Identification of Factors Contributing to the Decline of Traffic Fatalities in the United States from 2008 to 2012 (2020)

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NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

NCHRP RESEARCH REPORT 928

Identification of Factors Contributing to the Decline of Traffic Fatalities in the United States from 2008 to 2012

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2020

NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

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FOREWORD

By Mark S. Bush
Staff Officer
Transportation Research Board

This report describes a comprehensive analysis of the factors associated with fatality rates in states, especially as they relate to the substantial drop in fatalities occurring in the years from 2008 to 2011. The analysis included predictors representing a wide variety of potentially related factors including travel, demographics, the economy, vehicle safety systems, and state spending on several categories of infrastructure and safety improvements. Understanding the broad array of factors that influence traffic safety in the United States is particularly important for state highway safety planning.

From 2008 to 2011, the United States, along with several other countries, experienced a substantial drop in annual traffic fatalities. State departments of transportation are keenly interested in capturing the key contributing factors to this decline so that the information can be used to help focus resources on effective countermeasures in future years. Safety countermeasures are implemented in a wide variety of ways—changing behavior (e.g., through driver education), changing vehicles (e.g., with Electronic Stability Control and other safety technologies), and changing the environment (e.g., improving roadways, laws, and enforcement). Safety can be influenced by factors other than safety efforts themselves, so it can be difficult to know which changes are responsible for overall reductions in fatalities.

Under NCHRP Project 17-67, the research conducted by the University of Michigan, with support from Texas A&M was asked to provide a multidisciplinary analysis of the relative influence of the types of factors that contributed to the national decline in the number of highway fatalities and rates in the United States during the years of 2008–2011. The research team used the Haddon matrix to identify a large number of potential travel, demographic, economic, vehicle, and infrastructure influences on fatalities. Data on these factors were then collected from data sources publicly available at the state level (e.g., FHWA Highway Statistics). Annual state-level measures of these factors were compiled into a database covering the years from 2001 to 2012 and matched with fatalities from the Fatality Analysis Reporting System (FARS) database.

These data were analyzed using statistical methods to predict fatalities in states as well as changes over time. Because the statistical models closely approximated the reduction in fatalities from 2008 to 2011, the factors could then be evaluated in terms of their individual (and combined) contributions to fatalities. This report covers the scope of the problem, the data obtained to measure each factor, the statistical models, and the interpretation of results to understand how different factors play a role in total fatality counts. The knowledge gained from this process can be used to predict future fatality levels for planning at the state level and to provide insight into factors influencing these levels and actions that might reduce them.

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Note: Photographs, figures, and tables in this report may have been converted from color to grayscale for printing. The electronic version of the report (posted on the web at www.trb.org) retains the color versions.

ABBREVIATIONS

3R/4R	Relocation, resurfacing, restoration, rehabilitation and reconstruction
AIC	Akaike information criterion
BAC	Blood alcohol concentration
CMF	Crash modification factor
CPI	Consumer Price Index
DUI	Driving under the influence
EMS	Emergency medical service
ESC	Electronic stability control
FARS	Fatality Analysis Reporting System
FMVSS	Federal Motor Vehicle Safety Standards
GDL	Graduated driver licensing
GDP	Gross domestic product
GES	General Estimates System (of the National Automotive Sampling System)
GLM	Generalized linear model
GOF	Goodness-of-fit
HSIP	Highway Safety Improvement Program
IIHS	Insurance Institute for Highway Safety
IRTAD	International Traffic Safety Data and Analysis Group
LTV	Light truck vehicle
MAD	Mean absolute deviation
MCS	Model controlling for state
MCSAP	Motor Carrier Safety Assistance Program
MNCS	Model not controlling for state
MSPE	Mean squared prediction error
NB	Negative binomial (model)
NBER	National Bureau of Economic Research
NCAP	New Car Assessment Program
NHTS	National Household Travel Survey
NOPUS	National Occupant Protection Use Survey
OECD	Organization for Economic Cooperation and Development
PC	Principal component
PCA	Principal Components Analysis
QIE	Quasi-induced exposure
SUV	Sport utility vehicle
TTI	Texas A&M Transportation Institute
UMTRI	University of Michigan Transportation Research Institute
VIN	Vehicle identification number
VMT	Vehicle miles traveled

SUMMARY

Identification of Factors Contributing to the Decline of Traffic Fatalities in the United States from 2008 to 2012

Objective

The research objective, as outlined in the original request for proposal, 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 United States." Between 2005 and 2011, peak to trough, the number of traffic fatalities in the United States declined by 11,031, from 43,510 in 2005 to 32,479 in 2011 (see Figure S-1). This decline amounted to a reduction in traffic-related deaths by 25.4%, by far the greatest decline over a comparable period in the last 30 years.

Historically, significant drops in traffic fatalities over a short period have coincided with economic recessions. Figure S-2 displays the number of traffic fatalities by year from 1966 through 2016, along with the periods of the seven recessions during that span. Traffic fatalities for 2016 were projected from an early estimate by NHTSA of the number of fatalities during the first half of 2016 (NHTSA 2016a). Longer recessions have coincided with deeper declines in the number of traffic fatalities. This project provides an analysis that identifies the specific factors in the economic decline that affected fatal crash risk, while taking into account the long-term factors that determine the level of traffic safety.

The fundamental approach of this research project was based on the understanding that the number of fatalities in crashes is the product of risk times exposure:

$$\text{Fatalities} = \text{Risk} \times \text{Exposure} \qquad \text{Eq. S-1}$$

Figure S-3 displays the relationship between vehicle miles traveled (VMT) (exposure), traffic fatalities (outcomes), and traffic fatality rates by VMT (risk), from 2001 to 2012. The figure shows the ratio of the values for each year to the base year of 2001. Exposure as measured by VMT was relatively stable. However, a reduction in the risk of travel pulled down the number of traffic fatalities. Thus, the fatality risk of travel contributed significantly to the substantial decline in fatalities over the period. The decrease in exposure due to the recession and subsequent slowdown in economic activity contributed less. The goal of this project was to identify the sources of reduced risk.

Analysis Approach

Factors that affected the incidence and risk of fatal crashes and fatal crash injuries over the period were organized using the Haddon Matrix. The Haddon Matrix provides a framework that covers the factors comprehensively (Williams 1999). The utility of the

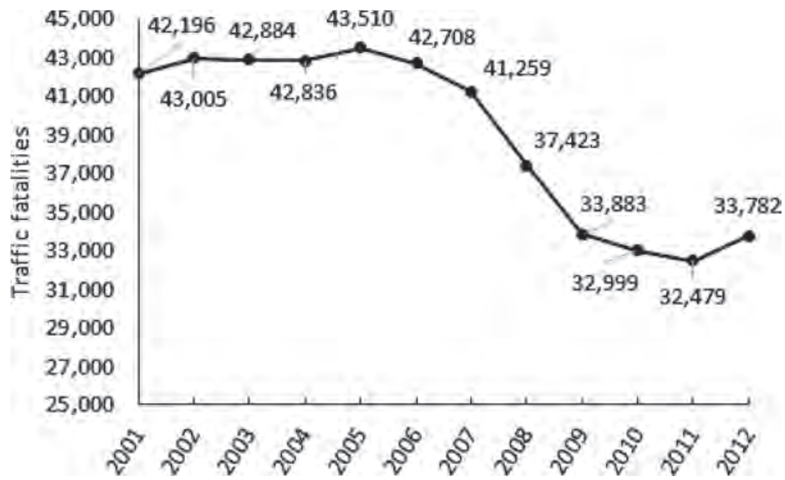


Figure S-1. Traffic fatalities, 2001–2012.

Haddon Matrix was to ensure that all components of what might be called the crash system—vehicle, drivers, and environment—were considered.

