motorcycle helmet wear, and the penetration of the post-1991 model year were chosen for representing the effects of the safety measures dedicated to occupant-protection. The capital and safety expenditures were chosen under the state expenditure variable group, and beer consumption and DUI laws were chosen under ‘alcoholism’. Finally, the penetration of the post-1991 model year was chosen under the ‘other’ variable group.

Table 5.1 Variables selected through factor analysis*

Variable group	Representative variable(s)	Correlated predictors**
Size of state	Total VMT	Population, GDP, and every other predictor
Ruralness	Rural VMT proportion	Total VMT, capital & safety expenditures, median household income, beer consumption per capita
Economy	GDP/capita, Median household income, Unemployment 16 to 24	Rural VMT proportion, capital & safety expenditures
Occupant Protection	Belt use, belt laws, motorcycle helmet laws, post-1991 model year penetration	Unemployment 16 to 24, pump price
State Highway Expenditures	Capital expenditures, safety expenditures	Rural VMT proportion, GDP/capita, median household income
Alcohol	Beer consumption per capita, DUI laws	Rural VMT proportion
Other	Pump price	Post-1991 model year

*Blower, D., C. Flannagan, S. Geedipally, D. Lord, and R. Wunderlich. Identification of factors contributing to the decline of traffic fatalities in the United States from 2008 to 2012. Final Report NCHRP Project 17-67. Transportation Research Board, Washington, D.C., 2019.Reprinted with permission from the National Academy of Sciences, Courtesy of the National Academies Press, Washington, D.C.
**correlation coefficients > ±0.3

The next step was to find the correlation between some of the variables, especially those related to the economy with the exposure term, VMT. This step was necessary to identify the predictors for the regression models of VMT to examine the effects of variables that were more related to the exposure than to risk in the fatality prediction models. The results of the correlation analysis between total, urban, and rural VMT and other economic variables are presented in Table 5.2

Table 5.2 Results of correlation analysis between VMT and other variables.

	Total population	**Unemployment of age 16-24**	**Unemployment of age 25+**	**Pump price**	**GDP per cap**	**Median income**
Total VMT	0.15	0.005	0.92	0.008	-0.014	-0.010
Urban VMT	0.18	0.004	0.654	0.018	-0.007	0.004
Rural VMT	0.092	0.0092	0.624	-0.012	-0.027	-0.036

According to the table, total VMT is most strongly correlated with the percentage of unemployment of age 25 and over, which is not consistent with the findings of the NCHRP 17-67 report (Blower et al., 2019). In fact, for both the urban and rural VMTs, the unemployment rate of the 25-year age-group was found to be the most strongly correlated variable, whereas the other age-group showed an almost nonexistent correlation with all VMTs. In the NCHRP report, the variable 'population' showed the strongest correlation with the total, urban, and rural VMTs. Here, with the updated dataset the correlation coefficients between the total, urban, and rural VMTs and the population (r=0.15, 0.18, 0.092) are much smaller than the ones found previously (r=0.98, 0.98, 0.81). The coefficients associated with the median income were consistent with the NCHRP 17-67 report. The rural VMT showed an insignificant negative correlation with the pump price, GDP, and median income. All other positive or negative correlations found in the results were insignificant and thus are not discussed in detail.

Based on the findings of the factor analysis, separate linear regression models were developed for the total, rural, and urban VMTs, and the results are presented below. Table 5.3 shows the parameter estimates of the total VMT model. To develop these models, a sequential regression approach was adopted, in which statistically non-significant variables at 10% level (α=0.1) were dropped from the model one by one to find the most significant predictors (backward regression). From the table, it is clear that the total population and the unemployment rate of 25-year age-group are the only variables sufficient to predict the total VMT that were also significant at the 15% level. The model fitness showed that the current model can explain 97% of the variability in the total VMT with the two selected predictors.

Table 5.3 Parameter estimates for the linear regression model on Total VMT

Variable	Estimate	Standard error	P-value
Intercept	4163.67	1099.56	0.0002
Total Population	0.0088	0.00006	<0.0001
Unemployment rate of age 25 and above	313.64	216.34	0.15
R^2 statistic	0.97		

Table 5.4 and Table 5.5 show the parameter estimates of the regression models of the urban and rural VMTs, respectively. The same predictors as the total VMT model were also found significant for the urban VMT model (considering α= 0.05), however,

for the rural VMT model, four variables, the total population, pump price, GDP per capita, and the median income, were found to be statistically highly significant at the 5% level. The negative coefficients for the pump price, GDP per capita, and median income do not mean that the states with economic constraints were traveling more on rural roads. Rather, it indicates that the states that were largely affected by the recession were likely to be more rural. Both the urban and rural VMT models had the same R-square value (0.64), which indicates a moderate fit for the dataset.

Table 5.4 Parameter estimates for the linear regression model on Urban VMT

Variable	Estimate	Standard error	P-value
Intercept	7242.56	924.87	<0.0001
Total Population	0.0018	4.87e-5	<0.0001
Unemployment rate of age 25 and above	425.07	181.97	0.0197
R^2 statistic	0.64		

Table 5.5 Parameter estimates for the linear regression model on Rural VMT

Variable	Estimate	Standard error	P-value
Intercept	50429.55	2165.56	<0.0001
Total Population	0.00186	0.00004	<0.0001
Pump price	-3930.96	431.08	<0.0001
GDP per capita	-1180.83	335.48	0.0005
Median income	-4281.21	438.52	<0.0001
R^2 statistic	0.64		

Figure 5.1, Figure 5.2, and Figure 5.3 present the graphical illustrations of the predicted versus the observed total, urban, and rural VMTs, respectively. From these

figures, it is seen that the regression models developed for the total and urban VMTs could almost perfectly predict the observed VMTs in the dataset (Figure 5.1 and Figure 5.2), whereas the rural VMT shows only reasonable goodness of fit (Figure 5.3).

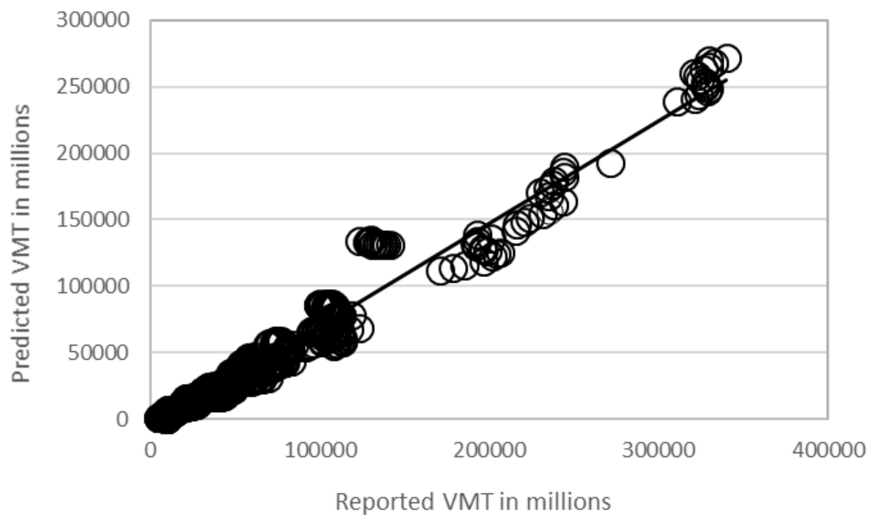


Figure 5.1 Predicted total VMT versus reported total VMT, 2001-2016

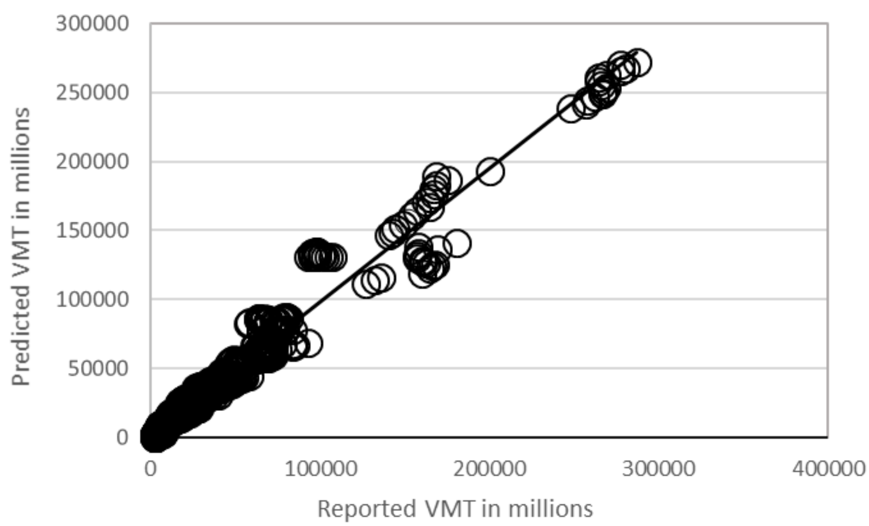


Figure 5.2 Predicted urban VMT versus reported urban VMT, 2001-2016

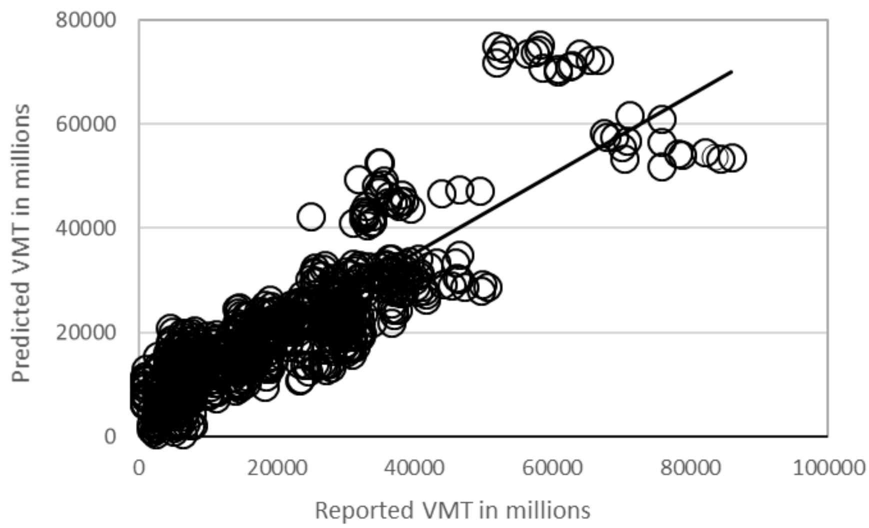


Figure 5.3 Predicted rural VMT versus reported rural VMT, 2001-2016

5.4 Statistical Modeling

This section presents the results of the statistical modeling effort employed to examine the effects of different variables in predicting the drastic decline and subsequent increase in fatalities on the U.S. highways during and after the Great Recession. As discussed in Section 5.2, two modeling approaches were employed in the statistical modeling of fatalities: one is the Poisson-gamma approach (also called the NB approach) and the other is the log-change linear model. According to the exploratory data analysis presented in Chapter 4, there were two different trends in action in relation to the variables chosen to be considered in the model. One of these is the spatial effects across different states, which are related to the size of the state, its population, environment, socio-economic, and traffic safety conditions, another one is the temporal effects from year to year (Blower et al. 2019).

In order to address these trends separately, the researchers of the NCHRP 17-67 proposed two different NB models, considering or not considering the effect of the states. The model considering the varying effect of the states allows variations to be captured in the effects of all variables and thus focusing more on the spatial trend of the dataset. The model not considering the varying effect of the states (called the 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. According to the NCHRP 17-67 report, considering two types of NB modeling is informative in deciphering the true effects of the variables (Blower et al., 2019). For example, if any variable shows similar trends in both of these 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).

Hence, to summarize the above discussion, two different NB models were developed: 1) models controlling for states (MCS), and 2) model not controlling for states (MNCS). To further expand the span of the analyses, two types of MCS models were developed: a) the MCS with VMT as exposure, and b) the MCS with Population as exposure. Apart from these NB models, one log-change model was developed to capture the yearly change, going beyond the constraints of states and/or any fixed (base-level) or long-term trend of any variable in the dataset. The functional forms of these models are presented below:

MNCS model $$\mu = VMT \times e^{\beta_0 + \sum_i (\beta_i x_i)} \quad (13)$$

MCS model with VMT as exposure $$\mu = VMT \times e^{(\beta_0 + \gamma_s) + \sum_i (\beta_i x_i)} \quad (14)$$

MCS model with Population as exposure $$\mu = Population \times e^{(\beta_0 + \gamma_s) + \sum_i (\beta_i x_i)} \quad (15)$$

Log-change model
$$\ln(Fat_t) - \ln(Fat_{t-1}) = \beta_0 + \sum_{j=1}^{k} \beta_j z_t = \beta_0 + \sum_{j=1}^{k} \beta_j (\ln(x_t) - \ln(x_{t-1})) \quad (16)$$
$$z_t = \frac{x_t}{x_{t-1}}$$

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 variables considered in the modeling containing data from each state from 2001 to 2016 are listed below (the list is compiled from the NCHRP 17-67 report (Blower et al., 2019), page 53):

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

The models were assessed based on their goodness of fit under three criteria: 1) Akaike information criteria (AIC), 2) Mean absolute deviation (MAD), and 3) Mean squared prediction error (MSPE). The general characteristics of the modeling results are presented in this section, which includes parameter estimates, standard error of the coefficients, associated *p*-values, and exponentiated terms of the estimates. 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 that the coefficient is statistically significantly greater than zero, hence statistically not significant.

Table 5.6 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 5.7 presents the modeling results from the MCS model with the VMT as exposure. The statistically significant variables (at α=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 5.8 presents the modeling results from the MCS model with the population as exposure. The first three variables, the rural VMT proportion, capital spending, safety spending that were found to be statistically not significant in the VMT model, are also not significant in the population model, alongside motorcycle helmet rating. The statistically significant variables for this model are GDP per capita, percent unemployment for ages 16 to 24, pump price, beer consumption, DUI rating, belt rating, median income, and the post-1991 model year.

Table 5.9 presents the results of the log-change model. In this model, only five variables were statistically significant at the 10% level, which are the proportion of rural VMT, percent unemployment for age 16 to 24, beer consumption, DUI rating, and the penetration of the post-1991 model year. It is to be noted here that for the log-change model, a separate dataset was prepared with the percent changes of variables from its previous years. Hence, in order to properly interpret the results of the log-change model, the effects of the parameters on changes of fatalities have to the examined separately, which is discussed in the next chapter.

Table 5.6 Parameter estimates for the MNCS model, VMT offset

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 5.7 Parameter estimates for the MCS model with VMT as exposure

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-4.1587	0.2059	<.0001	-
Rural VMT proportion	0.1502	0.1127	0.1826	1.162
Capital spending (in $1000)	0.0002	0.0001	0.1159	1.000
Safety spending (in $1000)	0.0011	0.0008	0.1657	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	0.2536	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			

Underlined values denote p-values > 0.1 (corresponding to statistically non-significant variables)

*Smaller values are preferred

Table 5.8 Parameter estimates for the MCS model with population as exposure

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-2.2896	0.2242	<.0001	-
Rural VMT proportion	0.1205	0.1183	0.3088	1.128
Capital spending (in $1000)	0.0002	0.0002	0.1632	1.000
Safety spending (in $1000)	0.0012	0.0009	0.1799	1.001
GDP per capita (in $10,000)	0.0838	0.0101	<.0001	1.087
Unemployment for age 16 to 24 (%)	-0.0131	0.0012	<.0001	0.987
Pump price ($ per gallon)	-0.0421	0.0084	<.0001	0.959
Beer (gallons)	0.5814	0.0602	<.0001	1.789
DUI rating	-0.0155	0.0026	<.0001	0.985
Belt rating	-0.0246	0.0069	0.0004	0.976
Motorcycle Helmet rating	-0.0203	0.0161	0.2068	0.980
Median Income (in $10,000)	-0.0284	0.0143	0.047	0.972
Post-1991 model year	-0.0049	0.0016	0.0016	0.995
Dispersion parameter	0.0044	0.0003	-	-
AIC*	8399.16			
MAD*	516.56			
MSPE*	1168243.50			

Underlined values denote p-values > 0.1 (corresponding to statistically non-significant variables)

*Smaller values are preferred

Table 5.9 Parameter estimates for change model

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-0.01061	0.005327	0.0468	-
Change in Total VMT	0.00458	0.010553	0.6644	1.005
Change in Proportion of Rural VMT	0.04064	0.019832	0.0408	1.042
Change in GDP per capita	0.05531	0.051426	0.2825	1.057
Change in Median Income	0.10103	0.088286	0.2529	1.106
Change in Unemployment for age 16 to 24	-0.13483	0.019706	<0.0001	0.874
Change in Pump price	0.02622	0.026485	0.3225	1.027
Change in capital spending	-0.00380	0.020217	0.8511	0.996
Change in safety spending	0.00392	0.013501	0.7716	1.004
Change in Beer consumption	0.45395	0.11921	0.0002	1.575
Change in DUI rating	-0.22095	0.096453	0.0023	0.802
Change in Belt rating	-0.05829	0.039201	0.1375	0.943
Change in Motorcycle Helmet rating	-0.02017	0.106330	0.8496	0.980
Change in penetration of Post-1991 vehicles	0.52938	0.295585	0.0737	1.698
R-square*	0.11604			
Adjusted R-square*	0.10008			

Underlined values denote p-values > 0.1 (corresponding to statistically non-significant variables)

*Greater values are preferred (max 1.0)

Based on the goodness of fit values, the MCS model with VMT as exposure provides the best fit in terms of the lowest AIC and MAD values (Table 5.7). The MCS model with population provides a very close fit to the other MCS model, and even a better one in terms of lowest MSPE value. However, in highway safety, the VMT is always considered to be a better measure of exposure than the population, and its estimation is unbiased. On the other hand, the log-change model does not provide a good fit to the dataset (R-square= 0.117). Hence, for further analysis (rural versus urban comparison), only the MNCS model and the MCS model with VMT as exposure are considered.

In order to model the fatalities based on land use, the dataset was restructured to incorporate the number of fatalities and VMTs on urban and rural roads. Additionally, the variable representing the rural VMT proportion, being redundant, was dropped from the model. Other variables were kept unchanged as those data series could not be disaggregated in terms of rural versus urban due to unavailability of land use information. Although this assumption might have a substantial and a consequential effect to the prediction of rural and urban fatalities, under the current circumstances of data unavailability, this can still be considered a reasonable assumption.

Table 5.10 and Table 5.11 represent the results of the MNCS and the MCS models for rural fatalities. In the MNCS model, the variables that were found to be statistically significant at 10% level include capital spending, GDP per capita, unemployment for age 25 and over, beer consumption, median income, and the post-1991. In the MCS model, all but three variables, including capital spending, GDP per capita, unemployment for age 16 to 24, unemployment for age 25 and over, beer consumption, DUI rating, motorcycle helmet rating, median income, and the post-1991 model year, are statistically significant at 10% level. The MCS model provides the lowest AIC value, whereas the MNCS model holds the lower MAD and MSPE values.

Table 5.12 and Table 5.13 represent the results of the MNCS and the MCS models for urban fatalities. Here, unlike the results of the models for rural fatalities, the MNCS model for urban fatalities had only two statistically not significant variables, which were DUI rating and belt rating. On the other hand, for the MCS model on urban fatalities, all variables were found to be statistically insignificant except for beer consumption, pump price, and GDP per capita. In terms of the goodness of fit values, the models for the urban fatalities provided results similar to the models for the rural fatalities.

Table 5.10 Parameter estimates for the MNCS model for Rural Fatalities with VMT as offset

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-1.6883	0.3078	<.0001	-
Capital spending (in $1000)	0.0008	0.0003	0.0055	1.001
Safety spending (in $1000)	0.0021	0.0015	<u>0.1466</u>	1.002
GDP per capita (in $10,000)	0.0256	0.0122	0.0362	1.026
Unemployment for age 16 to 24 (%)	0.0049	0.0036	<u>0.1697</u>	1.005
Unemployment for age 25 and over (%)	-0.0247	0.0070	0.0004	0.976
Pump price ($ per gallon)	-0.0319	0.0215	<u>0.1375</u>	0.969
Beer (gallons)	0.0883	0.0456	0.0527	1.092
DUI rating	-0.0014	0.0030	<u>0.6486</u>	0.999
Belt rating	-0.0002	0.0078	<u>0.9807</u>	1.000
Motorcycle Helmet rating	-0.0130	0.0083	<u>0.1170</u>	0.987
Median Income (in $10,000)	-0.1949	0.0157	<.0001	0.823
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	-0.0136	0.0034	<.0001	0.986
Dispersion parameter	0.0526	0.0030	-	-
AIC*	9036.69			
MAD*	256.53			
MSPE*	273299.57			

Underlined values denote p-values > 0.1 (corresponding to statistically non-significant variables)

*Smaller values are preferred

Table 5.11 Parameter estimates for the MCS model for Rural Fatalities with VMT as exposure

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-3.7635	0.3088	<.0001	-
Capital spending (in $1000)	0.0008	0.0003	0.0072	1.001
Safety spending (in $1000)	0.0015	0.0017	<u>0.3561</u>	1.002
GDP per capita (in $10,000)	0.0396	0.0166	0.0168	1.040
Unemployment for age 16 to 24 (%)	-0.0051	0.0031	0.0967	0.995
Unemployment for age 25 and over (%)	-0.0108	0.0058	0.0650	0.989
Pump price ($ per gallon)	-0.0076	0.0153	<u>0.6221</u>	0.992
Beer (gallons)	0.5983	0.1041	<.0001	1.819
DUI rating	-0.0242	0.0049	<.0001	0.976
Belt rating	-0.0154	0.0122	<u>0.2075</u>	0.985
Motorcycle Helmet rating	-0.0587	0.0298	0.0489	0.943
Median Income (in $10,000)	-0.0522	0.0255	0.0406	0.949
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	-0.0047	0.0026	0.0739	0.995
Dispersion parameter	0.0176	0.0012	-	-
AIC*	8427.82			
MAD*	275.62			
MSPE*	317580.82			

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

Table 5.12 Parameter estimates for the MNCS model for Urban Fatalities with VMT as offset

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-3.6017	0.4217	<.0001	-
Capital spending (in $1000)	0.0022	0.0004	<.0001	1.002
Safety spending (in $1000)	-0.005	0.002	0.0108	0.995
GDP per capita (in $10,000)	0.0811	0.0174	<.0001	1.084
Unemployment for age 16 to 24 (%)	0.0111	0.005	0.026	1.011
Unemployment for age 25 and over (%)	-0.049	0.0096	<.0001	0.952
Pump price ($ per gallon)	-0.0719	0.0291	0.0135	0.931
Beer (gallons)	0.1488	0.0625	0.0172	1.160
DUI rating	0.0049	0.004	0.2265	1.005
Belt rating	-0.0078	0.0105	0.4577	0.992
Motorcycle Helmet rating	0.0346	0.0111	0.0019	1.035
Median Income (in $10,000)	-0.1693	0.0216	<.0001	0.844
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	-0.0094	0.0046	0.0408	0.991
Dispersion parameter	0.0984	0.0058	-	-
AIC*	8726.57			
MAD*	262.14			
MSPE*	255430.4			

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

Table 5.13 Parameter estimates for the MCS model for Urban Fatalities with VMT as exposure

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	-5.2995	0.473	<.0001	-
Capital spending (in $1000)	0.0000	0.0004	0.9439	1.000
Safety spending (in $1000)	-0.0006	0.0022	0.7733	0.999
GDP per capita (in $10,000)	0.0833	0.0266	0.0017	1.087
Unemployment for age 16 to 24 (%)	-0.0056	0.0044	0.2108	0.994
Unemployment for age 25 and over (%)	-0.0123	0.0084	0.1437	0.988
Pump price ($ per gallon)	-0.0457	0.0223	0.0401	0.955
Beer (gallons)	0.3098	0.1589	0.0512	1.363
DUI rating	0.0060	0.0069	0.3804	1.006
Belt rating	0.0000	0.0175	0.9995	1.000
Motorcycle Helmet rating	-0.0058	0.0448	0.8968	0.994
Median Income (in $10,000)	0.0322	0.0375	0.3904	1.033
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	-0.0050	0.0039	0.2048	0.995
Dispersion parameter	0.0377	0.0026	-	-
AIC*	8427.82			
MAD*	272.95			
MSPE*	289040.29			

Underlined values denote p-values > 0.1 (corresponding to statistically non-significant variables)

*Smaller values are preferred

5.5 Chapter Summary

This chapter discusses the statistical modeling techniques used in this study. The key points of this chapter are listed below:

- Two separate trends were observed in the dataset, relating to the spatial distribution (states) and temporal distribution (years) of the data. Hence, separate modeling approaches were needed to address the differences in these trends.
- For modeling purposes, two Poisson-gamma (also known as negative binomial or NB) regression models considering or not considering the varying effects of states were developed.
- The models considering a state-fixed effect were called the models not controlling for states or MNCS and the models allowing for varying effects of the states on each variable are called the models controlling for states or MCS. Further, two MCS models were developed considering either of the VMT or population as exposure.
- Apart from these NB models, a log-change model was developed to account for the yearly change of variables to capture their short-term effect.
- Based on the goodness of fit, the MCS model with VMT as exposure provided better results compared to other models. In terms of rural and urban fatalities, both models produced similar goodness of fit values, although the statistically significant variables were different for the two models.

The next chapter provides a detailed discussion of the findings of the modeling results.

CHAPTER 6

RESULTS AND DISCUSSIONS

The previous chapter described the methodology of modeling employed to investigate the influence of different variables in the reduction and subsequent increase in traffic fatalities from 2007 to 2016. Some general characteristics of the results, such as the parameter estimates, standard error, and statistical significance in terms of *p*-values are presented in Chapter 5. This chapter presents a detailed discussion on the results of the statistical modeling to draw reasonable inferences on the findings of the study.

6.1 Model Comparisons

As stated in Chapter 1, the first objective of this study was to recalibrate the statistical models introduced in the NCHRP Project 17-67 (Blower et al., 2019) with an updated dataset. The researchers of the NCHRP 17-67 developed a panel dataset containing information from all 50 states of the U.S. to investigate the radical decline in fatalities from 2005 to 2012. This study goes beyond the scope of the NCHRP project by incorporating data up to 2016 and also investigating the increase in the number of fatalities in the subsequent years after the recession. This section focuses on comparing the quality of the models developed in Chapter 5 based on their goodness of fit values and prediction performances with the results from the previous dataset, as well as the observed fatalities on the U.S. highways between 2001 and 2016. A comparison of the models predicting rural fatalities in contrast to urban is also conducted using both descriptive and inferential statistics.

6.1.1 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 with VMT 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 11,22,646 and 11,71,622 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 to be noted 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. 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 in reality, 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 of the models, graphical representations of the predicted and observed values for each model are presented in Figure 6.1-6.3. The predictions by the MNCS model provide a poor fit to the observed fatality values over the entire period of analysis (Figure 6.1).

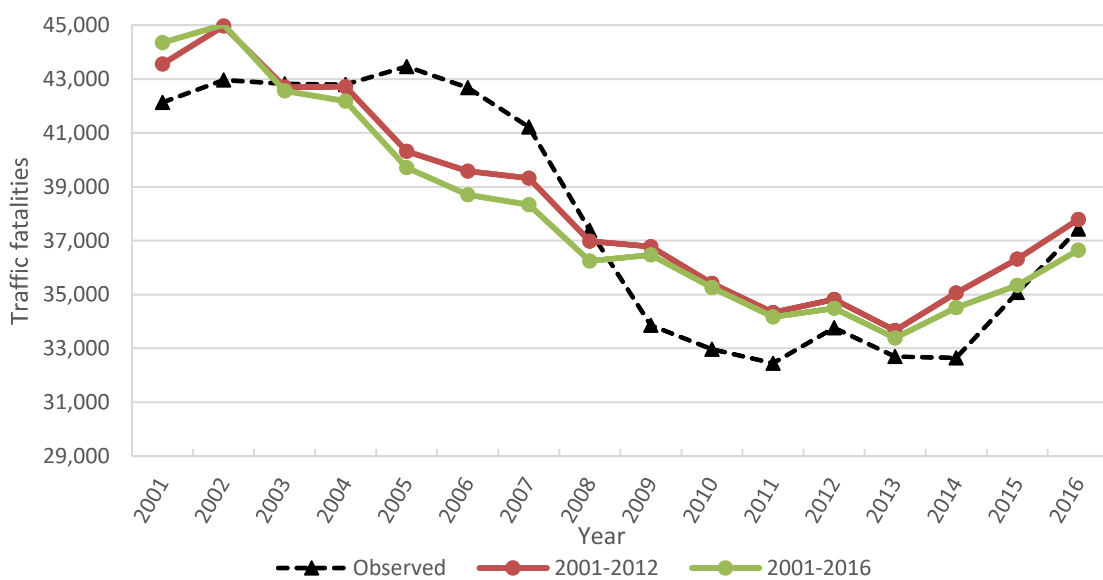


Figure 6.1 Comparison of predicted fatalities for MNCS model, 2001-2016

The MCS models do not fit well to the earlier years of the data from 2001 to 2006, however, starting from 2007, both models capture the fatality trend very well (Figure 6.2 and Figure 6.3). In fact, the MCS model considering VMT as exposure 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.

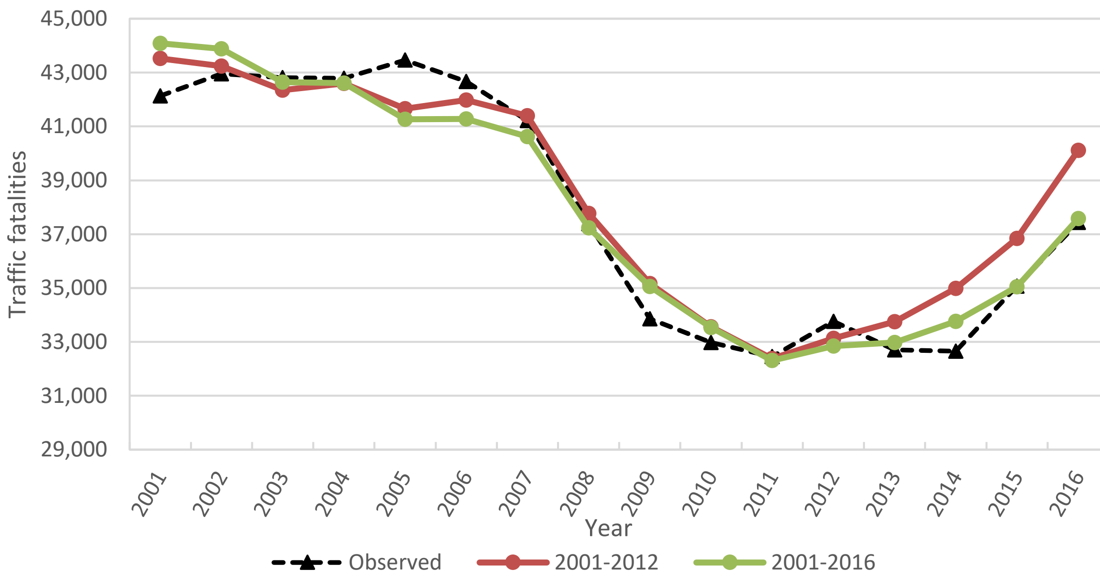


Figure 6.2 Comparison of predicted fatalities for the MCS model with VMT as exposure, 2001-2016

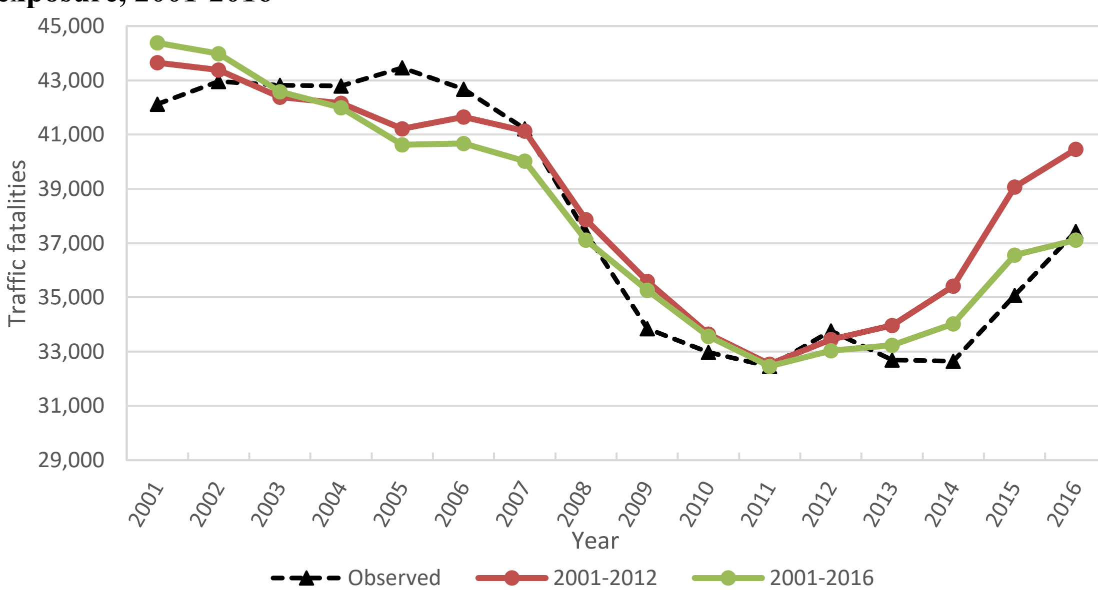


Figure 6.3 Comparison of predicted fatalities for the MCS model with Population as exposure, 2001-2016

It is to be noted here that the MCS model with population failed to predict the constant rise in the number of fatalities from 2014 to 2016. Also, the predictions by the population model from 2005 to 2007 deviated largely from the observed values, as compared to the VMT model. Hence, the MCS model considering population as exposure is discarded from further discussion from here on, as the other MCS model possesses a better estimation of exposure (i.e., VMT) and also a better fit over the observed fatalities. The other MCS model with VMT as exposure will thereafter be referred to as the 'MCS' model. Moreover, the log-change model is also discarded from the discussion as it failed to provide a reasonable fit to the data, generating a very low R-square of 0.117. The next section describes the prediction performance by the MNCS and MCS model to estimate the total fatalities and fatalities by land use.

6.1.2 Prediction of total fatalities

The predicted fatalities by the MNCS and MCS models are plotted against the observed number of fatalities in Figure 6.4 and 6.5, respectively. It shows that the MCS model predicts the total fatalities very closely throughout the entire analysis period from 2001 to 2016 (Figure 6.4). 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 6.5). Although the MNCS model could capture the trend of fatalities over the years, it failed to reflect all the variations in fatalities. The model underpredicted the fatalities prior to the recession and overpredicted 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 6.5). However, this model is still valuable in interpreting national trend of some predictors, which are transient in any local (state) effect.