Two fundamental processes were at work over the period. The first process set the baseline level of safety that influenced the number of traffic deaths each year. The baseline level was the product of long-term trends in factors known to affect traffic safety, such as safety-belt use, improvements in the crashworthiness of cars, highway infrastructure, traffic enforcement and safety campaigns, driver license laws, and other efforts to reduce the number of

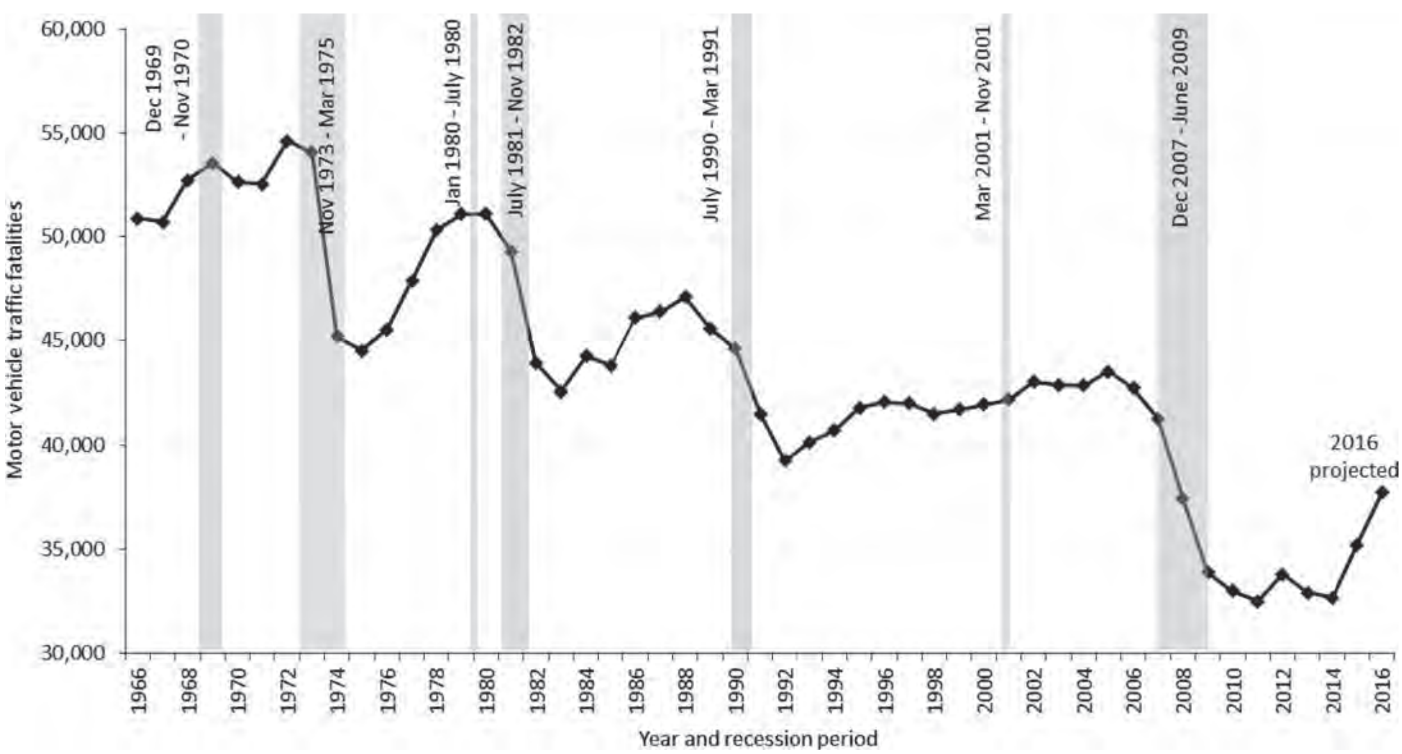


Figure S-2. Motor vehicle traffic fatalities and periods of recession, 1966–2012.

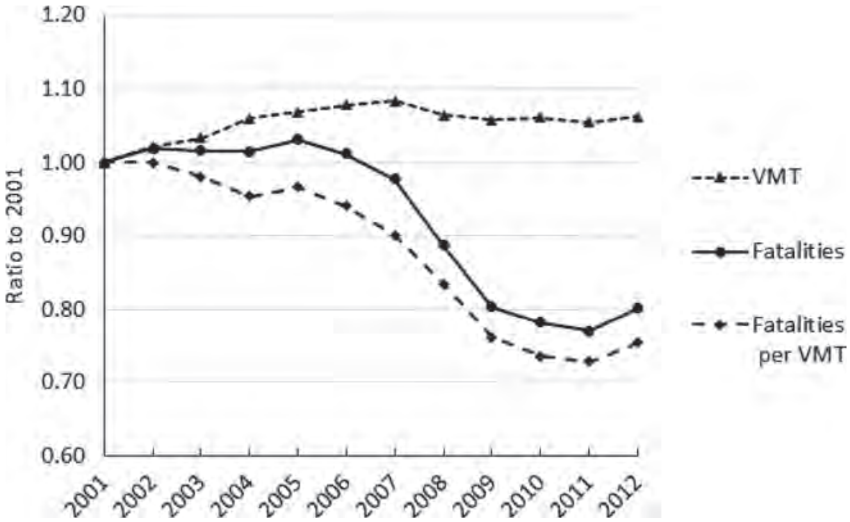


Figure S-3. Fatality rates by VMT and fatalities, normalized to 2001.

fatalities on U.S. roads. Most of these factors operated incrementally and changed relatively slowly over time. Highway infrastructure cannot change dramatically over a short period. Safety-belt use is known to be a primary safety intervention, but belt use increased slowly and monotonically over the period.

The second process consisted of the factors that precipitated the sharp decline in fatal crashes and deaths from 2008 to 2011. The major event in this period was the recession that started in December 2007 and ended in June 2009 (NBER 2010). Of the components of the crash system—vehicle, drivers, and environment—recessions have a short-term and substantial impact on drivers. Moreover, the recession affected some high-risk groups more than others, particularly younger drivers, so it may have taken some risky drivers off the road and reduced the amount of risky driving.

At the same time, the long-term factors that influenced safety continued, such as incremental increases in safety-belt use, the penetration of more crashworthy passenger vehicles into the fleet, safety campaigns to improve driver behavior, infrastructure improvements, and other factors. Explaining the drop in traffic fatalities between 2008 and 2011 was a major goal of the project, but the explanation is undertaken within the context of overall trends in traffic safety over the period.

Findings and Statistical Models

A key insight into the analysis of factors producing the sharp drop in traffic fatalities was that the young contributed disproportionately to the drop-off in traffic fatalities. Of the reduction in traffic fatalities from 2007 to 2011, persons younger than 26 years of age accounted for almost 48% of the drop, though they were only about 28% of total traffic fatalities prior to the decline. Figure S-4 shows that traffic deaths among persons 25 years old or younger dropped substantially more than other groups. Young drivers are known to be a high-risk group and can be readily identified in the crash data. Other high-risk groups also likely contributed to the decline, but they cannot be identified as well as age can.

Using the Haddon Matrix and the research team's broad expertise, a comprehensive set of parameters was identified, and their contribution to the drop in traffic fatalities after

4 Identification of Factors Contributing to the Decline of Traffic Fatalities in the United States from 2008 to 2012

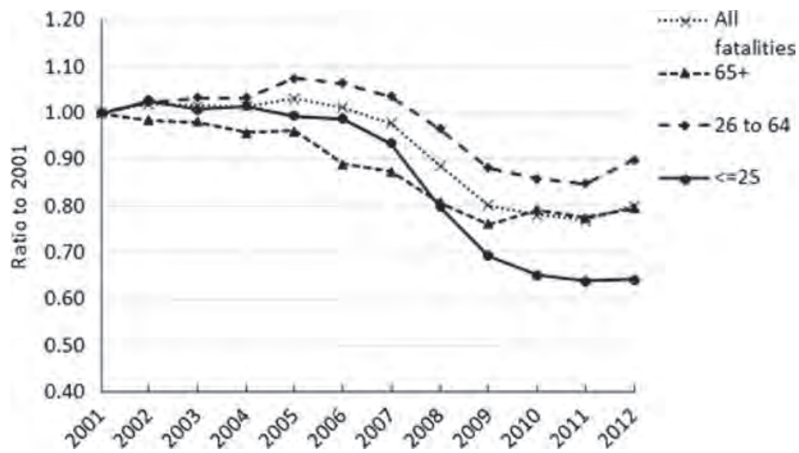


Figure S-4. Ratio of traffic fatalities by age groups, normalized to 2001.

2007 was evaluated. Statistical models of the incidence of traffic fatalities over the period were developed using these parameters. Table S-1 provides the expected association of the various parameters in the models and describes the mechanisms through which they were hypothesized to affect the number of traffic fatalities. Most of the modeling results were consistent with these expectations, though not all.

Two basic approaches were used to model the factors that were associated with the drop in traffic fatalities after 2007. The first approach was a set of count models, using negative binomial models to examine the associations between predictors (the variables in Table S-1) and raw fatality counts. Two count models were developed. One used a state fixed effect to remove the stable differences between states and focus on changes over time; this was labeled the model considering state or models controlling for state (MCS) model. The other model left out this fixed effect, allowing differences between states to be captured by the measured predictors; this was labeled the model not considering state (MNCS). The other statistical modeling technique was a log-change regression model, to model the association between the change in predictor variables in one year with the change in the outcome variable (traffic fatalities) in the following year. Table S-2 shows the results from the two count models. Table S-3 provides the results from the change model.

The two modeling approaches were in broad agreement. The most significant contributors to the drop in traffic fatalities after 2007 were the substantial increase in teen and young adult unemployment, the reductions in median household income, and the reduction in gross domestic product (GDP) per capita income. The right-most column in Table S-3 estimates the percentage decline contributed by each factor in the change model. The decline in rural VMT, increased strictness of DUI laws, and decreased beer consumption also contributed. State highway spending was not a significant contributor to the drop; the effect of changes in infrastructure was likely more cumulative and longer term. Changes in safety-belt use rates and fuel prices were not significant contributors to the decline in traffic fatalities after 2007 because they did not change much over the period.

Failing to find that certain well-established safety interventions (safety-belt usage, highway capital improvements) did not contribute significantly to the sharp drop in traffic fatalities during the recession does not mean that they are not essential tools to reduce

Table S-1. Explanatory factors and expected mechanisms of activity.

Variable	Expected association with traffic fatalities	Expected mechanism
Total VMT	Positive	Increase in VMT increases exposure to traffic crashes and therefore fatalities.
Proportion rural VMT	Positive	Increased proportion of rural VMT increases proportion of travel on riskier roads, leading to more fatalities.
Pump price	Negative	Increased pump price raises cost of travel, reducing total travel and discretionary travel, reducing exposure to fatal crashes.
Gross domestic product (GDP) per capita	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 spending/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 spending/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.
Driving under the influence (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 reduces 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 model year >1991	Negative	Increased penetration of vehicles that provide more occupant protection and more safety features reduces the probability of a crash, and reduces the probability of fatal injury, given a crash.

Table S-2. Effects of count-model factors.

Variable	Change in parameter value from 2007 to 2011	MNCS model		MCS model	
		Predicted change in fatalities	Statistically significant at 5% level?	Predicted change in fatalities	Statistically significant at 5% level?
Rural VMT proportion as percent of total	−0.8 %	−103	Yes	95	Yes
State gross domestic product per capita	−$6,301 per person	−617	Yes	−1236	Yes
Unemployment rate for 16- to 24-year-olds	+6.39%	−3305	Yes	−3125	Yes
Pump price	+$0.55/gallon	−877	No	127	No
Per capita beer consumption	−0.08 gallon/person	−835	Yes	−1312	Yes
Median income	−$3,760	2,677	Yes	−466	Yes
DUI laws rating	−1.05	−120	No	−261	Yes
Safety-belt laws rating	−0.16	5	No	−28	No
Motorcycle helmet law rating	0	0	Yes	0	No

traffic fatalities. It means that their impact was not detectable given the magnitude of the short-term effects of other factors. The long-term factors that set the baseline of traffic safety continued to operate. Overlaid on them were the short-term shock of the recession, which drove up unemployment, particularly among teens and young adults, and declining median income, which likely reduced driving and risky driving among high-risk populations.

Implications and Further Research

- Teens and young adults contributed disproportionately to the reduction in traffic fatalities from 2008 through 2011. It is suggested here that the mechanism was economic constraints that reduced total travel and risky (discretionary and leisure) travel. It has long been known that teens and young adults have disproportionately high crash risk, but the results from this study suggest that their behavior can be significantly modified over the short run, substantially reducing fatalities.
- The findings related to median household income are consistent with an income effect. This finding warrants further investigation, but interventions aimed at lower-income groups may have a disproportionately positive effect, similar to reducing crash risk among teens and young adults.
- DUI laws showed a significant positive effect in reducing traffic fatalities, even over the short term of this study and even within the substantial impact of the economic contraction. Reduced beer consumption similarly showed a significant positive effect. It is clear that continuing to focus on reducing drunk driving can have a disproportionate effect on reducing traffic fatalities.

Table S-3. Effects of change-model predictors for 2007–2011.

Variable	2007 Mean	2011 Mean	Percent change in predictor 2007–2011	Percent change in predicted fatalities 2007–2011
Total VMT	3,031,124	2,962,740	−2.3%	−1.2%
Proportion rural VMT	0.33	0.32	−1.6%	−0.1%
Pump price change	3.11	3.20	2.6%	−0.1%
Gross domestic product per capita change	59,687	54,519	−7.5%	−1.2%
Median income change	56,081	53,621	−4.3%	−2.2%
16–24 unemployment change	10.59	16.69	55.7%	−6.1%
Capital spending/mile (lag) change	73.69	81.27	7.9%	−0.1%
Safety spending/mile (lag) change	13.61	14.68	9.3%	0.1%
Belt-use rate change	85.77	88.10	2.4%	−0.1%
DUI law rating change	19.77	20.50	4.0%	−0.7%
Motorcycle helmet law rating change	2.91	2.91	0.0%	0.0%
Beer consumption change	1.21	1.15	−3.5%	−0.7%
Wine consumption change	0.37	0.39	5.0%	−0.1%
MY>1991 change	95.80	97.11	1.4%	0.1%

- Rural VMT bears a higher risk of fatal crashes across all road types; reduction in the proportion of rural VMT was significant in all models. Programs aimed at reducing the risk of rural travel can substantially reduce traffic fatalities.
- It may be difficult to discern in any given year the effects of safety countermeasures, due to the significant influence of other factors on traffic fatalities. There is a need to more fully document and assess safety advances from countermeasures because these other factors may obscure them.
- The results here clearly illustrate that factors outside the authority of safety professionals can have highly significant impacts on the level of highway safety. In the short term, shocks in the economy can overwhelm the effect of safety interventions that generally influence crash risk in the long term. It is clear that exogenous factors such as economic trends should be accounted for in setting realistic goals and evaluating traffic safety programs.

CHAPTER 1

Statement of the Problem

The research objective, as outlined in the original request for proposal, was to "provide a multi-disciplinary 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 United States." Between 2005 and 2011, peak to trough, the number of traffic fatalities in the United States declined by 11,031, from 43,510 in 2005 to 32,479 in 2011. This decline amounted to a reduction in traffic-related deaths by 25.4%, by far the greatest decline over a comparable period in the last 30 years.

Figure 1-1 shows counts of annual traffic deaths from 2001 through 2012, the period that is considered in this project. The figure shows that the number of traffic fatalities remained relatively stable over roughly the first half of the period, from 2001 to 2007, varying from 42,196 in 2001 to 43,510 in 2005. There were 41,259 deaths in 2007, which is within the relatively narrow range observed for the preceding 6 years. The number declined to 37,423 in 2008 and continued to decline to reach a low of 32,479 traffic fatalities. The pattern in Figure 1-1 suggests two processes. In the first part of the period, from 2001 to 2007, the number of traffic fatalities was relatively stable. The number averaged about 42,600, and varied by ±515. In the second period, from 2008 to 2012, the number of fatalities dropped dramatically to 32,479 in 2011, a decline of 8,780 traffic deaths, or about 21% from 2007. The number of traffic deaths increased in 2012, and in fact, subsequent years have seen increases as well. At the time this report was prepared, the number of fatalities has climbed to 35,092 in 2015 (NHTSA 2016b).