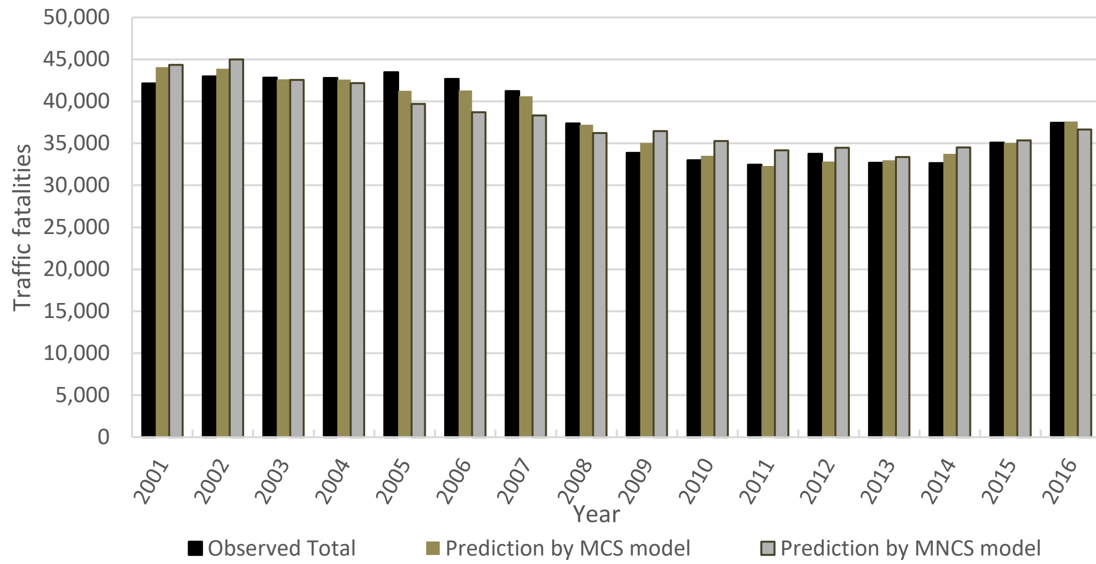


Figure 6.4 Observed versus predicted total fatalities by the MNCS and MCS model, 2001-2016

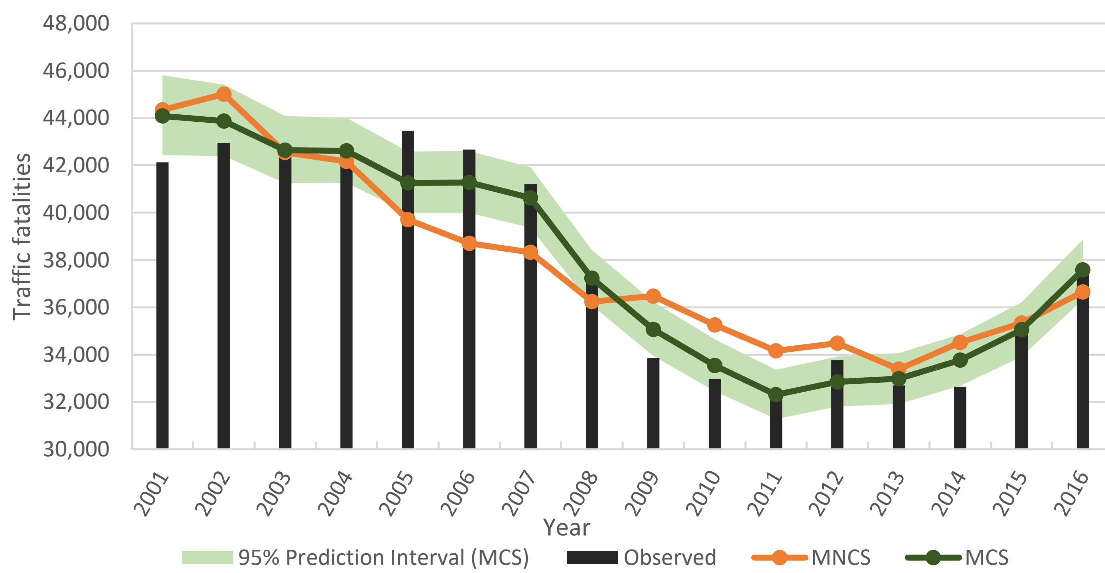


Figure 6.5 Comparison of predicted fatalities for MNCS and MCS model with observed fatalities on all U.S. highways, 2001-2016

6.1.3 Prediction of rural and urban fatalities

Figure 6.6 and Figure 6.7 present the predictions of fatalities by the MNCS and MCS models in contrast to the observed fatalities on rural and urban roads. The MCS model for rural roads used rural VMT as the exposure variable, whereas the urban model used urban VMT. All other variables remained unchanged from the total fatality model, which is a consequential assumption on the prediction models. However, other data series could not be disintegrated in terms of land use due to data unavailability.

Based on the prediction performance, the MCS model provides better estimations of both rural and urban fatalities as opposed to the MNCS model (Figure 6.8). In fact, in the case of rural fatalities, the MCS model could successfully capture all the variations in the trend with minor deviations. The MNCS model underpredicted the fatalities in the prior recession period and overestimated afterward, which is a similar pattern also seen in the MNCS model for the total fatalities.

The trend of the observed fatalities on urban roads showed frequent fluctuations over the period of analysis (Figure 6.9. In this case, none of the models could reflect the trend in fatalities perfectly. However, the predictions by the MCS model were considerable as these only fluctuated from the observed fatalities within a narrow band. The repeated fluctuations of urban fatalities can potentially be explained by factors such as the development of infrastructure, enforcement of occupant protection devices (e.g., safety belt, helmet, child seat), monitoring of DUI cases, change in traffic volume, control system, and others. These factors, often largely associated with crash risk, change rapidly in urban areas. Also, the effects of the economic downturn are more profound on the urban population, resulting in a recurring shift in travel pattern on urban roads responding to the seasonal fluctuation of the economy.

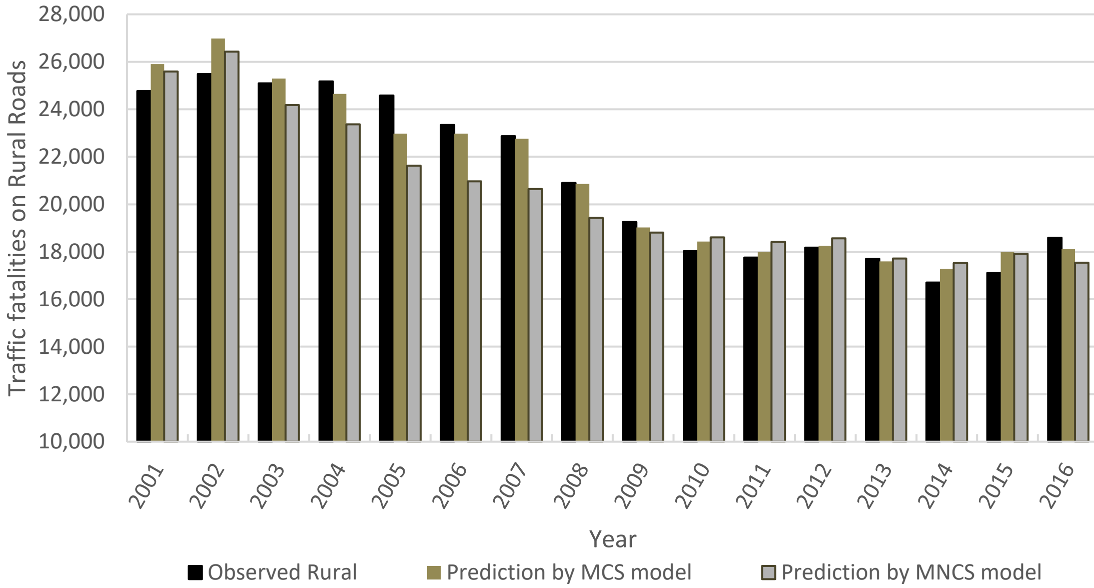


Figure 6.6 Observed versus predicted rural fatalities by the MNCS and MCS models, 2001-2016

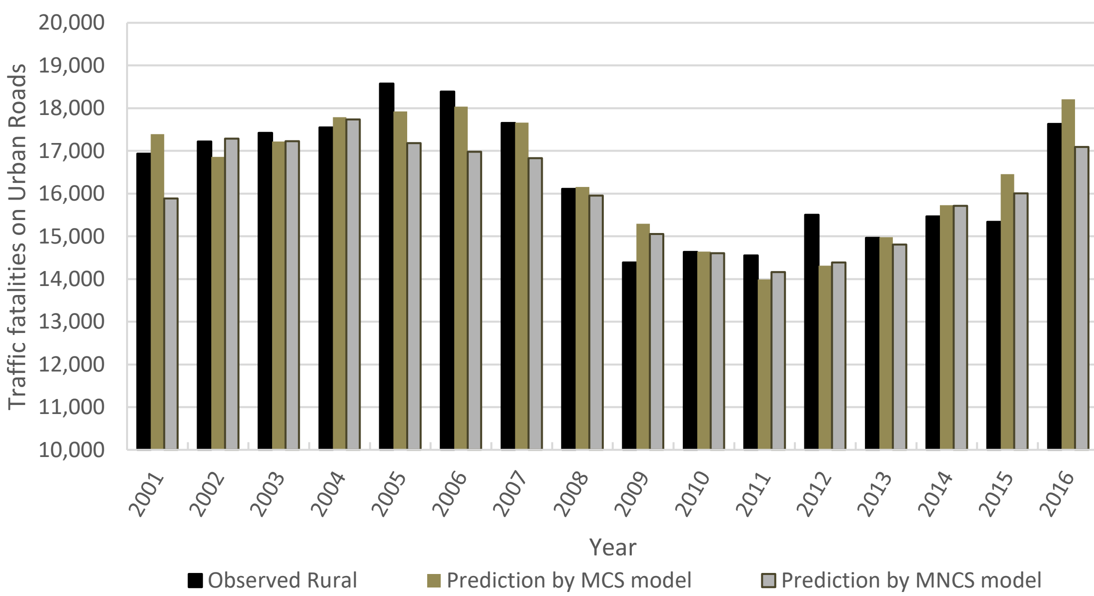


Figure 6.7 Observed versus predicted urban fatalities by the MNCS and MCS models, 2001-2016

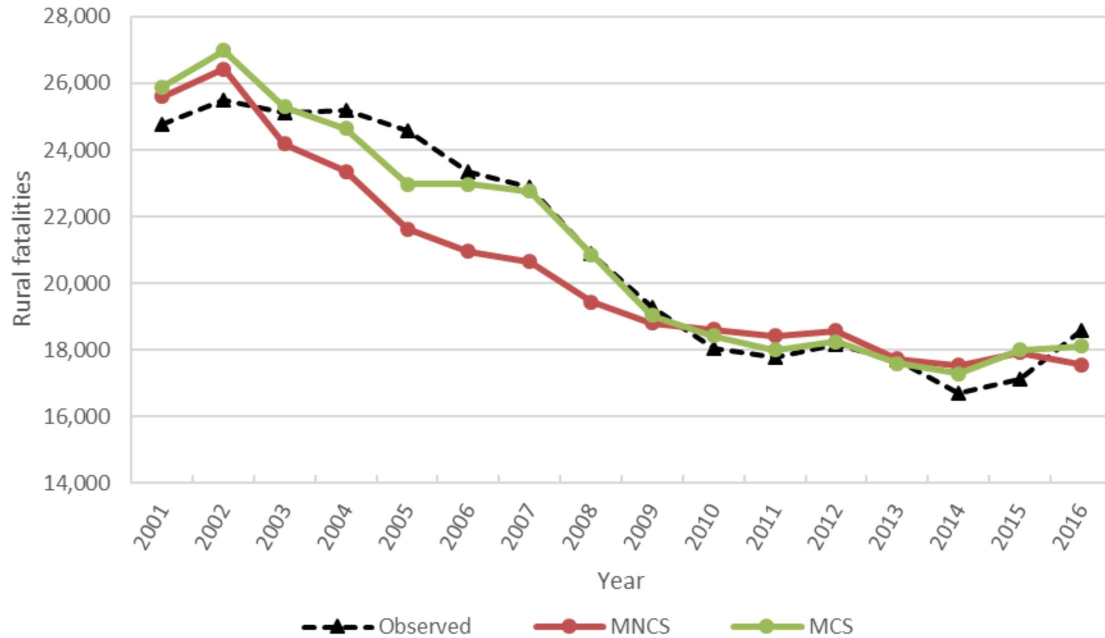


Figure 6.8 Comparison of predicted fatalities for MNCS and MCS model with observed fatalities on rural roads, 2001-2016

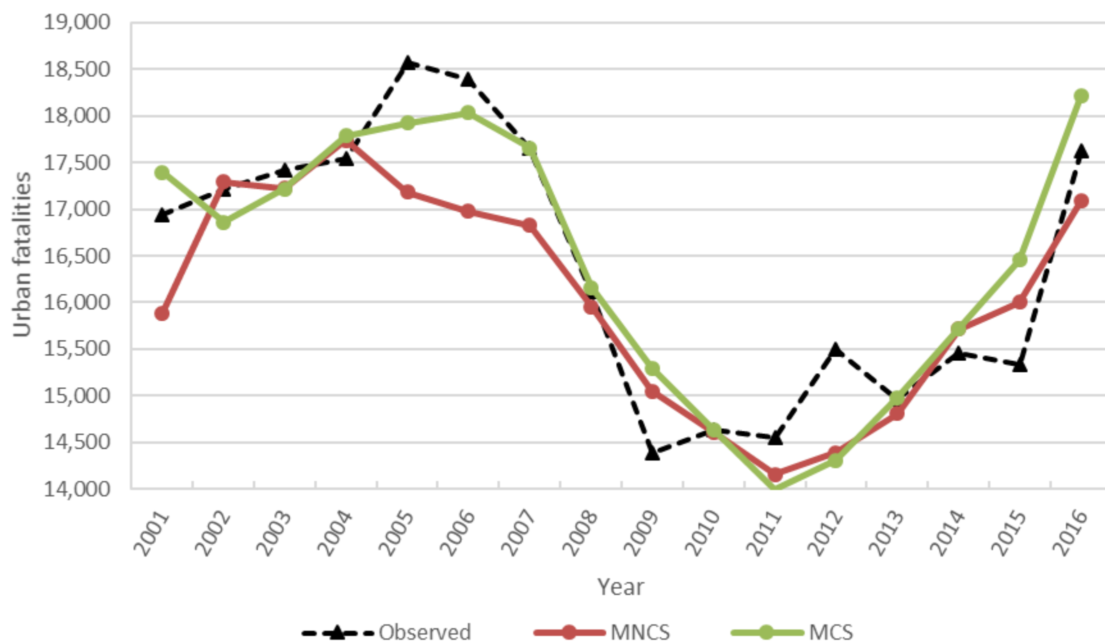


Figure 6.9 Comparison of predicted fatalities for MNCS and MCS model with observed fatalities on urban roads, 2001-2016

6.2 Effect Analysis

The effect analysis was carried out in order to interpret the coefficients of the variables without the influence of potential interactions. An interaction exists between two or more variables when the effect of one variable on the regression outcome depends on another variable. If an interaction exists between two or more variables, the interpretation of each individual variable needs to be examined separately, as their combined effect might not be directly inferential i.e., non-additive (Montgomery and Runger 2003). The data series considered for this study possess a greater possibility of having interactions between one-another, and some of the factors may be potentially correlated at a national scale. Hence, an effect analysis allows for drawing meaningful conclusions to the modeling results. The NCHRP Project 17-67 provides a thorough investigation of the variables influencing decline in fatalities during the recession. Therefore, in this study, the focus is put on investigating the effects of the variables that caused the subsequent increase in traffic fatalities after the recession ended.

In order to conduct the effect analysis on the coefficients, the variables were changed one at a time from the 2007 average to averages from 2012 to 2016, while keeping all other variables constant at the 2007 level. These changes in the data were applied to the models separately using the parameter estimations to predict the effect of an individual variable on the observed changes in fatalities from 2012 to 2016. The purpose was to record the percent changes in fatalities associated with each predictor variable independently over the period of 2011 to 2016. The results of the effect analyses on the MNCS and MCS models are presented in Table 6.1 and Table 6.2.

In these tables, notably larger percent changes attributable to individual variables are marked in bold fonts. A positive effect on the percent change in predicted fatalities indicates an agreeable association of the variable with the predicted change in fatalities, whereas a negative effect of the percent change indicates a contrasting mechanism (i.e., the variables were decreasing while the predicted values were increasing) between the predictor and the predicted values. Based on the results of the effect analysis on the MNCS model (Table 6.1), three variables, i.e., the median income, percent unemployment for age 16 to 24, and pump price accounted for 86.3% of the overall change in the predicted fatalities during 2011 to 2016, which were also statistically significant in the model at 10% level. Among these variables, unemployment and pump price contributed negatively, whereas median income contributed positively towards the change in fatalities from 2011 to 2016, which are consistent with the mechanisms associated with these variables. To explain briefly, when the rate of unemployment for the young age group goes down, fatality is expected to go up. The reason is that this age group is identified as having high crash-risk, which increases the probability of fatal crashes resulting in an increase in fatalities. Similarly, a decrease in the price of fuel is expected to encourage people to drive more, resulting in an increased risk of crashes. On the other hand, when the median income in a household goes up, people tend to take more leisure trips, which ultimately turns up the number of fatalities. Besides these, three other statistically significant variables, rural VMT proportion, capital spending, and the post1-991 model year, accounted for another 10% change in the predicted fatalities. Other variable effects were negligible and/or not statistically significant in the model, hence are not discussed in detail.

Table 6.1 Effect analysis for the MNCS model with the VMT as offset

Variable	Estimate	Maximum deviation from CURE plot	2011 mean	2012-2016 mean	Percent change in predictor 2011-2016	Percent change in predicted fatalities 2011-2016
Intercept	-2.3155	-	-	-	-	-
Rural VMT proportion	0.2729	167.19	0.414	0.396	4.3	4.0
Capital spending (in $1000)	0.0007	140.96	72.129	67.814	6.0	2.5
Safety spending (in $1000)	-0.0018	235.73	10.401	10.595	-1.9	0.3
GDP per capita (in $10,000)	0.023	178.10	5.179	5.148	0.6	0.6
Unemployment for age 16 to 24 (%)	-0.0087	**145.44**	16.342	12.585	23.0	**-26.6**
Pump price ($ per gallon)	-0.0672	**170.23**	3.687	3.358	8.9	**-18.0**
Beer (gallons)	0.263	187.92	1.185	1.172	1.1	2.8
DUI rating	-0.0024	97.30	20.34	20.61	-1.3	0.5
Belt rating	-0.0022	231.44	2.48	2.52	-1.6	0.1
Motorcycle Helmet rating	0.0009	106.53	2.72	2.72	0.0	0.0
Median Income (in $10,000)	-0.1999	**226.51**	5.221	5.477	-4.9	**41.7**
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	-0.0124	295.79	97.6	97.9	-0.3	3.0

*Bold numbers represent largest and statistically significant (at α=0.10) effects of variables

For the MCS model (Table 6.2), four variables, i.e., the percent unemployment for age 16 to 24, pump price, beer consumption, and median income contributed 84.6% change in the predicted fatalities during the focus period, among which the unemployment rate of the young age group alone contributed over 55% to the predicted change. These variables are also statistically significant in the model at the 10% level. Among the above-mentioned variables, unemployment and pump price contributed negatively, and beer consumption and median income contributed positively towards the change in fatalities being consistent with the expected mechanisms. Besides these, two other statistically significant variables, the rural VMT proportion and the post-1991, accounted for another 7% change in the predicted fatalities. Other variable effects were negligible and/or not statistically significant in the model, hence are considered out of scope for the discussion.

In order to evaluate the effect of adding each variable to the model, CUmulative REsidual (CURE) plots are generated using the SAS 9.4 statistical software and are presented in Figure 6.10 and Figure 6.11. From the CURE plots of the MNCS model, it is evident that the addition of the percent unemployment of the 16 to 24-year age-group provided a significant improvement to the model. Other two significantly effective variables, pump price and median income, show regions of concerns in the plots. The CURE plots of the MCS model depict that the addition of the percent unemployment of the 16 to 24-year age-group and median income improves the model fit. However, the addition of the pump price and beer consumption do not show significant improvement in the model. Two columns are added in Table 6.1 and Table 6.2 containing the maximum deviation values from the CURE plots.