The goal of this project is to identify the factors that contributed to the substantial decline in traffic fatalities between 2008 and 2011.

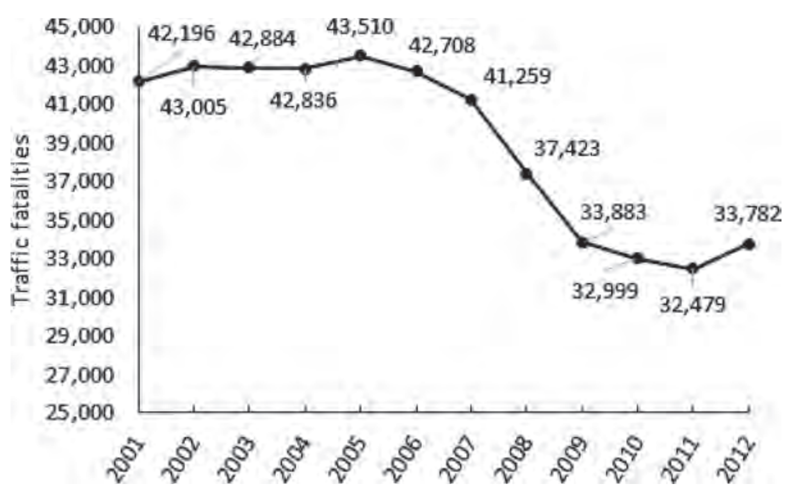


Figure 1-1. Traffic fatalities, 2001–2012.

CHAPTER 2

Analytical Approach

Two fundamental processes were at work over the period. The first process set the baseline level of safety that influenced the number of traffic deaths each year. This baseline level was the product of long-term trends in the factors that are known to affect traffic safety, such as safety-belt use, improvements in the crashworthiness of cars, the spread of crash-avoidance technologies, alcohol consumption, speed limits, highway infrastructure, traffic enforcement and safety campaigns, driver license laws, and other efforts to reduce the number of fatalities on U.S. roads.

The second process consisted of the factors that precipitated the sharp decline in fatal crashes and deaths in 2008–2011. The major event in this period was the recession that started in December 2007 and ended in June 2009 (NBER 2010). At the same time, the factors that influenced long-term trends in safety continued, such as incremental improvements in safety-belt use, the introduction of more crashworthy passenger vehicles into the fleet, safety campaigns to improve driver behavior, infrastructure improvements, and other factors. Explaining the drop between 2008 and 2011 is the major goal of the project, but the explanation is undertaken within the context of overall trends in traffic safety over the period.

2.1 Risk vs. Exposure

The number of fatalities and injuries in crashes is the product of risk times exposure:

$$\text{Fatalities} = \text{Risk} \times \text{Exposure} \qquad \text{Eq. 1}$$

Risk is expressed as the number of fatalities (in this case) per some unit of exposure, such as vehicle miles traveled (VMT) or the number of drivers or registered vehicles. Therefore, fewer traffic fatalities can be the result of lower risk of travel or less exposure to travel, or some combination of the two.

The risk/exposure equation suggests several possible general and high-level explanations for the drop. The dramatic decline of 2008 through 2011 coincided with and followed a significant economic recession, so naturally the economic slowdown is one possible explanation, though not the only one. Possible explanations for the decline in traffic fatalities include the following hypotheses:

1. The economic decline resulted in reduced VMT. The reduction in exposure to traffic crashes in turn resulted in fewer fatalities.
2. The economy had a differential impact on travel on certain types of risky roads. For example, rural areas tend to have higher fatal crash rates than urban areas for similar classes of roadways. (See Table 6-1 for fatality rates over the period.)

10 Identification of Factors Contributing to the Decline of Traffic Fatalities in the United States from 2008 to 2012

3. The economic decline led to changes in driver behavior such that drivers may have driven more cautiously. For example, drivers may have slowed down to conserve fuel, or they may have reduced leisure and discretionary driving, and thus reduced the risk of driving.
4. The economic decline may have reduced travel by high-risk drivers. Younger drivers and other high-risk drivers may have reduced their travel disproportionately, thus reducing the exposure to travel of particularly risky drivers.
5. Other factors, independent of the recession, may have reduced the risk of travel. These factors, including increased penetration of electronic stability control (ESC), improved crashworthiness, state programs to improve highway safety and reduce drunk driving, as well as other safety efforts, may have combined with the economic factors to reduce the risk of travel.

2.2 Use of the Haddon Matrix

Factors that affected the incidence of fatal crashes and fatal crash injuries over the period were organized using the Haddon Matrix (Williams 1999). The Haddon Matrix provides a framework to cover comprehensively the factors related to crash risk (Table 2-1). Within the Haddon Matrix, factors are disaggregated into pre-crash, crash, and post-crash factors, and by human, vehicular, and environmental factors. The factors in the pre-crash row of cells affect the probability of crashes; those in the crash row include factors that affect the severity of crashes; and those in the post-crash row affect severity of outcomes. Human factors include who drives and how they are prepared and licensed (pre-crash); how they drive and what occupant protections they use (crash); and their resilience to injury (post-crash). Vehicle factors cover design and performance; how well or poorly they protect occupants in crashes; and post-crash systems such as event notification and technologies to reduce the probability of post-crash fires. The environment component includes roadway design and conditions that affect the probability of crash involvement; designs and structures that reduce the severity of crashes that occur; and the post-crash infrastructure to treat crash injuries quickly and effectively. The utility of the Haddon Matrix is that it ensures that all aspects of what might be called the crash system—vehicle, occupants, and environment—are considered.

2.3 Economic Framework

Drivers, vehicles, and the infrastructure environment are all embedded within current economic conditions. VMT is in part a response to pure economic demand. Increased economic activity is supported by increased travel (especially for commercial motor vehicles). The state of the economy also influences private drivers' decisions about travel. Increases in GDP and higher

Table 2-1. Haddon Matrix to organize factors related to crash risk and severity.

	Human	Vehicle	Environment
Pre-crash	Factors that affect who drives and how they drive, such as graduated driver licensing and public information campaigns	Factors related to the condition and performance of vehicles, such as crash-avoidance technologies	Factors that affect the road and built environment to reduce crashes, such as rumble strips, wide shoulders, etc.
Crash	Choices occupants make to protect themselves, such as safety-belt use	Factors that affect how vehicles protect occupants in crashes, such as crush spaces and restraint effectiveness	Roadway design and structures to reduce crash severity
Post-crash	Factors that affect how occupants respond to crash injury, such as age, physical condition	Vehicle design and technologies to reduce post-crash harm, such as crash notification	Better/faster access to crash scenes, improved emergency medical service

incomes allow more discretionary travel. Increases in the unemployment rate, to the contrary, tend to reduce income and thus reduce travel and exposure to crashes. Reduced income might also affect the decision to buy newer vehicles, which are generally more crashworthy and which may be equipped with crash-avoidance technologies. Similarly, increased fuel costs raise the price per mile of travel and would be expected to lower the amount of travel, and thus exposure to crashes. Economic contraction might also slow the funding of infrastructure improvement that could reduce the number and severity of crashes.

The recession in this period officially began in December 2007 and ended in June 2009. The period of relative stability in the number of traffic fatalities corresponds to the period up to the beginning of the recession. The initial period of the decline in the number of traffic fatalities occurred at the same time as the recession was occurring. The National Bureau of Economic Research (NBER) defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales." (NBER 2013) Each change identified in the definition of a recession would tend to affect traffic safety by affecting the amount of exposure as well as, more subtly, decisions about who drives and where they drive.

The first part of the analytical approach was to identify the factors and trends that contributed to the underlying level of safety with respect to fatal injuries in traffic crashes. These are the factors that have contributed to the overall reduction in fatal crash rates over the past 50 years. The focus in the current project is on the years from 2001 to 2012, as a way of constraining the problem to a manageable time frame, but the factors that have contributed to the overall downward slope to fatal crash risk are reasonably well known. They include such elements as (to work through the Haddon Matrix) graduated driver licensing, improved headlights, improved road design with wide lanes and predictable geometry, increased safety-belt use, more crashworthy vehicles equipped with airbags, more effective guardrails and crash cushions, and quicker responses from emergency medical service (EMS), with more effective trauma care.

2.4 Study Outline

Chapter 3 of this report outlines international parallels, in which countries with advanced economies experienced a decline of similar magnitude in traffic fatalities coincident with the economic recession. Chapter 4 discusses evaluating the relative contribution of changes in risk and exposure to the drop in traffic fatalities. Chapter 5 outlines the data sources used in the analysis, followed in Chapter 6 by an analysis of the most important trends in fatal traffic crashes and VMT in the United States over the period 2001 to 2012. Chapter 7 provides the results of statistical modeling to understand the contribution of different factors to the drop in traffic fatalities, 2007 to 2012. Chapter 8 provides a discussion of the overall results. Chapter 9 outlines the major limitations of the current study, and Chapter 10 describes needed future research and the data necessary to support it.

CHAPTER 3

International Parallels

The U.S. decline in motor vehicle fatalities over the period from 2007 through 2011 was paralleled in many other countries with advanced economies that were affected by the global recession. Several studies in European countries examined the relationship between the state of the economy and traffic safety in general, and the particular effect of the 2007–2009 recession.

A recent comprehensive report by the International Traffic Safety Data and Analysis Group (IRTAD) of the International Transport Forum addressed the relationship between economic conditions and road safety. The report showed that traffic fatalities declined significantly over the period. One analysis considered 18 European countries, including Ireland and the United Kingdom, France, Germany, Spain, Austria, and Sweden, and several smaller countries (Table 3-1). In this analysis, each country experienced a substantial decline, ranging from 14% in France to 60% in Lithuania. Germany experienced a 19% decline, the United Kingdom 35%, and Spain 40% (Antoniou, Yannis et al. n.d.). In comparison, the reduction in the United States over the same period was about 21.3%, which fit within the range observed for the IRTAD countries, and only somewhat less than the overall reduction for the sum of the IRTAD countries.

Elvik (2013) studied the remarkable drop in traffic fatalities in the countries of the Organization for Economic Cooperation and Development (OECD), which overlaps with IRTAD. Traffic fatalities in the OECD countries dropped by a combined 12.6% from 2008 through 2010. Elvik attributed 65% of the reduction to the recession. Decreases in VMT accounted for relatively little of the decline, implying that a decline in fatal crash *risk* was the primary factor. Although data were not available to test directly, he suggested factors could have included a disproportionate reduction in travel by high-risk groups (e.g., young people) or more cautious driving, including reduced leisure travel (Elvik 2013). Lloyd and colleagues (2015) studied the decline in traffic fatalities in Great Britain from 2007 through 2010. They also found that changes in VMT contributed relatively little to the reduction, other than for heavy trucks (similar to the U.S. experience). The researchers found that the largest drop in fatalities was for young males and females, and that more recent passenger vehicle model years were associated with a lower proportion of crash fatalities, suggesting that newer cars provided more protection in crashes. In addition, they observed a decline in crashes associated with alcohol impairment, which the authors attributed to people imbibing at home rather than going out, i.e., less leisure and discretionary driving. Finally, the researchers observed a reduction in the percentage of speeders on motorways (the highest road class), which was consistent with the hypothesis that people drove more cautiously in the economically difficult times (Lloyd, Wallbank et al. 2015).

Forsman and colleagues (n.d.) examined the substantial drop in traffic fatalities in Sweden during the recession years of 2008 to 2009. Consistent with the other studies, they found that

Table 3-1. Reduction in traffic fatalities, selected European countries and the U.S., 2007–2011.

Country	Decline 2007 to 2011	Country	Decline 2007 to 2011
Belgium	21.3%	Hungary	48.1%
Czech Republic	37.0%	Netherlands	22.4%
Germany	19.1%	Austria	24.6%
Estonia	48.5%	Poland	25.4%
Ireland	44.4%	Portugal	19.7%
Greece	31.8%	Finland	23.7%
Spain	39.9%	Sweden	34.0%
France	14.1%	United Kingdom	34.7%
Italy	23.2%	IRTAD countries	27.3%
Lithuania	59.6%	U.S.	21.3%

Adapted from (Antoniou, Yannis et al. n.d.)

the drop in fatalities was greater than could be explained by the recession-related decline in VMT. While the reduction in fatalities was associated with the recession, the researchers' goal was to identify mechanisms beyond changes in VMT that produced the decline. The study compared the recession period with prior periods of economic growth. The researchers found that growth periods had higher numbers of crashes with multiple vehicles and multiple fatalities. They speculated that in periods of growth, more vehicles would be on the road, increasing exposure to multiple vehicle crashes. Most other factors examined, including time of day, age and sex, alcohol-impaired driving, and seat-belt use, were not statistically significant, primarily because of relatively small sample sizes. For example, the proportion of younger drivers in fatal crashes was only 15%, compared with almost 27% during periods of economic growth. This difference was in the expected direction and was of substantial magnitude but not statistically significant because of the small sample size (Forsman, Simonsson et al. n.d.). However, the difference is consistent with the hypothesis that the composition of VMT (e.g., less travel by young drivers) rather than the magnitude of VMT was significant in the decline.

CHAPTER 4

Trends in Risk and Exposure

Figure 4-1 shows trends in fatal crashes, traffic fatalities, and crashes of all severities over the period. All crashes are estimated from NHTSA's General Estimates System (GES). Fatal crashes and fatalities are derived from NHTSA's Fatality Analysis Reporting System (FARS) file.[1] The trends are shown normalized to 2001, the number of crashes and fatalities for each year shown as a ratio to the number in 2001. Normalizing in this way facilitates comparisons of trends in frequencies of significantly different magnitudes—there were around 6 million crashes per year but only around 38,000 fatal crashes. The trends illustrated in the figure are notable in four ways:

1. The numbers of fatal crashes and fatalities in traffic crashes from 2001 through 2007 were relatively stable. In 2001, there were 37,862 fatal crashes, resulting in 42,196 deaths. In 2007, there were 37,435 fatal crashes with 41,259 deaths.
2. In contrast, the total number of traffic crashes, as estimated from GES, declined by 11%, from 6.3 million to 5.6 million.
3. Between 2007 and 2011, which was the low point in the series, the number of fatal crashes and fatalities dropped by about 20%, from 37,435 crashes and 41,259 fatalities in 2007 to 29,757 fatal crashes and 32,479 fatalities in 2011.
4. Though the patterns for fatal crashes and fatalities are very similar, their curves increasingly diverge over time, and this divergence is observed over the whole period. In addition, there was a greater drop in fatal crashes than in crashes of all severities.

Changes in the volume of exposure to fatal crashes, as measured by VMT or vehicle registrations, were not sufficient to account for the drop in fatalities, as is clear from Figure 4-2. The figure shows traffic fatalities, VMT, and vehicle registrations normalized to 2001. VMT and vehicle registrations increased steadily from 2001 to 2007, while the number of fatalities increased more slowly and tended to fluctuate slightly. VMT declined slightly from 2007 and then remained relatively constant through 2011, while traffic fatalities decreased sharply. Vehicle registrations plateaued in 2008, declined slightly to 2010, and then increased slightly. Thus, exposure, measured by VMT or vehicle registrations, either declined slightly or stayed relatively flat over the period, while traffic fatalities dropped dramatically.

That fatalities declined sharply while exposure remained relatively stable or declined only slightly implies that there was a change in the risk of travel. This is the necessary implication of Equation 1: Fatalities = Risk × Exposure. Figure 4-3 shows the trends in VMT, traffic fatalities, and traffic fatality rates by VMT, relative to 2001. The rate of traffic fatalities per mile traveled

[1]In this report, all traffic crash and related statistics are derived either from the FARS or GES. See the data discussion in Chapter 5 for more information about FARS and GES.