It is to be noted here that the black lines in the plots provide simulated paths of the residuals from regression models with different combinations of variables without the variable being investigated. Hence, the deviations of the predicted CURE plots from these simulated paths are not completely reliable. However, these plots can be informative to compare the model fit in terms of small bias presented as horizontal stretches, and concealed outliers presented as vertical drops (Hauer, 2015).

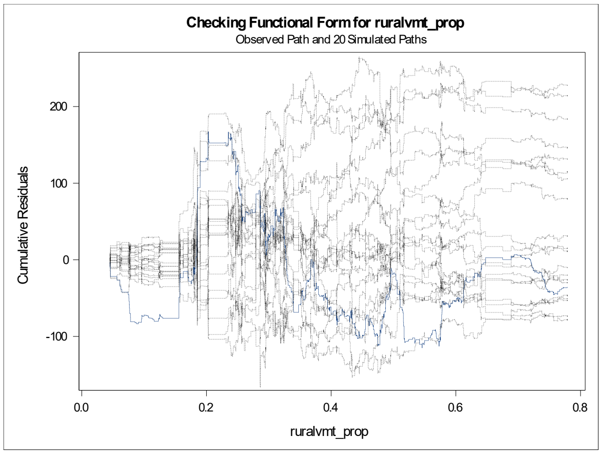
6.3 Discussion on Statistical Inference

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., 2019). As discussed in Section 3.1, 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 6.12 and Figure 6.13 present graphical representations of the hypothetical numbers of fatalities with constant risk or constant exposure over observed fatalities.

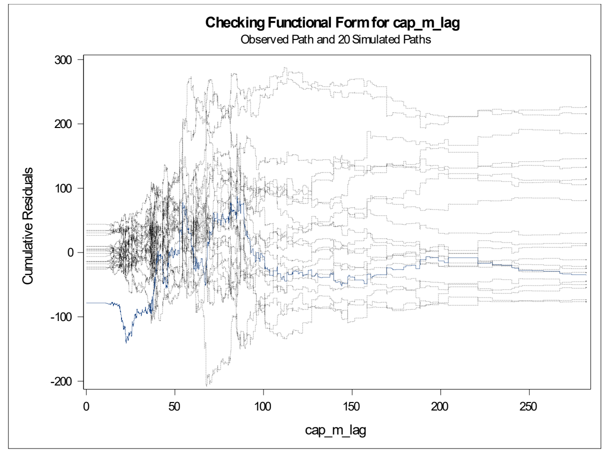
Table 6.2 Effect analysis for the MCS model with VMT as exposure

Variable	Estimate	Maximum deviation from CURE plot	2011 mean	2012-2016 mean	Percent change in predictor 2011-2016	Percent change in predicted fatalities 2011-2016
Intercept	-4.1587	-	-	-	-	-
Rural VMT proportion	0.1502	37.63	0.414	0.396	4.3	3.8
Capital spending (in $1000)	0.0002	70.97	72.129	67.814	6.0	1.2
Safety spending (in $1000)	0.0011	82.90	10.401	10.595	-1.9	-0.3
GDP per capita (in $10,000)	0.0596	86.23	5.179	5.148	0.6	2.6
Unemployment for age 16 to 24 (%)	-0.0105	**59.82**	16.342	12.585	23.0	**-55.2**
Pump price ($ per gallon)	-0.0311	**119.17**	3.687	3.358	8.9	**-14.3**
Beer (gallons)	0.5209	**81.71**	1.185	1.172	1.1	**9.5**
DUI rating	-0.0093	56.37	20.34	20.61	-1.3	3.5
Belt rating	-0.0152	44.92	2.48	2.52	-1.6	0.9
Motorcycle Helmet rating	-0.0347	15.09	2.72	2.72	0.0	0.0
Median Income (in $10,000)	-0.0156	**56.80**	5.221	5.477	-4.9	**5.6**
Post-1991	-0.0077	101.75	97.6	97.9	-0.3	3.2

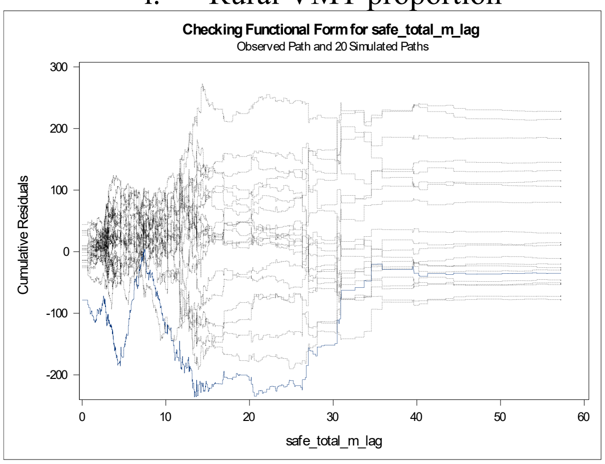
*Bold numbers represent largest and statistically significant (at α=0.10) effects of variables



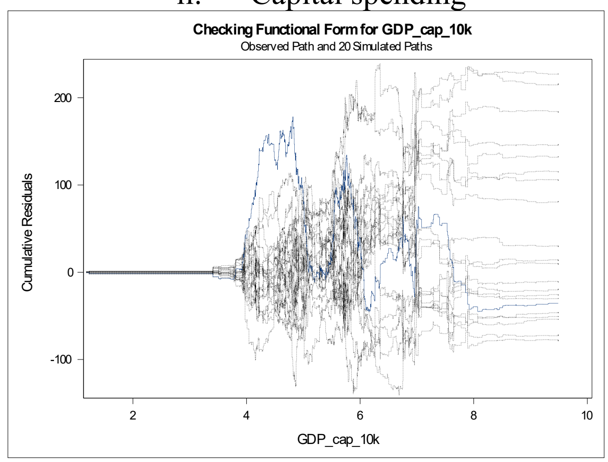
i. Rural VMT proportion



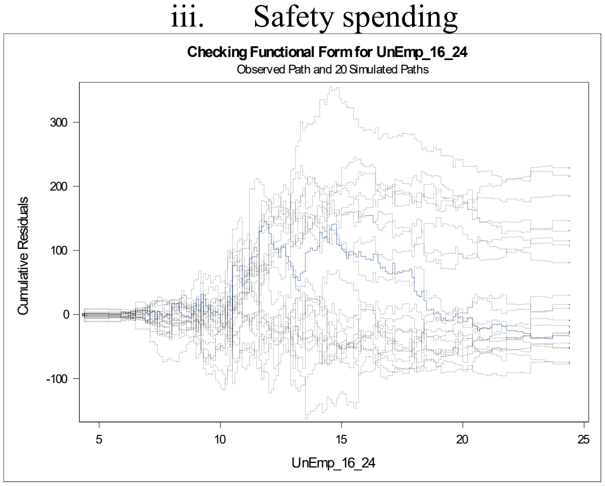
ii. Capital spending



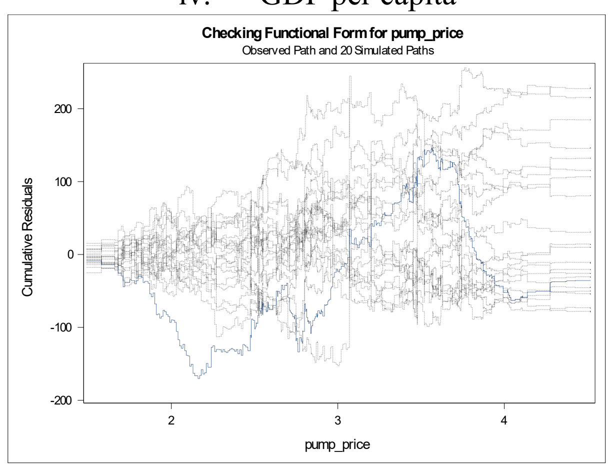
iii. Safety spending



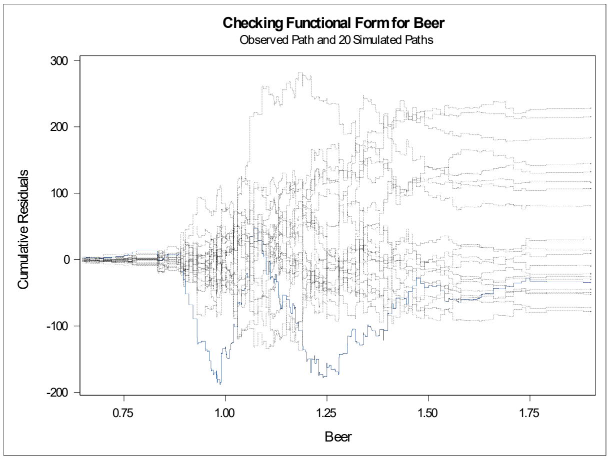
iv. GDP per capita



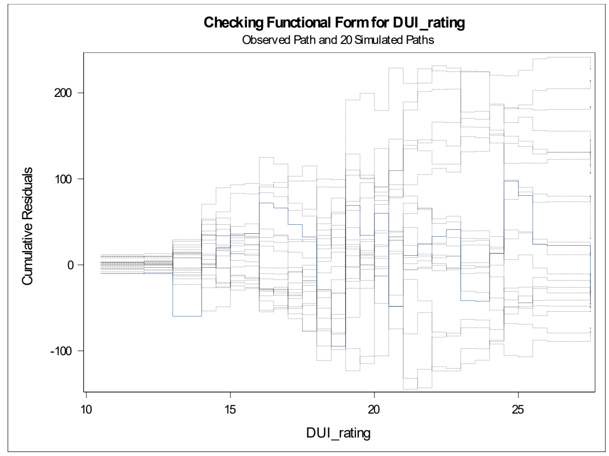
v. Unemployment for age 16 to 24



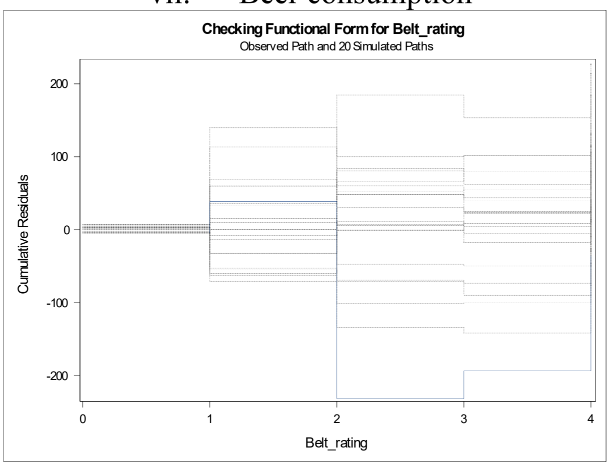
vi. Pump price



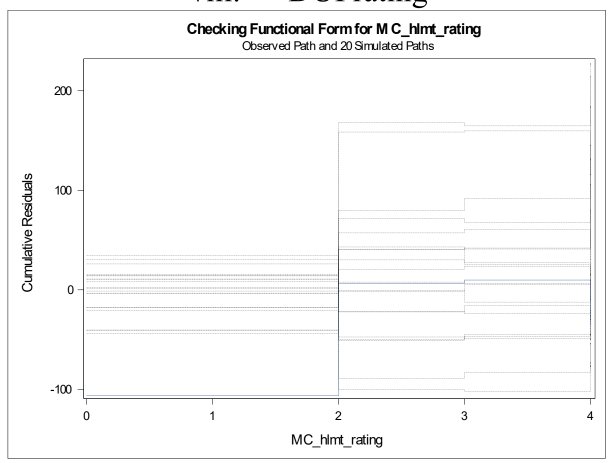
vii. Beer consumption



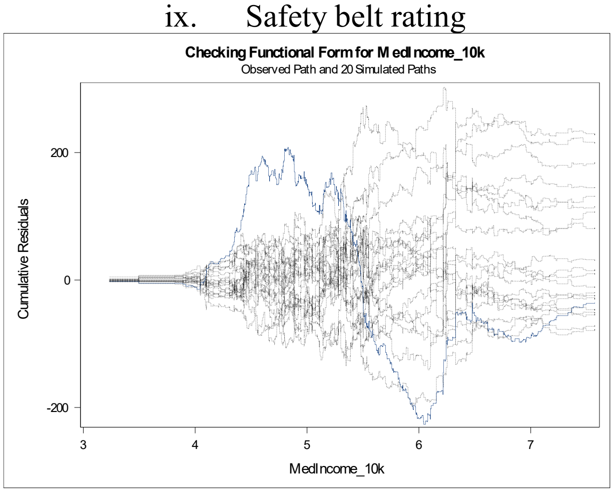
viii. DUI rating



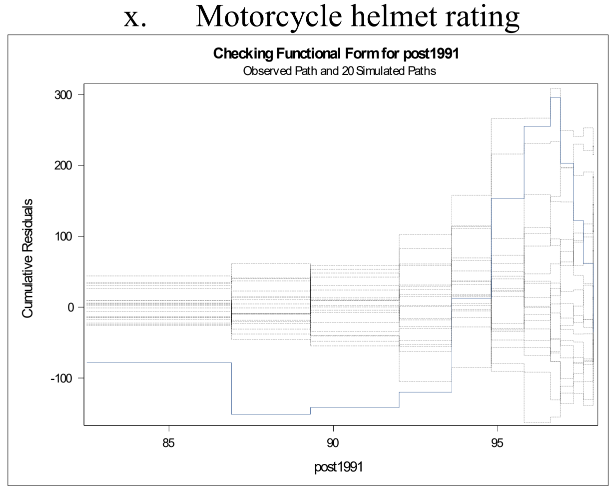
ix. Safety belt rating



x. Motorcycle helmet rating

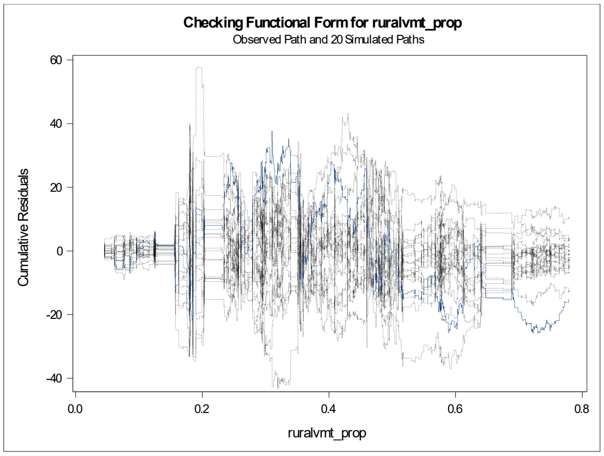


xi. Median household income

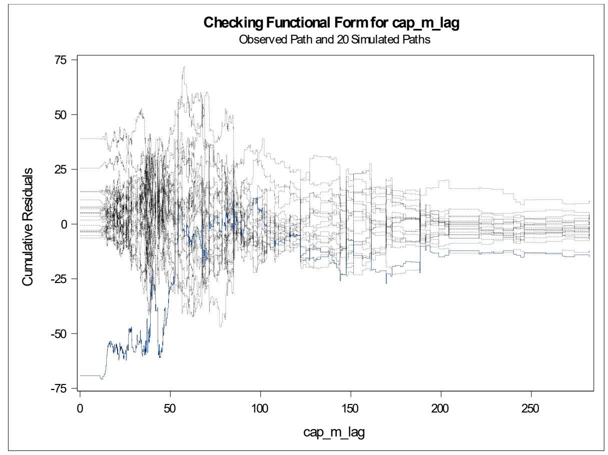


xii. Penetration of post-1991 models

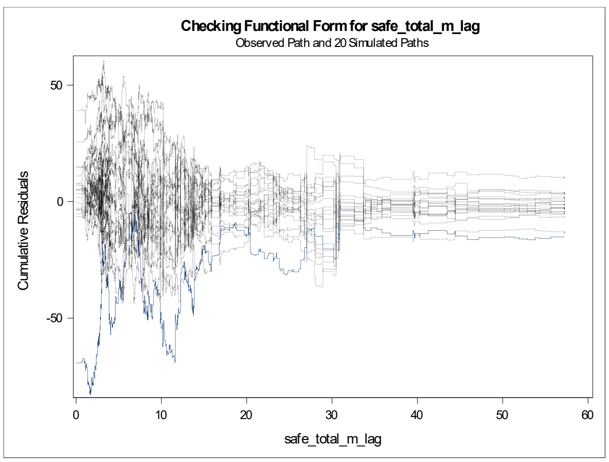
Figure 6.10 CURE plots for the MNCS model



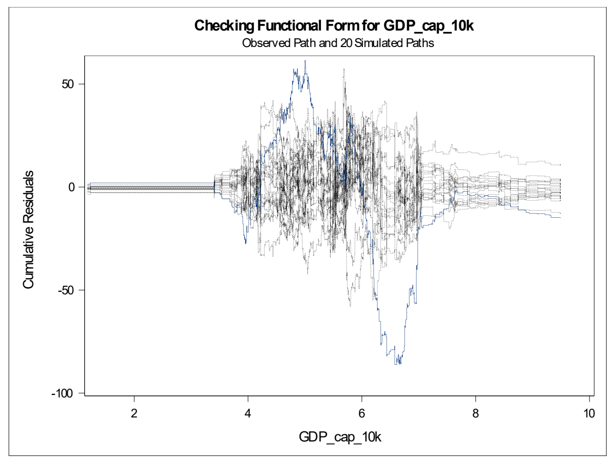
i. Rural VMT proportion



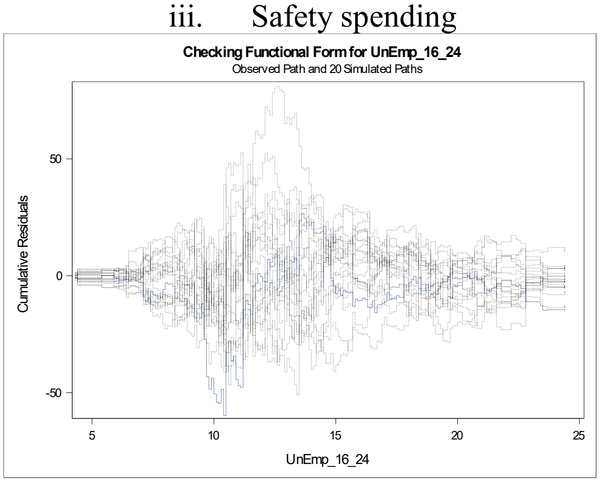
ii. Capital spending



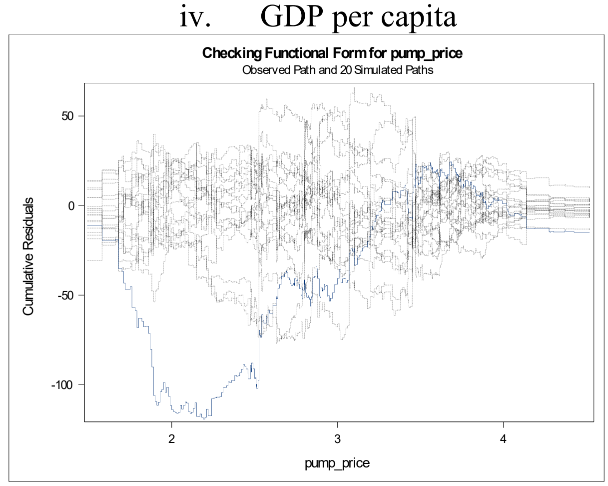
iii. Safety spending



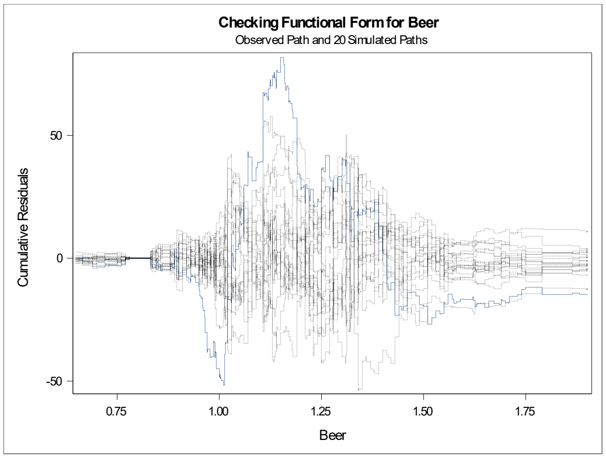
iv. GDP per capita



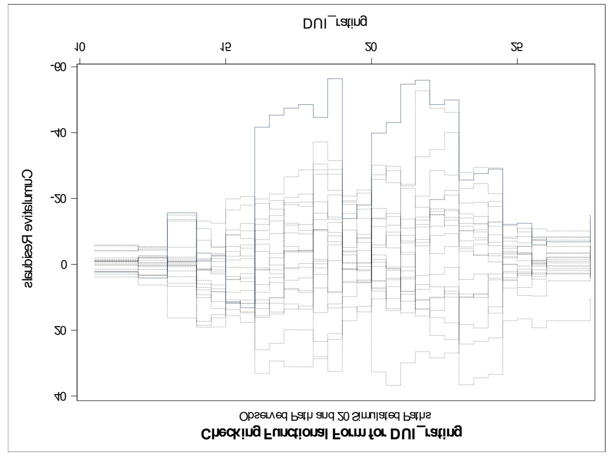
v. Unemployment for age 16 to 24



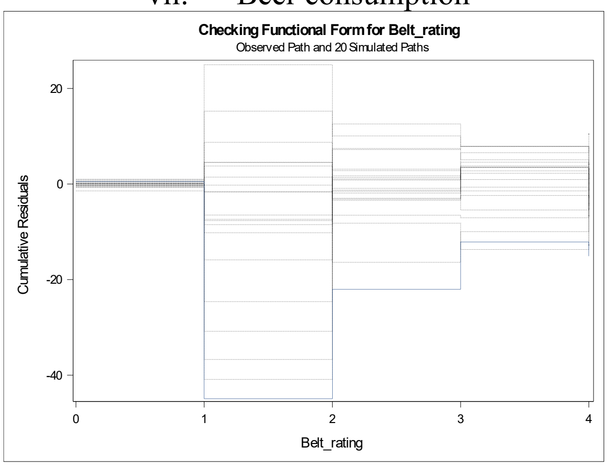
vi. Pump price



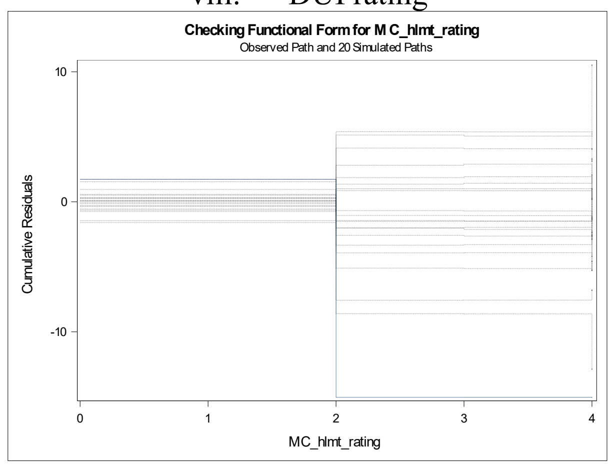
vii. Beer consumption



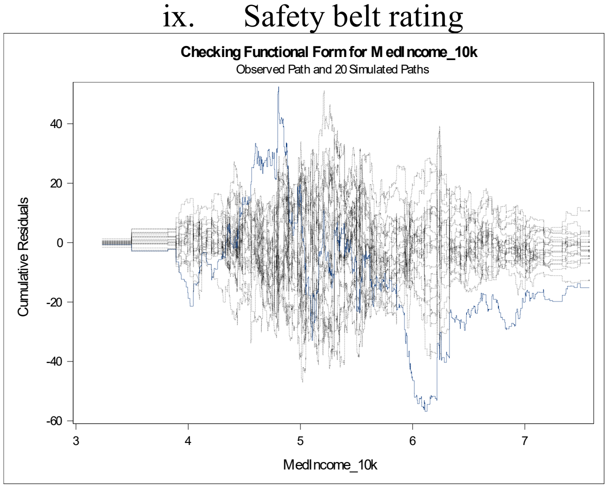
viii. DUI rating



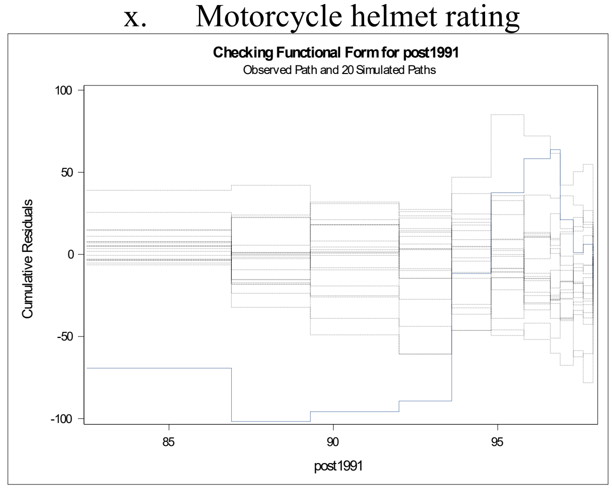
ix. Safety belt rating



x. Motorcycle helmet rating



xi. Median household income



xii. Penetration of post-1991 models

Figure 6.11 CURE plots for the MCS model with total VMT as exposure

It is evident that during the 2008 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 6.12). For this reason, even though VMT did not change much during the 2008 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 6.12). On the other hand, after the recession, the relationship between risk and exposure to fatalities is not so straightforward (Figure 6.13). 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 level of risk declined from 2015 to 2016.

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 6.3 (Blower et al., 2019). The economic variable was further divided into two groups considering the closeness of their association to traffic safety. Table 6.4 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 6.4 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. 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.

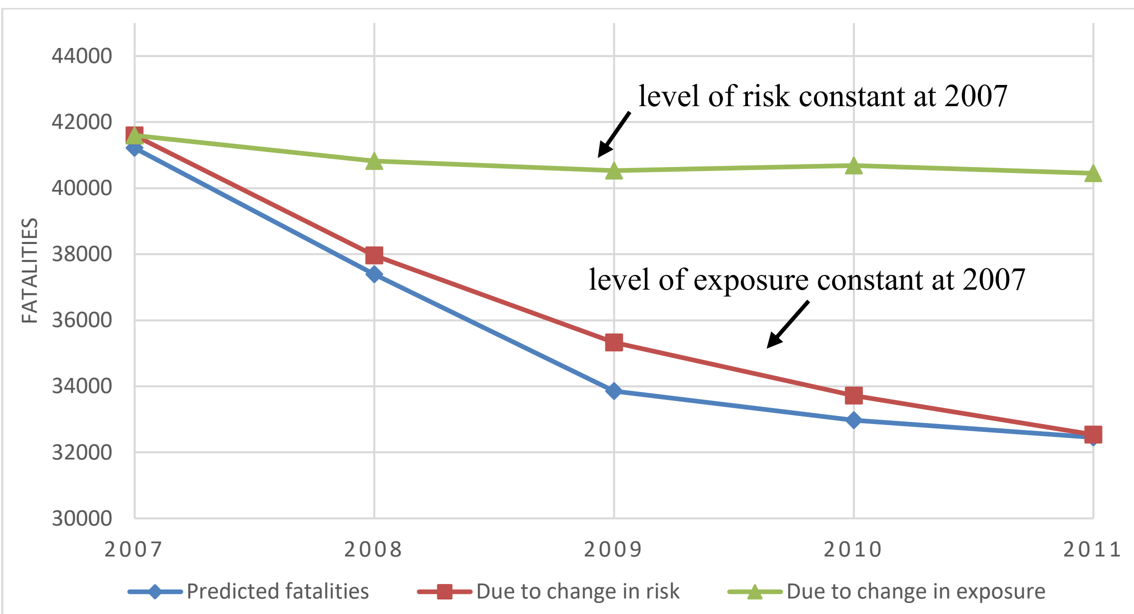


Figure 6.12 Predicted fatalities versus fatalities with constant risk or exposure, 2007-2011

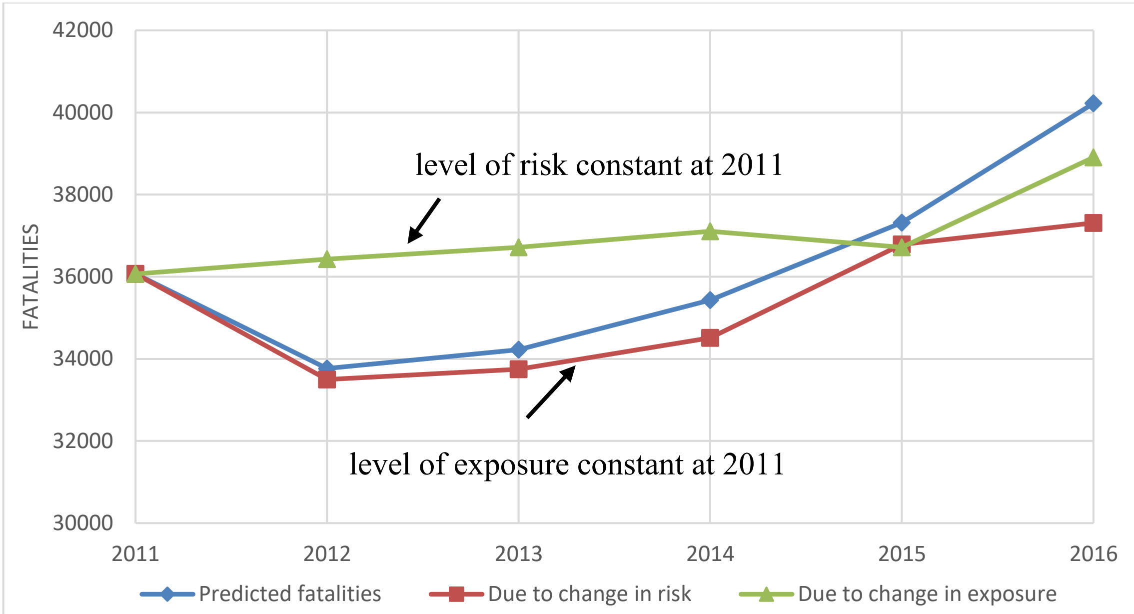


Figure 6.13 Predicted fatalities versus fatalities with constant risk or exposure, 2011-2016

Table 6.3 Groupings of variables for individual effect quantification

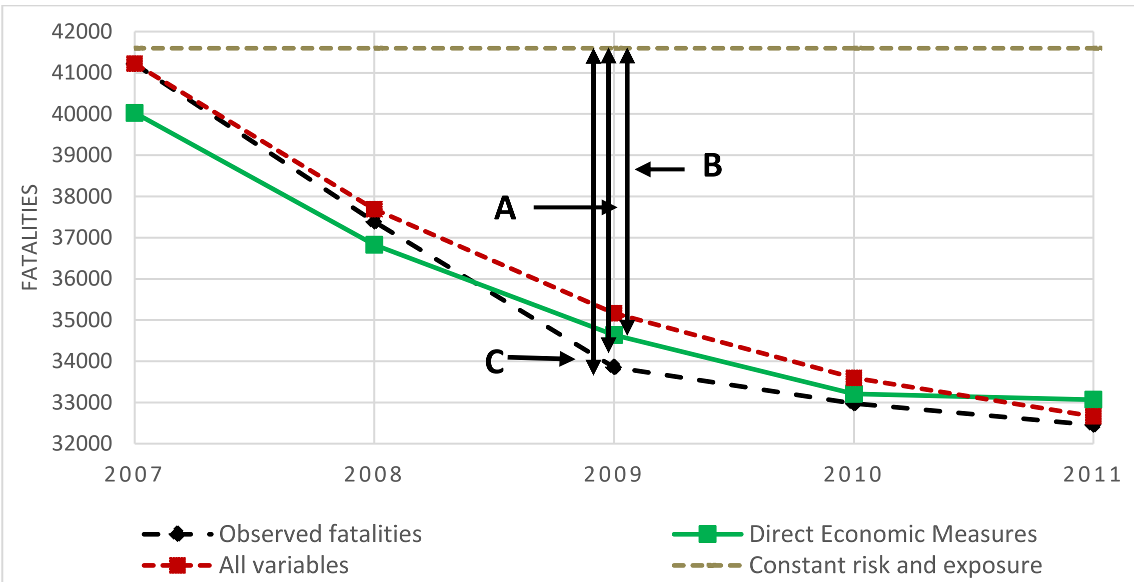
	Variable Groupings				
	Economic	**Safety Expenditures**	**Roadway Capital Expenditures**	**Regulatory**	**Vehicle Safety**
Variables	**Direct** • Unemployment % for 16-24-year age-group • Rural VMT proportion	• Safety Expenditure per highway mile	• Capital Expenditure per highway mile	• DUI rating •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

Table 6.4 Percent Reduction in Fatalities Accounted for by Variable Groupings

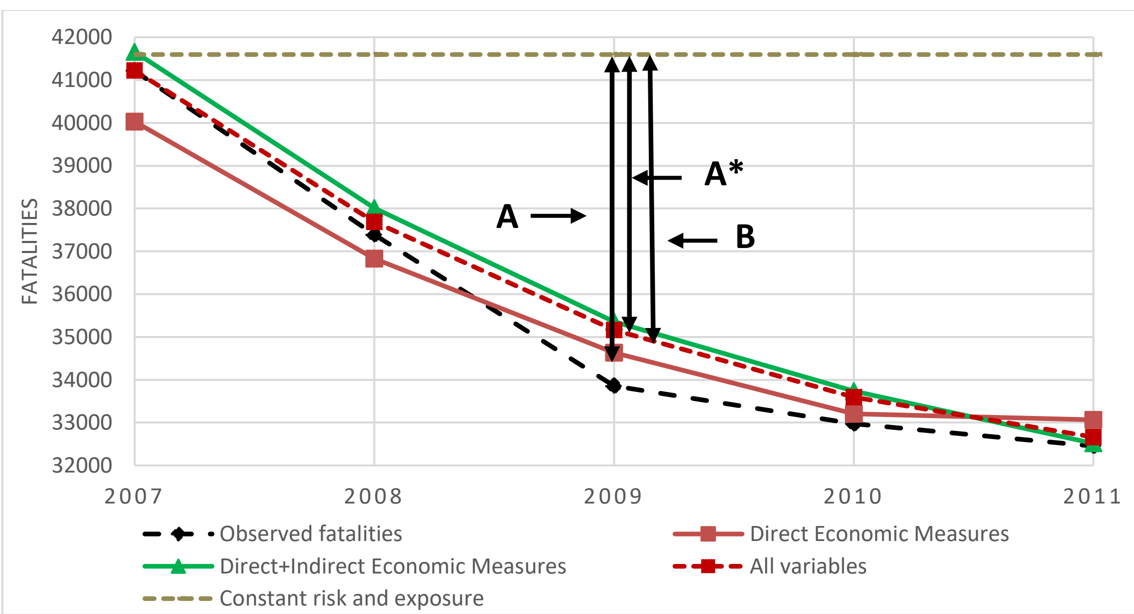
MCS model	Percent Reduction in Fatalities Accountable to the Variable Group from 2007-2011		Percent Increase in Fatalities Accountable to the Variable Group from 2011-2016	
Model / Variable Group	MNCS	MCS	MNCS	MCS
All Variables	100	100	100	100
Direct Economic Measures	**-43.1**	**-40.2**	**-44.6**	**-69.5**
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**	**+3.2**

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

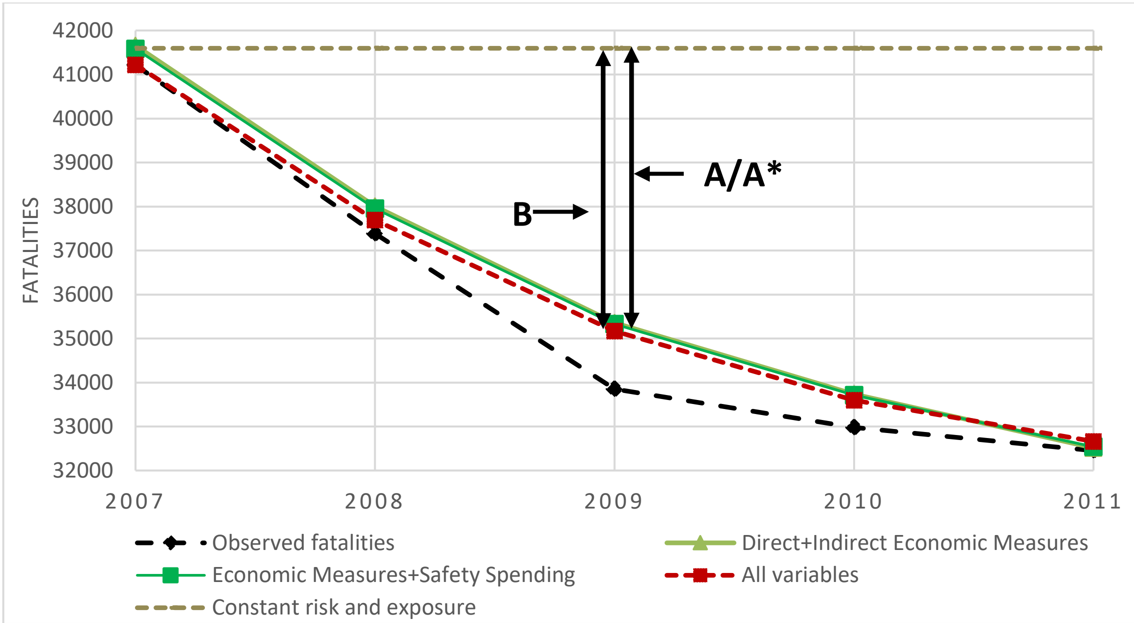
Another approach was adopted to quantify the effects of each variable group in the reduction and increase in the number of fatalities during and after the recession (Blower et al., 2019). Figure 6.14 (a-f) and Figure 6.15 (a-f) represent graphical illustrations of the proportion of reduction and increase to total reduction and increase in fatalities during and after the recession. The probable mechanisms associated with each variable is described in Appendix C. In these figures, the A/A* trend lines represent the predicted reduction due to individual variable group or groups, the B lines represent the predicted reduction (from 2007 to 2011) or increase (from 2012 to 2016) by all variables, and the C lines represent the observed reduction. Here, the ratio (A-A*)/B attribute to the proportion of the reduction contributed by the variable group as depicted in the figures. Again, the figures evince that the proportions contributed by the economic variable group are the maximum in both the predicted reduction and increase in fatalities during and after the recession.