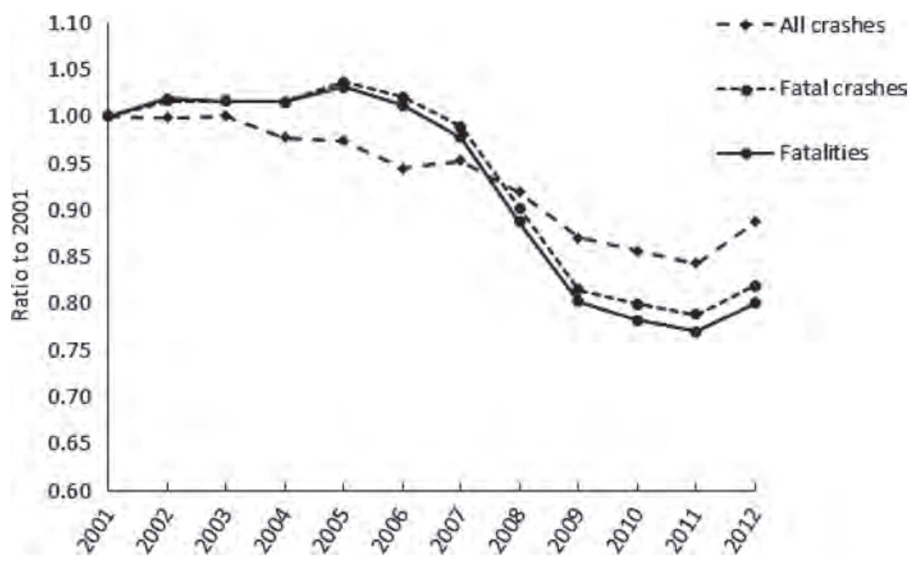


Figure 4-1. Trends in crashes, fatal crashes, and fatalities, 2001–2012.

declined relative to the rates in 2001. In the period from 2001 through about 2007, the decline was gentle, reflecting the overall reduction of risk reflective of the steady pressure to increase traffic safety, i.e., the first process of the analytical approach as identified in Chapter 2. Figure 4-3 shows the ratio of the rates for each year to 2001, and by 2007 the ratio for fatalities per VMT was down to 0.90. The line for normalized fatalities is shown for comparison; the ratio to 2001 remained around 1.0 through 2007, when it was 0.98, before plunging to a low of 0.77 in 2011. This suggests the second process, which is the target of the analytical approach. In contrast, VMT normalized to 2001 was 1.08 in 2007 and 1.06 in 2011. In effect, the reduction in the risk of travel pulled down the number of traffic fatalities, despite the relative stability of exposure as measured by VMT. This pattern is consistent with the hypothesis that the fatality *risk* of travel contributed to the significant decline in fatalities over the period. The decrease in *exposure* due to the recession and subsequent slowdown in economic activity contributed less.

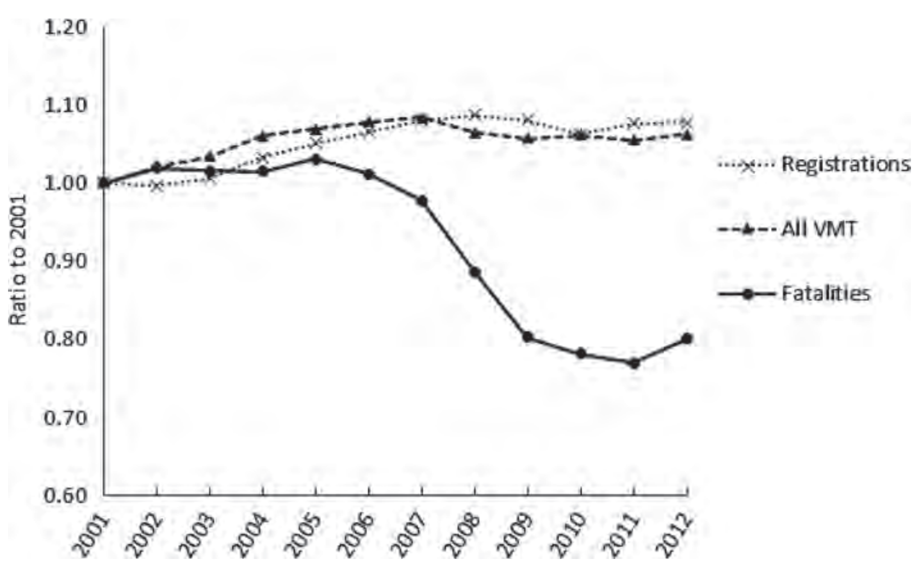


Figure 4-2. Trends in traffic fatalities, VMT, and vehicle registrations, 2001–2012.

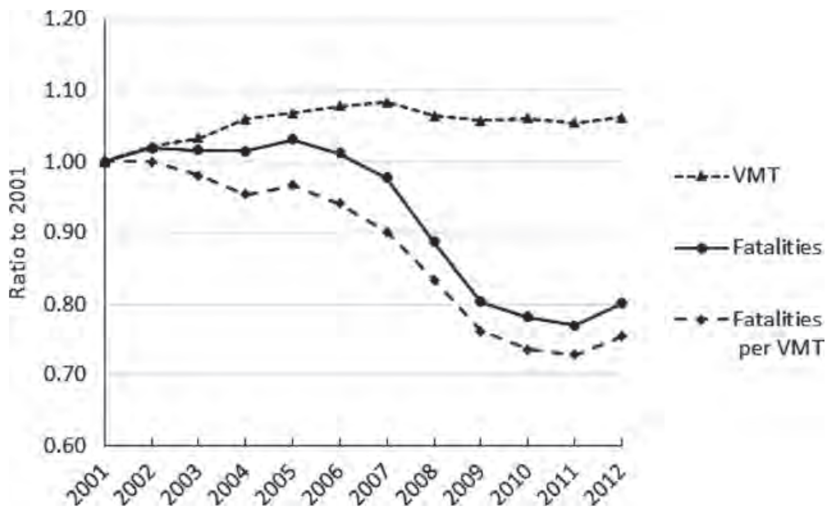


Figure 4-3. Fatality rates by VMT and fatalities, normalized to 2001.

CHAPTER 5

Data

Data series were assembled to cover the vehicle, driver, and environmental factors identified as related to traffic safety. In addition, numerous economic series were collected to reflect the influence of the economy on traffic safety. This chapter provides a list and discussion of the data and sources used.

The data series collected were largely at the state level, meaning that the data were collected for each state and year within the period 2001 through 2012. However, data were not available at the state level on vehicle fleets. Accordingly, data on vehicle characteristics at the national level were used in the models. However, unless otherwise identified, all data series are by year and state. The data included all 50 states. The District of Columbia was excluded because it introduced excessive variance and only accounted for 0.1% of traffic fatalities in the period.

5.1 Crash Data

The NHTSA FARS is the standard source for data on fatal traffic crashes in the United States. FARS provides a census file of all motor vehicle crashes in the United States that occurred on a trafficway customarily open to the public, and in which one or more persons died of crash injuries within 30 days of the crash. The FARS data set is composed of data compiled by analysts who are housed within each state. Data elements cover crash-level, vehicle-level, and person-level information. The data are collected from police accident reports, death certificates, vehicle registration files, hospital and coroner records, EMS reports, state highway department data, and other state records. There is one record for each crash, vehicle, and person involved in a fatal crash (NCSA 2014). FARS data were used for all analyses of fatal traffic crashes in this report.

NHTSA's General Estimates System data were used where it was informative to examine crashes of all severities. GES is a nationally representative probability sample of police-reported crashes in the United States. Crashes are sampled by a stratified, hierarchical sampling system from about 400 police jurisdictions nationally. About 50,000 crash reports are sampled each year. All data in GES were coded from police reports, without any additional investigation. The variables and code levels are largely consistent with variables and code levels in FARS (NHTSA 2014). GES data are sampled through a national sampling structure, and cannot be used to form state-level estimates.

5.2 Sources of Other Data Used

Exposure includes all types of measures that reflect the opportunity or exposure to the possibility of a crash. Table 5-1 lists the primary sources of exposure data. Population data are available from the U.S. Census Bureau (2016) for each state, including counts by state, age cohort,

Table 5-1. Exposure data series.