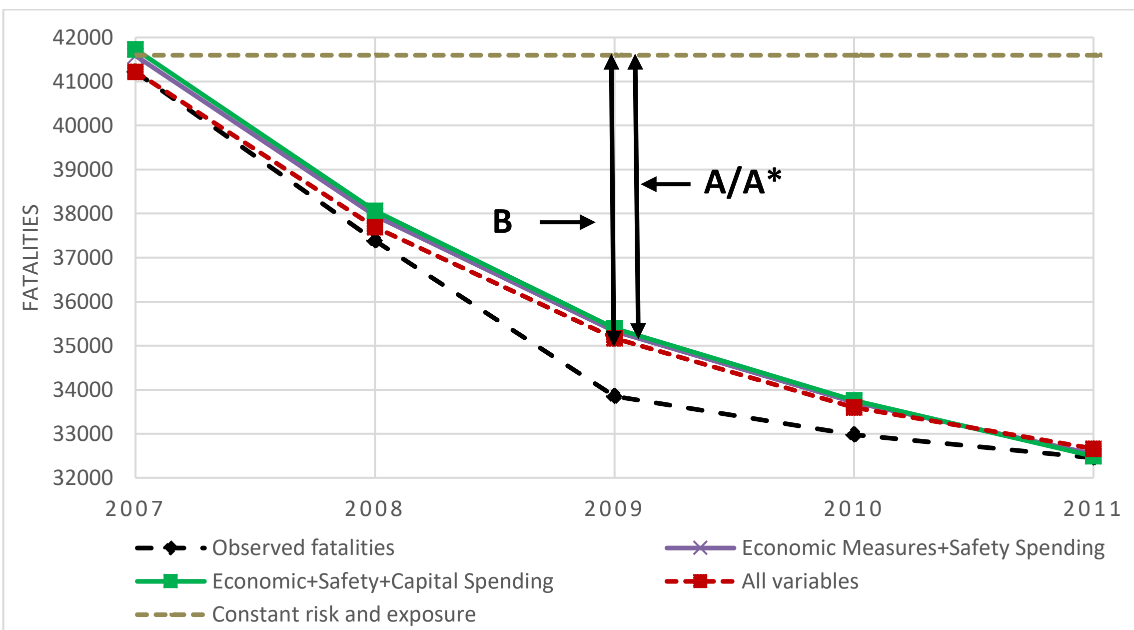
(a) Direct economic variables



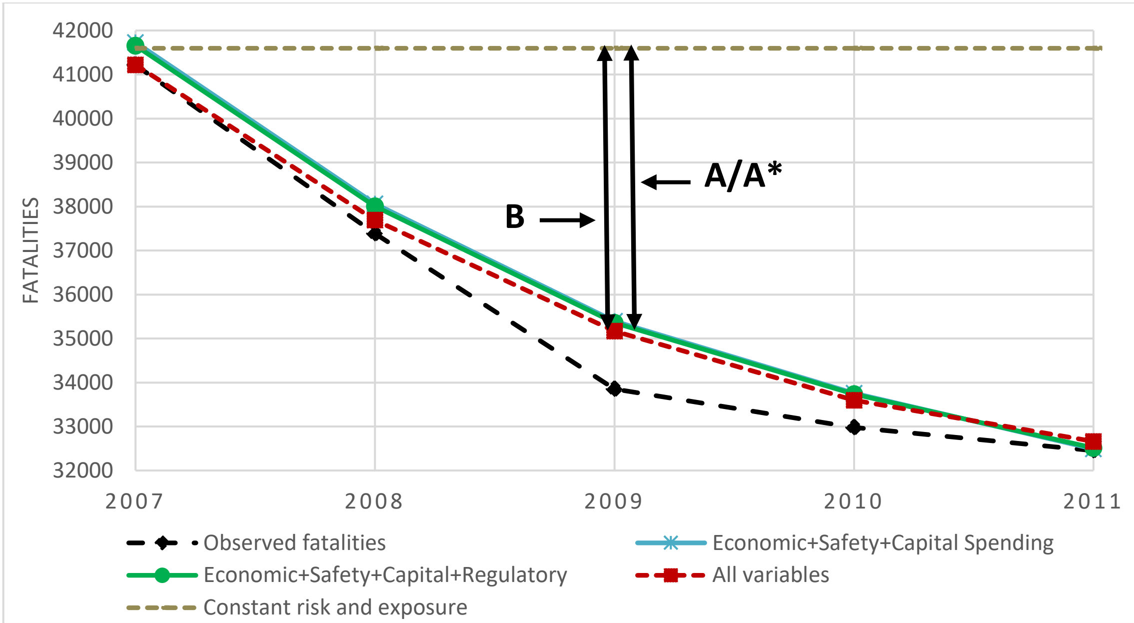
(b) Indirect economic variables



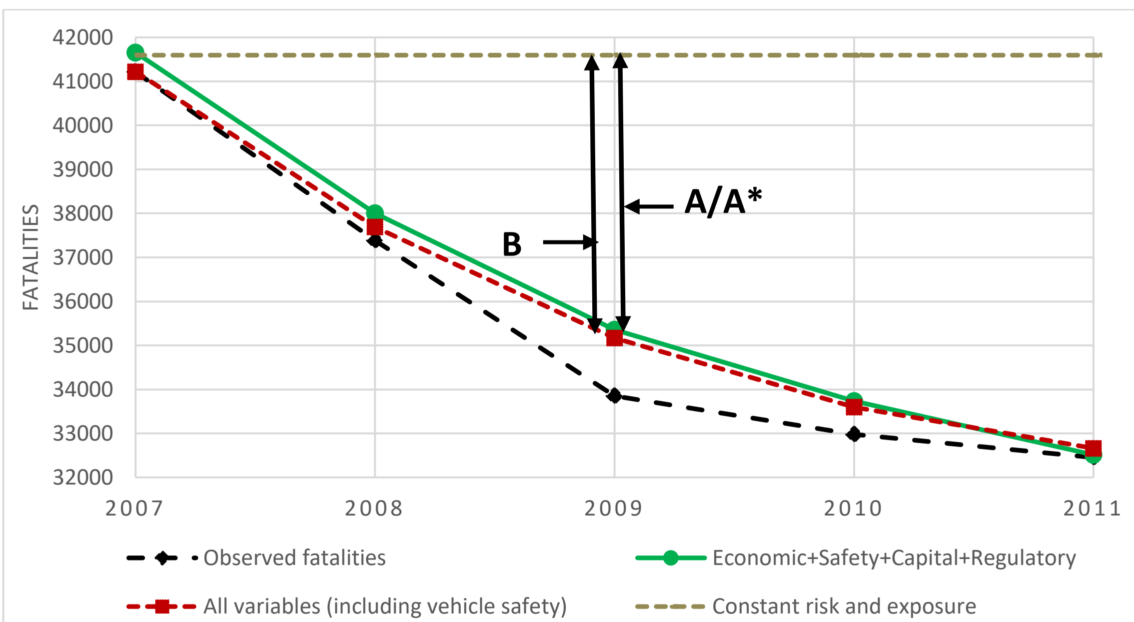
(c) Safety expenditures



(d) State capital expenditures

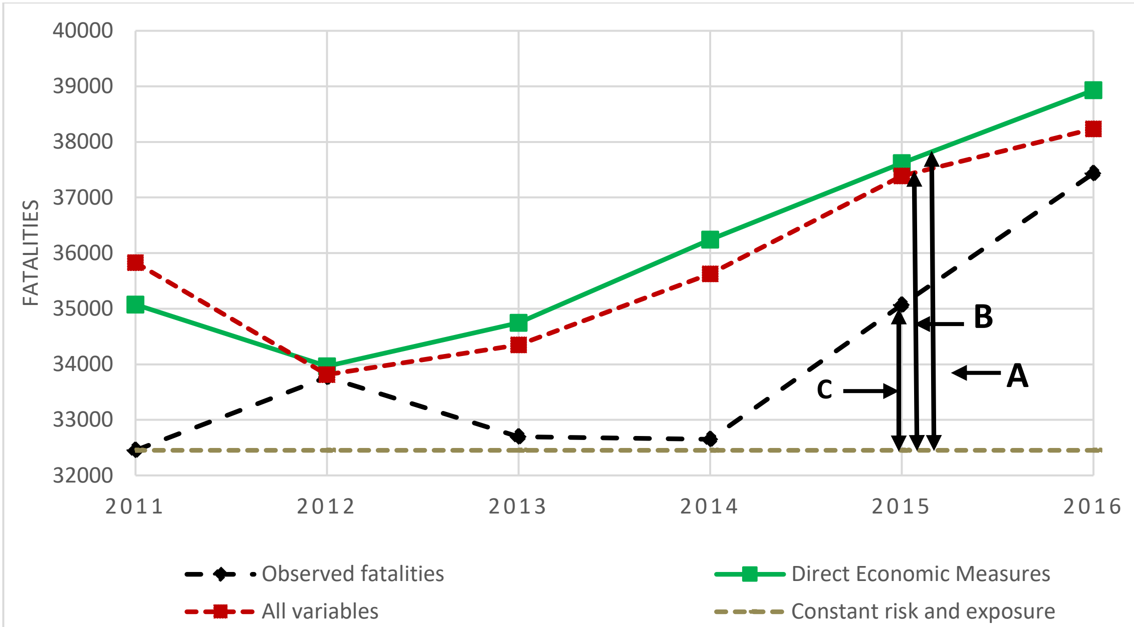


(e) Regulatory measures

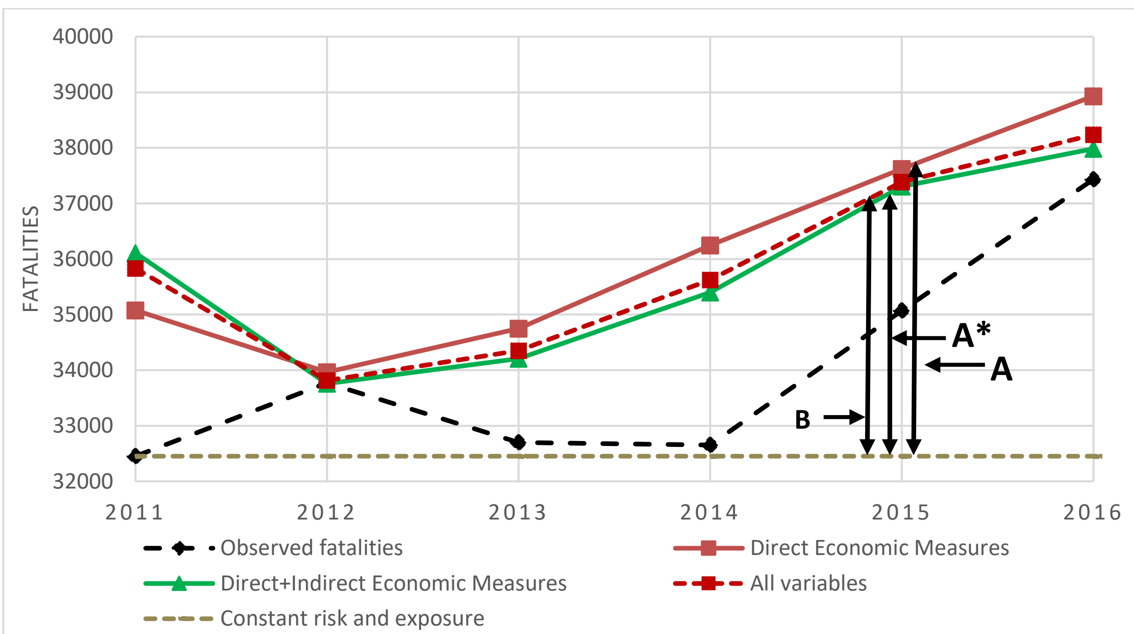


(f) Vehicle safety measures

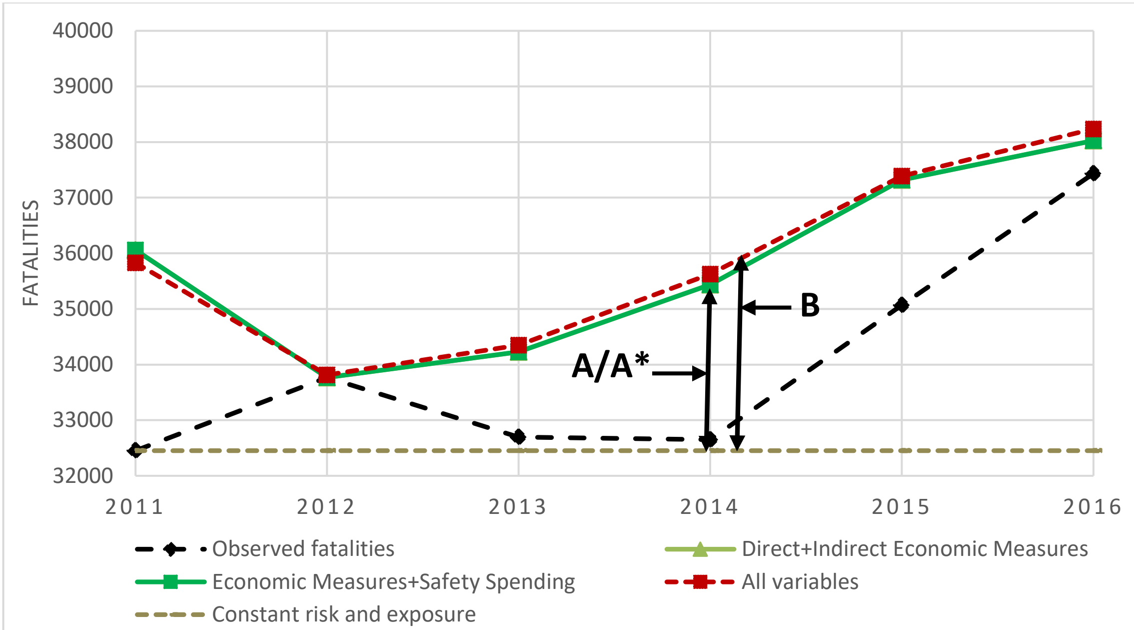
Figure 6.14 (a-f) Quantification of effects on fatalities by variable groups from 2007 to 2011