Data	Source
Population by state and age	Census Bureau (2016) Table 2. Intercensal Estimates of the Resident Population by Sex and Age
Square miles by state	Census Bureau, Geography, accessed at https://www.census.gov/geo/reference/state-area.html
Road miles by roadway function class and year	*Highway Statistics,* FHWA, Table HM-10 for each year, 2001–2012
VMT by roadway function class, vehicle type, urban/rural, national	*Highway Statistics*, FHWA, Table VM-1 for each year, 2001–2012
VMT by roadway function class, urban/rural, by state	*Highway Statistics,* FHWA, Table VM-202 for each year, 2001–2012
Vehicle registrations by type and state	*Highway Statistics,* FHWA, Table MV-1 for each year, 2001–2012

and year. Years between the census years of formal counts are estimated by interpolation. The bureau also has estimates of state area, which were used to compute population density. Road miles by FHWA function classes were used to normalize state highway expenditures, controlling for differences in the sizes of states.

VMT most directly captures exposure to crashes and is probably the most important measure of exposure used. The FHWA *Highway Statistics* publication provides annual estimates by roadway function class (including urban and rural) and vehicle type. *Highway Statistics* also includes vehicle registration data by year and state, and many other relevant data series, which will be discussed later (FHWA 1992-2014).

Data series on employment, the labor force, and unemployment were obtained from the Bureau of Labor Statistics (2016), based on the Current Population Survey (Table 5-2). The data are available by year and month for each state; annual state-level estimates were obtained by summing across the employment and labor force counts and taking the average. Employment was defined as the total number of persons on establishment payrolls employed full or part time who received pay for any part of the pay period that included the twelfth day of the month. Unemployed persons were defined as all persons 16 or older who had no employment, were available for work, and had made specific efforts to obtain employment. The labor force was defined as all persons either employed or unemployed according to those definitions. The full definitions can be obtained at http://www.bls.gov/sae/790faq2.htm#Ques3.

GDP estimates by state and year were obtained from the U.S. Department of Commerce. GDP measures the gross productive output of a state, so it is used as a gross estimate of economic activity. The estimates were divided by population estimates to produce GDP per capita estimates. Median household income estimates were obtained from the Bureau of Census Current Population Survey. The estimates available were for 2- to 3-year periods, not for individual years. Estimates for individual years were obtained by averaging over spans of years. For example, to obtain an estimate for 2010, estimates for 2009–2010 and 2010–2011 were averaged. Household income combines all incomes within a household, while GDP per capita is on a per person basis. All monetary estimates were converted to constant 2013 dollars using the Consumer Price Index (CPI) calculator at the Bureau of Labor Statistics (Bureau of Labor Statistics 2013).

Table 5-2. Economic data series.

Data	Source
Employment, total counts of employed by state, month, and year	Bureau of Labor Statistics, Current Population Survey, Local Area Unemployment Statistics
Labor force, by state, month, and year	Bureau of Labor Statistics, Current Population Survey
Unemployment rate, by state, month, and year	Bureau of Labor Statistics, Current Population Survey
State GDP by year	U.S. Department of Commerce, Bureau of Economic Analysis, Regional Economic Accounts: Download
State median household income by year	U.S. Census Bureau, Current Population Survey, Annual Social and Economic Supplements
Fuel tax by state by year	*Highway Statistics*, FHWA. Table MF-205
Fuel costs	U.S. Energy Information Administration (2016), State Energy Data System, prices for regular gasoline. Data are converted from prices per million BTUs.

Fuel prices were obtained from the U.S. Energy Information Administration, State Energy Data System (2016). Prices for regular-grade gasoline were selected for fuel prices because they represent the most common grade of fuel used. The prices were converted from prices per million BTUs to gallons, and then converted to constant 2013 dollars. Fuel taxes, in terms of cents per gallon, were available in the FHWA's *Highway Statistics Series*, Table MF-205, which tabulates fuel taxes for each state. Again, tax values were converted to constant 2013 dollars and summed with the fuel cost to produce an estimate of the price at the pump.

The Insurance Institute for Highway Safety (IIHS) maintains a valuable set of digests of state laws concerning critical aspects of traffic safety. These data were used to develop the indexes on the strength of state belt laws and motorcycle helmet requirements. Belt-use rates are available from the continuing National Occupant Protection Use Survey (NOPUS), published annually by NHTSA (reported in Chen 2014; Chen and Ye 2009). The National Institute of Alcohol Abuse and Alcoholism publishes estimates of per capita consumption of beer, wine, and alcoholic spirits. These are available by state and year. Kathleen Klinich of UMTRI (2016) has been compiling state laws related to drunk driving and shared data that were used to develop an index of state penalties and regulations. ESC penetration rates were estimated from a Highway Loss Data Institute report (2014). And finally, the penetration of post-1991 model year vehicles into the fleet was estimated using quasi-induced exposure methods. The rate of penetration was used as a surrogate for the spread of more crashworthy vehicles, in response to NHTSA's New Car Assessment Program (2007) and the strengthening of the Federal Motor Vehicle Safety Standards (see Table 5-3).

Data series on state highway expenditures are available in the FHWA's *Highway Statistics* series (1992–2014) (see Table 5-4). This series is an exceedingly valuable resource for highway safety. Each year, states report highway spending disaggregated by several types of activities, using a set of common forms, definitions, and instructions. Funding under the Highway Safety Improvement Program (HSIP) was compiled from FHWA funding tables under SAFETEA-LU (2005) and MAP-21 (2012), which are available on the FHWA website (see FHWA 2016a).

Table 5-3. Driver- and vehicle-related framework.

Data	Source
Seat belt, primary vs. secondary, by state and year	Compiled from Insurance Institute for Highway Safety, digest of state laws, available at http://www.iihs.org/iihs/topics/laws/safetybeltuse
Belt-use rates	Compiled from NHTSA's NOPUS program (Chen 2014; Chen and Ye 2009)
Blood alcohol concentration limit, per se, other alcohol-related laws and penalties, by state by year	Compiled from state laws, index developed from Klinich (2016)
Motorcycle helmet by state by year	Digest of motorcycle helmet laws from IIHS website, accessed at http://www.iihs.org/iihs/topics/laws/helmetuse/helmethistory?topicName=Motorcycles#tableData
Alcohol consumption	Compiled from National Institute of Alcohol Abuse and Alcoholism (Haughwout, LaVallee et al. 2015)
ESC penetration	Compiled from Highway Loss Data Institute report on the penetration of collision avoidance technologies (Highway Loss Data Institute 2014)
Post-1991 model year	Estimated from GES using a quasi-induced exposure technique

Table 5-4. Highway expenditures.

Data	Source
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 administration, 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 the Motor Carrier Safety Assistance Program (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

Highway spending was used in the statistical models to capture the effects of infrastructure and state highway programs on safety. Clearly, highway spending is an imperfect surrogate because the cost-benefit ratios of projects differ. However, it is believed that this surrogate is the best currently available. There are evaluations of specific projects, and crash-modification factors (CMFs) have been developed for different types of projects (AASHTO 2010a, 2010b). But there are no comprehensive data to translate CMFs into variables that capture the effects of modifications in a system-wide fashion. For example, there is ample literature evaluating the safety effect of installing rumble strips on shoulders and centerlines, but no comprehensive data on the penetration of rumble strips into the roadway system. Moreover, a safety-related spending variable was constructed that aggregates all spending that states themselves identified as safety related: law enforcement, state educational safety programs, and the portion of capital spending that the states declared to be safety related. Finally, it is assumed that state departments of transportation attempted to deploy their resources effectively. There are, no doubt, variations in effectiveness, but in light of currently available data, highway spending should be a reasonable approximation.

CHAPTER 6

Trends in Contributing Factors

It appears from Chapter 5 that the very large drop in the number of traffic fatalities was the product of a relatively small decrease in exposure and a decline in the risk of a fatal crash and/or the risk of fatal injury, given the occurrence of a crash. That is, a decline in the risk of traffic fatalities can be the product of fewer crashes or better protection for people involved in a crash, or both.