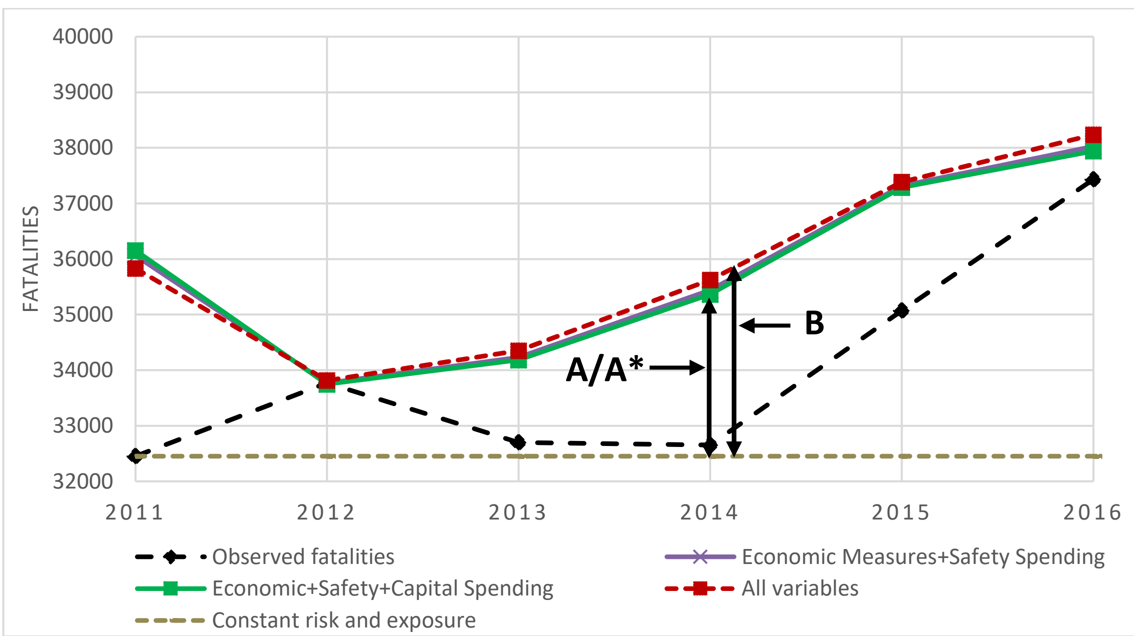
(a) Direct economic measures



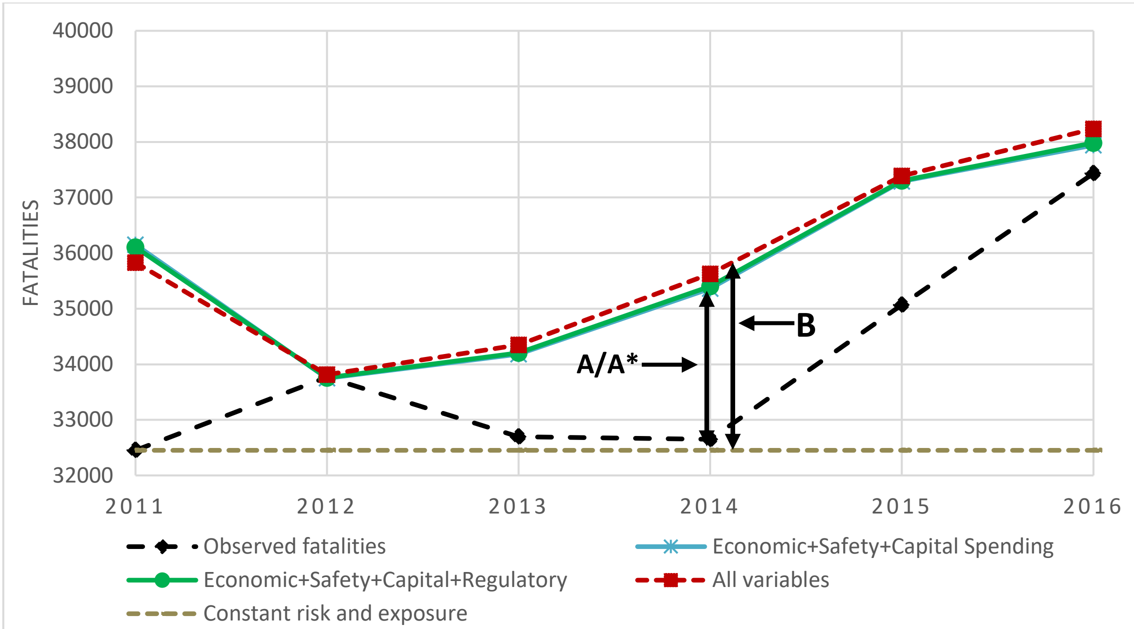
(b) Indirect economic measures



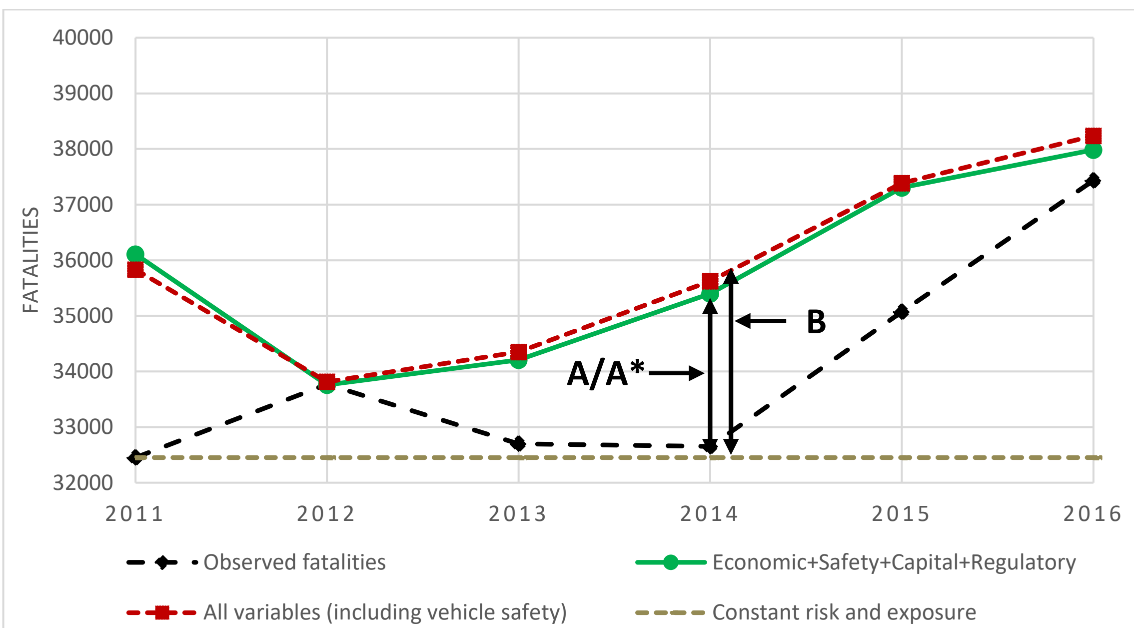
(c) Safety expenditures



(d) State capital expenditures



(e) Regulatory measures



(f) Vehicle safety

Figure 6.15 (a-f) Quantification of effects on fatalities by variable groups from 2011 to 2016

6.4 Chapter Summary

This chapter presents a detailed discussion on the interpretation and statistical inferences based on the modeling results. The key points are summarized below:

- At the beginning of this chapter, a discussion on model comparisons is presented, where the models are compared based on improvements from the previous results using updated dataset and prediction performances.
- A detailed analysis was conducted to quantify the effects of each variable in the reduction and increase in the number of fatalities during and after the recession. Statistical inferences were drawn based on the results of the effect analysis on the modeling results.

CHAPTER 7

SUMMARY AND CONCLUSIONS

A dramatic decline in the number of fatalities across nations during a period of economic downturns has been recorded many times around the world. The probable association of economic changes influencing road safety and the investigation of the associative mechanism behind this process is the motivations of this research undertaking. There are numerous documentations of different statistical approaches that attempted to model this relationship, one of which is the NCHRP Project 17-67. The researchers of the Project NCHRP 17-67 developed generalized multiple linear regression models based on a Poisson-Gamma distribution (also known as NB model) and a log-change regression model to investigate the influencing factors in the recession of 2008 using fatality data from all U.S. states from 2001 to 2012 (Blower et al., 2019). To further separate the scope of analysis, two separate Poisson-gamma models were developed considering (i.e., the MCS model) or not considering (i.e., the MNCS model) a varying effect among states. Moreover, to account for varying effects of the VMT and total population as a measure of exposure, two different MCS models were considered.

The aim of this study was to recalibrate the models developed under the NCHRP Project 17-67 with an updated dataset from 2001 to 2016 to examine the adequacy of the models to predict fatalities after the recession. Another objective was to find the association of rural VMT versus urban VMT with traffic fatalities by developing separate models for the two scenarios. This study also tried to quantify the robustness of the inconsistent relationship that exists between risk and exposure in terms of VMT with that of traffic safety, when only rural VMT is considered in the model in place of overall VMT.

The modeling results show 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 with VMT as exposure 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. Discussions on the MCS model with the population as exposure and the log-change model were kept at a minimum as the prediction quality of these models was outperformed by the other two models. The

MCS models developed for the rural versus urban fatalities showed better prediction performance over the MNCS models.

Chapter 2 presented reviews and summaries of the existing literature that invested research efforts in analyzing the association of economic factors with traffic fatalities. Chapter 3 and 4 discussed the types of data used in the analysis, sources of data series, and the trends of factors over the focus period that help in interpreting the results of the statistical models. Chapter 5 covered the methodology used in the modeling. Chapter 6 described the inferences drawn from the results and their interpretation. Finally, Chapter 7 will identify the methodological issues associated with the current statistical approaches, limitations of the study, and future directions of research with data needs.

7.1 Methodological Issues

With the availability of innovative statistical techniques and modern software tools, investigating the association of fatalities with economic and other relevant variables has become much easier than it was a few decades ago. The digital recording system and automation have allowed the agencies to record more comprehensive datasets than the ones that were available before. Despite having these newly available techniques and data, the analysis results from recent studies are occasionally inconsistent with one another. This section describes the methodological issues identified in the existing state-of-the-art modeling techniques including the limitations of this study. Following are the issues with the existing methodologies that may lead to model biases or over-fitting:

7.1.1 Time-dependent variables

The first issue addresses the potential correlation of the independent variables considered in the model with the time trend. The interpretation of a significant variable in influencing the number of fatalities may not be entirely due to the effect of its expected mechanism during recessions. Rather, if a variable is included in the model that naturally shows a structural growth with time, such as GDP per capita, vehicle safety technology, occupant protection system, roadway design improvements, safety countermeasures, and so on, in that case the significance of the variable in model fitting and estimation will be biased, and model over-fitting may occur (Hakim et al., 1991). One solution to this problem can be using an economic indicator in the model that does not change rapidly with time, such as the percentage of unemployment.

7.1.2 Collinearity among variables

Another issue is that these independent variables together may be correlated to each other over a common time trend, which makes it difficult to interpret the actual causal mechanism influencing the number of fatalities (Wijnen and Rietveld, 2015). This is a more common phenomenon frequently encountered in such type of time-series analyses between time-dependent variables, such as GDP per capita income and variables related to the measure of exposure (e.g., VMT, traffic volume, the price of fuel). This issue can be addressed by developing separate regression models for each collinear pairs of variables to distinguish their individual effects in the total regression models.

7.1.3 Modeling assumption based on time consideration

Another issue that can raise concerns involves types of modeling being employed in these investigations based on time consideration. If a model is employed to capture only the fluctuation of fatalities during turbulent economic conditions, such as a recession, it will only interpret a short-term trend that cannot be used later for prediction when the economy is recovered to its normal state. On the other hand, if the modeling assumption is such that it should capture the long-term trend or a comparatively fixed trend of the relationship, the effect of a few variables that does show a fluctuation during recessions may be underestimated due to the moving average effect. To address this phenomenon, a combined short term and long-term model needs to be proposed.

7.1.4 The assumption of an equal variance in pooled panel data analysis

As pointed out by the Bureau of Labor Statistics (BLS, 2012), the state-based unemployment rates during the 2008 recession did not affect all the states equally. By considering a pooled panel data analysis with datasets from all U.S. states makes the highest or lowest effect of unemployment rates for different states regress to the mean and causes overestimation or underestimation of the effect of unemployment on the changes in fatalities (Antonio et al., 2015). Similarly, other factors, such as ratings of DUI laws, seat belt laws also differ by states. Hence, a methodology needs to be formulated that groups all the states based on their trend order (0-static, 1-linear, 2-quadratic) of economic indicators with that of fatalities.

7.2 Limitations of the Study

This study serves as an extension of the NCHRP Project 17-67 to examine the adequacy of the models proposed in the study with an updated dataset. Although the findings of this study provide 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. The limitations of this study 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. More robust statistical techniques need to be employed to fully understand the causal relationships of these factors to the number of fatalities.
- The data series of this study used some surrogate measures for factors on which data were not readily available. More granular data on these surrogate measures will allow to closely predict the primary outcomes of these factors on fatalities.
- The exploratory analysis revealed that the number of fatalities was not the same for all states, rather it varied based on the size of the state. For example, the number of fatalities in Texas was 50 times more than the fatalities in Alaska in 2016. Some smaller states had very few numbers of fatalities to have any leverage on the regression. In order to account for this variability in state size, data on other severity levels can be included in the analysis.

- 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.

7.3 Direction for Future Research

This section discusses some potential research ideas to improve the applicability of this study.

7.3.1 Better surrogate measures

The study used a number of surrogate measures in the analysis. Better assumptions on these surrogate measures can significantly improve the prediction performance of the models. For example, research efforts can be employed with better estimations of vehicle safety effects instead of using the penetration of post-1991 model year cars.

7.3.2 Associating household-economy with fatalities

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 research scope can be further expanded to examine the variations in effects by age-group influencing crash risk. Also, variations in household income on travel pattern can be investigated to further shed light on the association between economy and safety.

7.3.3 Issues related to the modeling approach

Certain issues related to the modeling approach can be improved in the future, which will allow for providing better statistical inferences. Some probable solutions are listed here:

- Sensitivity analysis will allow for sourcing the uncertainty in the predicted values to the proportions of uncertainties in input variables.
- A functional form of the model can be proposed in developing the future SHSP target 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 the recession on crash risk more clearly.
- Using data with more temporal granularity for forecasting will enhance the effect of the economy on short-term fluctuations of fatalities during the recession.

7.3.4 Database on safety effects of countermeasures

There are various ways to evaluate the safety effects of countermeasures including before-after analysis. However, no database is available to systematically 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.

7.3.5 Integrated modeling approach

In order to address the issues summarized in Section 7.1, an integrated short and long-time modeling approach needs to be adopted. A short-term trend model is generally applicable on multivariate panel dataset containing data series on multiple entities (states, nations, etc.) collected over short intervals of time-period (monthly or quarterly). These models are dynamic in nature and correspond to changes in the economic and safety indicators under the following assumptions: i) capable of capturing the true effects of influencing factors considering a wide range of variables, such as economic, demographic, safety-related, etc., and ii) the variables are unbiased and independent of the time-trend. On the other hand, a long-term model is generally applied on univariate time-series data considering linear equilibrium relationship between the economic factors and safety indicators. Integration between these two types of modeling approach will enable understanding of long-term and short-term effects of each variable separately, which can be informative in developing a causal relationship.

7.3.6 Improving the reliability of predictions

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. Also, the models were not validated based on their prediction performance with data from the subsequent years. It is to be noted here that the primary objective of this study was to investigate the effects of different variables influencing the number of fatalities during and after the Great Recession, not forecasting. One plausible approach to solve this issue can be found in the concept of Bayes' theorem, which improve the predictions of models by obtaining information from newer data as it becomes available (Stigler, 1990). In order to improve the reliability of the model predictions, the parameters need to be recalibrated for each year, which can then be used to forecast the number of fatalities for the next year. The forecasted number of fatalities can be tracked over the years to update the models based on the pattern of prediction errors and improve prediction performance. This approach will change the nature of the models from static to dynamics considering yearly changes although the modeling assumptions was based on long-term effects of the parameters. An obstacle to this approach is that the variable data considered in this model do not become available immediately at the end of each year. In fact, data on most of the variables become available after 1 or 2 years. However, a Bayesian approach like this can be explored as a potential research scope in the future.

7.3.7 Addressing vulnerable road-users

Multiple studies have employed research efforts in investigating a decline in traffic fatalities during recessions, however, most of these studies focus only on motor vehicle crashes. 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.

7.4 Data Needs

As discussed previously, 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 effects of overall vehicle design in traffic safety

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APPENDIX A

STATE-SPECIFIC PARAMETER ESTIMATES FOR THE MCS MODEL

Table A.1 State-specific parameter estimates for the MCS model with VMT as exposure using previous dataset (2001-2012)

Parameter	State code	Estimate	Standard Error	p-value
Alabama	1	0.3649	0.0598	<.0001
Alaska	2	0.0664	0.0674	0.3246
Arizona	4	0.2219	0.0706	0.0017
Arkansas	5	0.5659	0.0554	<.0001
California	6	-0.0992	0.0877	0.2579
Colorado	8	-0.199	0.0664	0.0027
Connecticut	9	-0.4342	0.0971	<.0001
Delaware	10	-0.3106	0.0749	<.0001
Florida	12	0.0595	0.081	0.4624
Georgia	13	0.0851	0.0651	0.1913
Hawaii	15	-0.1817	0.0797	0.0227
Idaho	16	0.2809	0.0537	<.0001
Illinois	17	-0.2773	0.0813	0.0006
Indiana	18	-0.0813	0.0576	0.1576
Iowa	19	-0.1479	0.0576	0.0102
Kansas	20	0.171	0.0586	0.0035
Kentucky	21	0.4415	0.0499	<.0001
Louisiana	22	0.3633	0.0589	<.0001
Maine	23	-0.0218	0.0521	0.6759
Maryland	24	-0.1809	0.0883	0.0405
Massachusetts	25	-0.6175	0.1005	<.0001
Michigan	26	-0.1371	0.0699	0.0496
Minnesota	27	-0.5154	0.0554	<.0001
Mississippi	28	0.556	0.0597	<.0001
Missouri	29	0.109	0.0603	0.0704
Montana	30	0.3738	0.0554	<.0001
Nebraska	31	-0.1487	0.0561	0.0081
Nevada	32	0.0073	0.0786	0.9255
New Hampshire	33	-0.7227	0.0766	<.0001

Parameter	State code	Estimate	Standard Error	p-value
New Jersey	34	-0.3912	0.1034	0.0002
New Mexico	35	0.2335	0.053	<.0001
New York	36	-0.1801	0.0816	0.0272
North Carolina	37	0.2196	0.0621	0.0004
North Dakota	38	-0.1297	0.0494	0.0087
Ohio	39	-0.2392	0.0639	0.0002
Oklahoma	40	0.2198	0.0592	0.0002
Oregon	41	0.0757	0.0654	0.2468
Pennsylvania	42	-0.0915	0.0592	0.1225
Rhode Island	44	-0.3664	0.0944	0.0001
South Carolina	45	0.4336	0.0499	<.0001
South Dakota	46	0.1426	0.0491	0.0037
Tennessee	47	0.3596	0.0662	<.0001
Texas	48	0.0207	0.0678	0.7595
Utah	49	-0.0646	0.0849	0.4469
Vermont	50	-0.3127	0.0638	<.0001
Virginia	51	-0.1511	0.0753	0.0448
Washington	53	-0.1579	0.0781	0.0433
West Virginia	54	0.568	0.0627	<.0001
Wisconsin	55	-0.2625	0.0518	<.0001
Wyoming	56	0	0	.

Table A.2 State-specific parameter estimates for the MCS model with VMT as exposure using updated dataset (2001-2016)

Parameter	State code	Estimate	Standard Error	p-value
Alabama	1	0.4156	0.0539	<.0001
Alaska	2	0.1865	0.0611	0.0023
Arizona	4	0.3576	0.0613	<.0001
Arkansas	5	0.5768	0.0456	<.0001
California	6	0.0953	0.078	0.222
Colorado	8	-0.0414	0.0559	0.4589
Connecticut	9	-0.1606	0.0824	0.0511
Delaware	10	-0.1439	0.0709	0.0423
Florida	12	0.2463	0.0705	0.0005
Georgia	13	0.2216	0.0586	0.0002
Hawaii	15	0.0003	0.0708	0.9967
Idaho	16	0.3581	0.0433	<.0001
Illinois	17	-0.089	0.074	0.2286
Indiana	18	0.0445	0.0483	0.3565
Iowa	19	-0.1029	0.0526	0.0502
Kansas	20	0.2649	0.0468	<.0001
Kentucky	21	0.4943	0.042	<.0001
Louisiana	22	0.407	0.056	<.0001
Maine	23	-0.0178	0.0455	0.6958
Maryland	24	0.0288	0.0749	0.7006
Massachusetts	25	-0.4023	0.0879	<.0001
Michigan	26	0.031	0.0607	0.6095
Minnesota	27	-0.4005	0.0459	<.0001
Mississippi	28	0.5239	0.0571	<.0001
Missouri	29	0.1747	0.0545	0.0013
Montana	30	0.3099	0.0519	<.0001
Nebraska	31	-0.0988	0.0515	0.0548
Nevada	32	0.1218	0.0726	0.0936
New Hampshire	33	-0.6194	0.0708	<.0001
New Jersey	34	-0.1396	0.0897	0.1196
New Mexico	35	0.2819	0.0468	<.0001
New York	36	-0.0391	0.0713	0.5838
North Carolina	37	0.3068	0.0564	<.0001

Parameter	State code	Estimate	Standard Error	p-value
North Dakota	38	-0.1848	0.0439	<.0001
Ohio	39	-0.1341	0.0553	0.0153
Oklahoma	40	0.3187	0.0472	<.0001
Oregon	41	0.1868	0.0594	0.0017
Pennsylvania	42	-0.0011	0.0526	0.9827
Rhode Island	44	-0.1783	0.0812	0.0281
South Carolina	45	0.5006	0.0461	<.0001
South Dakota	46	0.1153	0.0458	0.0118
Tennessee	47	0.4376	0.0575	<.0001
Texas	48	0.1691	0.0609	0.0055
Utah	49	0.1561	0.0632	0.0135
Vermont	50	-0.334	0.0599	<.0001
Virginia	51	-0.0051	0.0622	0.9344
Washington	53	0.0069	0.0688	0.9199
West Virginia	54	0.5434	0.0573	<.0001
Wisconsin	55	-0.2055	0.0459	<.0001
Wyoming	56	0	0	.

Table A.3 State-specific parameter estimates for the MCS model with Population as exposure using previous dataset (2001-2012)

Parameter	State code	Estimate	Standard Error	p-value
Alabama	1	0.129	0.0613	0.0355
Alaska	2	-0.768	0.0687	<.0001
Arizona	4	-0.2941	0.0723	<.0001
Arkansas	5	0.2479	0.0566	<.0001
California	6	-0.7155	0.0901	<.0001
Colorado	8	-0.747	0.068	<.0001
Connecticut	9	-1.0605	0.0995	<.0001
Delaware	10	-0.7919	0.0765	<.0001
Florida	12	-0.3814	0.0832	<.0001
Georgia	13	-0.2534	0.0668	0.0001
Hawaii	15	-0.983	0.0816	<.0001
Idaho	16	-0.1549	0.0548	0.0047
Illinois	17	-0.9113	0.0835	<.0001
Indiana	18	-0.3969	0.059	<.0001
Iowa	19	-0.5739	0.059	<.0001
Kansas	20	-0.2371	0.0599	<.0001
Kentucky	21	0.0828	0.051	0.1042
Louisiana	22	-0.1298	0.0603	0.0314
Maine	23	-0.3683	0.0531	<.0001
Maryland	24	-0.712	0.0907	<.0001
Massachusetts	25	-1.3266	0.1032	<.0001
Michigan	26	-0.6581	0.0717	<.0001
Minnesota	27	-0.9551	0.0567	<.0001
Mississippi	28	0.3765	0.0611	<.0001
Missouri	29	-0.264	0.0618	<.0001
Montana	30	0.031	0.0566	0.5842
Nebraska	31	-0.6209	0.0574	<.0001
Nevada	32	-0.7099	0.0805	<.0001
New Hampshire	33	-1.2416	0.0784	<.0001
New Jersey	34	-1.1085	0.1062	<.0001
New Mexico	35	0.0018	0.0542	0.9741
New York	36	-1.0594	0.0837	<.0001
North Carolina	37	-0.1777	0.0637	0.0053

Parameter	State code	Estimate	Standard Error	p-value
North Dakota	38	-0.4653	0.0503	<.0001
Ohio	39	-0.7802	0.0655	<.0001
Oklahoma	40	-0.0013	0.0606	0.983
Oregon	41	-0.4507	0.067	<.0001
Pennsylvania	42	-0.812	0.0607	<.0001
Rhode Island	44	-1.1513	0.0966	<.0001
South Carolina	45	0.0758	0.051	0.1372
South Dakota	46	-0.2621	0.0499	<.0001
Tennessee	47	0.0014	0.0679	0.9839
Texas	48	-0.4799	0.0695	<.0001
Utah	49	-0.5492	0.087	<.0001
Vermont	50	-0.5946	0.065	<.0001
Virginia	51	-0.6261	0.0773	<.0001
Washington	53	-0.7753	0.0802	<.0001
West Virginia	54	0.1899	0.0642	0.0031
Wisconsin	55	-0.7164	0.053	<.0001
Wyoming	56	0	0	.

Table A.4 State-specific parameter estimates for the MCS model with Population as exposure using updated dataset (2001-2016)

Parameter	State code	Estimate	Standard Error	p-value
Alabama	1	0.2206	0.0564	<.0001
Alaska	2	-0.6328	0.0632	<.0001
Arizona	4	-0.1148	0.064	0.073
Arkansas	5	0.2983	0.0473	<.0001
California	6	-0.4912	0.0818	<.0001
Colorado	8	-0.5578	0.0583	<.0001
Connecticut	9	-0.7359	0.0862	<.0001
Delaware	10	-0.5872	0.0738	<.0001
Florida	12	-0.1486	0.0738	0.0442
Georgia	13	-0.1013	0.0613	0.0986
Hawaii	15	-0.7449	0.0738	<.0001
Idaho	16	-0.0379	0.0448	0.3971
Illinois	17	-0.6512	0.0776	<.0001
Indiana	18	-0.2146	0.0504	<.0001
Iowa	19	-0.4712	0.0549	<.0001
Kansas	20	-0.0902	0.0487	0.0638
Kentucky	21	0.1629	0.0437	0.0002
Louisiana	22	-0.055	0.0585	0.3474
Maine	23	-0.3293	0.047	<.0001
Maryland	24	-0.4497	0.0785	<.0001
Massachusetts	25	-1.0545	0.0922	<.0001
Michigan	26	-0.4586	0.0636	<.0001
Minnesota	27	-0.7947	0.0479	<.0001
Mississippi	28	0.347	0.0596	<.0001
Missouri	29	-0.1726	0.057	0.0025
Montana	30	-0.0006	0.0538	0.9909
Nebraska	31	-0.5541	0.0536	<.0001
Nevada	32	-0.5492	0.076	<.0001
New Hampshire	33	-1.0833	0.0738	<.0001
New Jersey	34	-0.7934	0.0942	<.0001
New Mexico	35	0.0901	0.0486	0.0638
New York	36	-0.9063	0.0748	<.0001
North Carolina	37	-0.0697	0.0591	0.2379

Parameter	State code	Estimate	Standard Error	p-value
North Dakota	38	-0.4789	0.0452	<.0001
Ohio	39	-0.6276	0.0578	<.0001
Oklahoma	40	0.1375	0.0491	0.0051
Oregon	41	-0.3251	0.0621	<.0001
Pennsylvania	42	-0.7035	0.0549	<.0001
Rhode Island	44	-0.9203	0.0846	<.0001
South Carolina	45	0.1633	0.0479	0.0006
South Dakota	46	-0.2622	0.0472	<.0001
Tennessee	47	0.0998	0.0603	0.0978
Texas	48	-0.3005	0.0637	<.0001
Utah	49	-0.264	0.066	<.0001
Vermont	50	-0.6114	0.0621	<.0001
Virginia	51	-0.4451	0.0652	<.0001
Washington	53	-0.5855	0.0721	<.0001
West Virginia	54	0.1761	0.0598	0.0032
Wisconsin	55	-0.6162	0.0477	<.0001
Wyoming	56	0	0	.

Table A.5 State-specific parameter estimates for the MCS model for Rural Fatalities with VMT as exposure (2001-2016)

Parameter	State code	Estimate	Standard Error	p-value
Alabama	1	0.4921	0.0924	<.0001
Alaska	2	0.3944	0.0964	<.0001
Arizona	4	0.6216	0.0768	<.0001
Arkansas	5	0.6975	0.0786	<.0001
California	6	0.7546	0.1063	<.0001
Colorado	8	0.3371	0.0688	<.0001
Connecticut	9	0.245	0.1012	0.0155
Delaware	10	0.1734	0.1001	0.0833
Florida	12	0.6576	0.0811	<.0001
Georgia	13	0.417	0.0877	<.0001
Hawaii	15	0.2438	0.0842	0.0038
Idaho	16	0.4604	0.0718	<.0001
Illinois	17	0.2176	0.0981	0.0265
Indiana	18	0.2996	0.0688	<.0001
Iowa	19	0.0773	0.0936	0.4089
Kansas	20	0.6257	0.074	<.0001
Kentucky	21	0.5029	0.0705	<.0001
Louisiana	22	0.4021	0.088	<.0001
Maine	23	0.0386	0.0749	0.6058
Maryland	24	0.3032	0.1122	0.0069
Massachusetts	25	-0.0101	0.1158	0.9306
Michigan	26	0.3086	0.089	0.0005
Minnesota	27	-0.1593	0.0654	0.0149
Mississippi	28	0.563	0.1035	<.0001
Missouri	29	0.3924	0.089	<.0001
Montana	30	0.3105	0.0874	0.0004
Nebraska	31	0.1248	0.0924	0.1767
Nevada	32	0.3218	0.0983	0.0011
New Hampshire	33	-0.3954	0.1123	0.0004
New Jersey	34	0.2162	0.1231	0.0789
New Mexico	35	0.3287	0.0774	<.0001
New York	36	0.4493	0.103	<.0001
North Carolina	37	0.6658	0.0904	<.0001

Parameter	State code	Estimate	Standard Error	p-value
North Dakota	38	-0.1286	0.0719	0.0737
Ohio	39	0.258	0.0682	0.0002
Oklahoma	40	0.567	0.0727	<.0001
Oregon	41	0.5955	0.0996	<.0001
Pennsylvania	42	0.0741	0.0699	0.2889
Rhode Island	44	-0.103	0.1077	0.3389
South Carolina	45	0.7434	0.0719	<.0001
South Dakota	46	0.1718	0.0751	0.0222
Tennessee	47	0.6103	0.0939	<.0001
Texas	48	0.4835	0.0753	<.0001
Utah	49	0.6756	0.0913	<.0001
Vermont	50	-0.3099	0.0992	0.0018
Virginia	51	0.3931	0.1028	0.0001
Washington	53	0.5944	0.1021	<.0001
West Virginia	54	0.5829	0.1037	<.0001
Wisconsin	55	-0.0807	0.0683	0.2373
Wyoming	56	0	0	.

Table A.6 State-specific parameter estimates for the MCS model for Urban Fatalities with VMT as exposure (2001-2016)

Parameter	State code	Estimate	Standard Error	p-value
Alabama	1	0.5112	0.1436	0.0004
Alaska	2	0.1848	0.1442	0.2001
Arizona	4	0.5505	0.1196	<.0001
Arkansas	5	0.5311	0.1237	<.0001
California	6	0.1094	0.1589	0.4913
Colorado	8	0.0036	0.1076	0.9732
Connecticut	9	-0.0333	0.1473	0.8211
Delaware	10	-0.1285	0.1402	0.3592
Florida	12	0.4123	0.1239	0.0009
Georgia	13	0.3437	0.1359	0.0114
Hawaii	15	0.2168	0.1215	0.0745
Idaho	16	0.1116	0.1173	0.3413
Illinois	17	0.035	0.1481	0.8132
Indiana	18	0.0014	0.108	0.9894
Iowa	19	-0.212	0.1458	0.146
Kansas	20	-0.1329	0.1167	0.2546
Kentucky	21	0.4737	0.1121	<.0001
Louisiana	22	0.6845	0.1384	<.0001
Maine	23	-0.6422	0.1323	<.0001
Maryland	24	0.0607	0.168	0.7176
Massachusetts	25	-0.2221	0.1665	0.1822
Michigan	26	0.1703	0.1387	0.2194
Minnesota	27	-0.5724	0.1037	<.0001
Mississippi	28	0.3139	0.1614	0.0517
Missouri	29	0.223	0.1388	0.1082
Montana	30	-0.2006	0.1495	0.1796
Nebraska	31	-0.2397	0.1444	0.0969
Nevada	32	0.3842	0.149	0.0099
New Hampshire	33	-0.5897	0.1756	0.0008
New Jersey	34	0.0455	0.179	0.7995
New Mexico	35	0.4085	0.1229	0.0009
New York	36	-0.0722	0.1576	0.6468
North Carolina	37	0.1113	0.1398	0.4259

Parameter	State code	Estimate	Standard Error	p-value
North Dakota	38	-0.4822	0.1291	0.0002
Ohio	39	-0.1771	0.1077	0.0999
Oklahoma	40	0.2239	0.1148	0.0511
Oregon	41	-0.1318	0.1526	0.3879
Pennsylvania	42	0.3144	0.1086	0.0038
Rhode Island	44	0.1506	0.125	0.2282
South Carolina	45	-0.1107	0.1175	0.3463
South Dakota	46	-0.151	0.1293	0.2431
Tennessee	47	0.5416	0.1448	0.0002
Texas	48	0.1963	0.1169	0.093
Utah	49	-0.0481	0.1397	0.7304
Vermont	50	-0.4143	0.1676	0.0134
Virginia	51	-0.1943	0.1561	0.2132
Washington	53	-0.2523	0.1555	0.1047
West Virginia	54	0.5382	0.1609	0.0008
Wisconsin	55	-0.1116	0.1108	0.3138
Wyoming	56	0	0	.

APPENDIX B

RESULTS OF EFFECT ANALYSIS ON THE LOG-CHANGE MODEL

Table B.1 Effects of change model predictors for changes in fatalities during 2007-2011

Variable	Estimate	2007 mean	2008-2011 mean	Percent change in predictor 2007-2011	Logworth of predictors 2007-2011
Intercept	-0.01061	-	-	-	-
Total VMT	0.00458	3027515	2957888	-2.3	0.7
Proportion of Rural VMT	0.04064	0.422	0.415	-1.7	0.8
GDP per capita	0.05531	5.809	5.373	-7.5	0.4
Median Income	0.10103	5.597	5.356	-4.3	**1.1**
Unemployment for age 16 to 24	-0.13483	9.952	15.491	55.7	**1.0**
Pump price	0.02622	3.134	3.214	2.6	0.3
Capital spending	-0.00380	62.482	67.390	7.9	0.3
Safety spending	0.00392	10.203	10.129	-0.7	0.2
Beer consumption	0.45395	1.264	1.219	-3.6	0.8
DUI rating	-0.22095	19.290	20.060	4.0	0.8
Belt rating	-0.05829	2.320	2.410	3.9	**1.0**
Motorcycle Helmet rating	-0.02017	2.720	2.720	0.0	0.0
Penetration of Post-1991 vehicles	0.52938	95.8	97.1	1.4	0.0

*Bold numbers represent largest and statistically significant (at α=0.10) effects of variables

Table B.2 Effects of change model predictors for changes in fatalities during 2011-2016

Variable	Estimate	2011 mean	2012-2016 mean	Percent change in predictor 2011-2016	Logworth of predictors 2011-2016
Intercept	-0.01061	-	-	-	-
Total VMT	0.00458	2942564	15128367	-414.1	0.6
Proportion of Rural VMT	0.04064	0.414	0.396	4.3	0.1
GDP per capita	0.05531	5.179	5.148	0.6	0.2
Median Income	0.10103	5.221	5.477	-4.9	0.3
Unemployment for age 16 to 24	-0.13483	16.342	12.585	23.0	**2.0**
Pump price	0.02622	3.687	3.358	8.9	0.2
Capital spending	-0.00380	72.129	67.814	6.0	0.5
Safety spending	0.00392	10.401	10.595	-1.9	0.2
Beer consumption	0.45395	1.185	1.172	1.1	0.0
DUI rating	-0.22095	20.340	20.610	-1.3	0.1
Belt rating	-0.05829	2.480	2.520	-1.6	**1.3**
Motorcycle Helmet rating	-0.02017	2.720	2.720	0.0	0.0
Penetration of Post-1991 vehicles	0.52938	97.6	97.9	-0.3	0.0

*Bold numbers represent largest and statistically significant (at α=0.10) effects of variables

APPENDIX C

EXPECTED MECHANISMS OF PREDICTORS

Table C.1 Expected mechanisms of predictors impacting traffic fatalities*

Variable	Influence on traffic fatalities	Expected mechanism
Total VMT	Positive	Increase in VMT increases exposure to traffic crashes and therefore fatalities.
Proportion of rural VMT	Positive	Increased proportion of rural VMT increases the proportion of travel on riskier roads, leading to more fatalities.
Pump price	Negative	Increased pump price raises the cost of travel, reducing total travel and discretionary travel, reducing exposure to fatal crashes.
GDP per cap	Positive	GDP per capita reflects economic activity which in turn leads to more travel, more exposure to crashes, and more fatalities.
Median Income	Positive	Increased median income increases discretionary and leisure travel, resulting in more exposure and more fatalities.
16-24 Unemployment	Negative	Increased unemployment reduces total travel and discretionary, leisure travel, resulting in fewer fatalities.
Capital spend/mile (lag)	Mixed	Improved infrastructure would be expected to shift travel to higher quality roads. It may also induce more travel, thus more exposure to fatalities.
Safety spend/mile (lag)	Negative	Increased traffic enforcement, education, and safety programs would reduce risky driving and reduce fatalities.
Belt use rate	Negative	Increased belt use provides more protection to vehicle occupants and reduces the probability of fatal injury, given a crash.
DUI law rating	Negative	Increased stringency of DUI laws reduces drunk (risky) driving and traffic fatalities.
Motorcycle helmet law rating	Negative	Increased stringency of motorcycle helmet laws provides more protection to motorcycle riders and reduce the probability of fatality given a crash.
Beer consumption	Positive	Increased beer consumption may increase driving while under the influence of alcohol, increase risky driving, and increase traffic fatalities.
Wine consumption	Positive	Increased wine consumption may increase driving while under the influence of alcohol, increase risky driving, and increase traffic fatalities.
Penetration of post-1991 model year	Negative	Increased penetration of vehicles that provide more occupant protection and more safety features reduces the probability

*Blower, D., C. Flannagan, S. Geedipally, D. Lord, and R. Wunderlich. Identification of factors contributing to the decline of traffic fatalities in the United States from 2008 to 2012. Final Report NCHRP Project 17-67. Transportation Research Board, Washington, D.C., 2019.Reprinted with permission from the National Academy of Sciences, Courtesy of the National Academies Press, Washington, D.C.