The Haddon Matrix provides a comprehensive coverage of factors that affect the risk of a crash and risk of injury within a crash. This chapter describes the most important trends in the factors that affected crash and fatal injury risk over the period considered. The purpose is to describe the trends in the areas of drivers, occupants, vehicles, highways, state regulatory laws, infrastructure and safety programs, and economic environment. Each trend affected the baseline of traffic safety over the period.

6.1 Age

The researchers studied trends in the age distribution of both drivers and victims in fatal traffic crashes, 2001–2012. Drivers were aggregated into four groups, reflecting crash risk and legal status: 15–17, the group subject to graduated driver licensing (GDL) laws; drivers 18–25, who typically have higher crash rates; drivers 26–64, with typically lower crash rates; and drivers 65 and older, when crash rates typically increase (Massie, Campbell et al. 1995). The trends were important in terms of the overall impact on fatal crash rates; in addition, the younger age groups were disproportionately involved in the decline in traffic fatalities beginning in 2008.

Figure 6-1 illustrates long-term trends as well as changes in driver-age distribution that occurred at about the time of the recession. The share of younger drivers in fatal crashes declined, while the share of older drivers increased. The proportion of drivers aged 15 to 17 declined from about 5% in 2001 to 2.4% in 2012 (left axis). The decline was relatively constant and not apparently affected by the recession. At the same time, the percentage of drivers 26 to 64 steadily increased over the entire period, from 60% to about 63% annually (right axis). However, the 18- to-25-year-old group showed a marked decline beginning around 2008, from around 22% of drivers in fatal crashes to 20%. Older drivers increased their percentage at the start of the recession from around 10% to almost 13% by the end of the period.

It is likely there was an actual reduction in travel by teens and young adults (age 25 and under) at about this period. VMT data by driver age and each year in the period are not available, but there is some evidence of a reduction in travel from the National Household Travel Survey (NHTS). The NHTS (formerly the Nationwide Personal Transportation Survey) collected data from a representative sample of respondents on daily trips of individuals and households. The data are self-reported but collected using a reasonably consistent methodology,

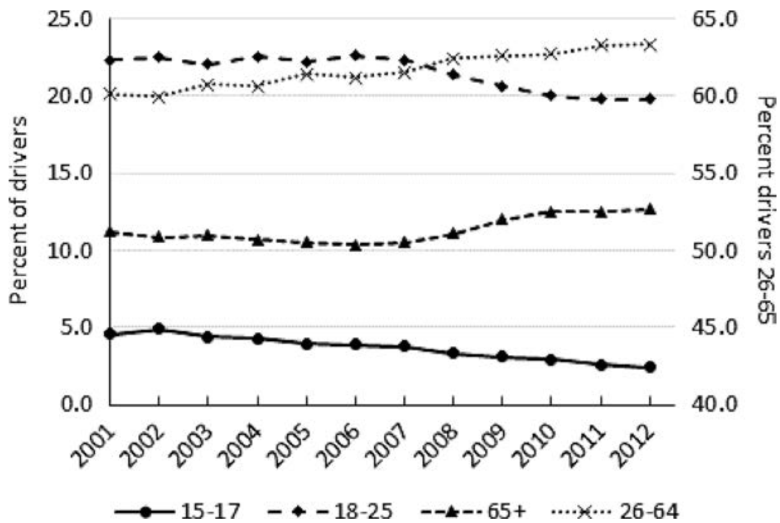


Figure 6-1. Percentage of driver age bands by crash year in fatal crashes.

so trends should be reliable. The surveys have been conducted every 5 to 8 years. The most recent surveys were conducted in 1990, 1995, 2001, and 2009. The youngest age group reported (16 to 19) showed a consistent reduction in average yearly travel from 1990 in subsequent survey years. Older age groups reported increases in yearly travel from 1990 through 2001. However, each age group reported a decline in average travel in 2009—during the recession—except the oldest group, 65 and older. Moreover, the reported decline in annual travel in 2009 for drivers 20 to 34 was substantially greater than those of the older groups. Drivers 20 to 34 reported a 12.4% decline in travel from the previous survey in 2001, and drivers 16 to 19 reported a 14.8% reduction. The reported decline for drivers 35 to 54 was only 3.3%, while drivers 55 to 64 report driving 4.9% fewer miles in 2009 than in 2001 (Santos, McGuckin et al. 2011). The data are just a snapshot of travel estimates in 2001 and 2009; it is unfortunate that VMT estimates by driver age were not available for the years between and after the NHTS surveys. However, the evidence from the NHTS is consistent with the hypothesis that one effect of the recession was to reduce driving by teens and young adults more than older age cohorts.

Figure 6-1 shows how the distribution of drivers' age in fatal crashes changed over the period. Figure 6-2 enlarges the scope to the age distribution of those who were actually killed in the crashes, including drivers, passengers, pedestrians, and other non-motorists. The ratio of fatalities in each year by age group to the number of fatalities in 2001 illustrates how traffic fatalities for the age groups changed. Traffic fatalities for the younger groups dropped proportionately more than for other groups. The total traffic deaths fluctuated within a narrow band prior to 2008, dropping thereafter. Disaggregating by age group, however, revealed different patterns. Traffic fatalities for persons 65 and older were actually increasing prior to 2008 relative to 2001 (ratio was greater than 1.0), while traffic fatalities for persons 26–64 started declining in 2006 and continued to decline until 2009, when the number leveled off. Fatalities among the younger group, those up to age 25, declined the most over the period. The number was reasonably stable from 2001 to 2006 (ratio about 1.0), but then declined so that by 2010 almost 40% fewer persons 25 and younger were being killed annually in traffic crashes, compared with 2001. The sharp decline began in 2008, which is roughly coincident with the recession.

The percentage of drivers 25 and under declined beginning in 2008, and the decline continued through 2012. Considering all fatalities, not just drivers involved in fatal crashes (whether or not

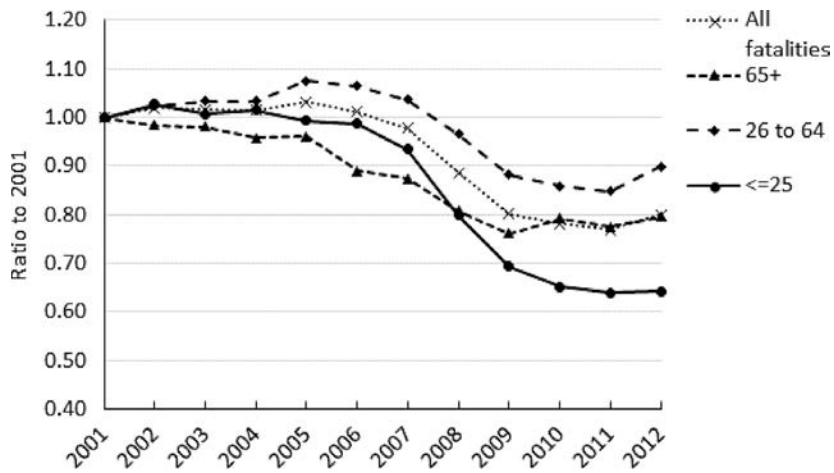


Figure 6-2. Ratio of traffic fatalities by age groups, 2001 to 2012.

they were fatally injured), the reduction in traffic fatalities in 2008 and later was disproportionately a decline in the number of people under 26 who died in traffic crashes. A simple estimate of the reduction in traffic fatalities 2008 through 2012, compared with 2007, was computed by assuming that each year after 2007 would have the same number of fatalities as 2007, taking the difference from the actual number, and then summing across the years from 2008 through 2012.

In Figure 6-3, the group of columns on the left shows the percent distribution of traffic fatalities in 2007 by age group, while the group of columns on the right shows the percentage of reduction in traffic fatalities accounted for by the different age groups. If the decline in fatalities was proportional for each age group, the shapes of the distributions would be the same, but they are substantially different. In 2007, the under-26 group accounted for 31.1% of fatalities. However, that group accounted for 47.7% of the decline in fatalities in 2008 through 2012. In comparison, persons 26 to 64 were 54.9% of fatalities in 2007, but accounted for only 44.2% of the reduction. The decline in traffic fatalities 2008 to 2012 was driven more by reductions in the younger age cohorts than the older.

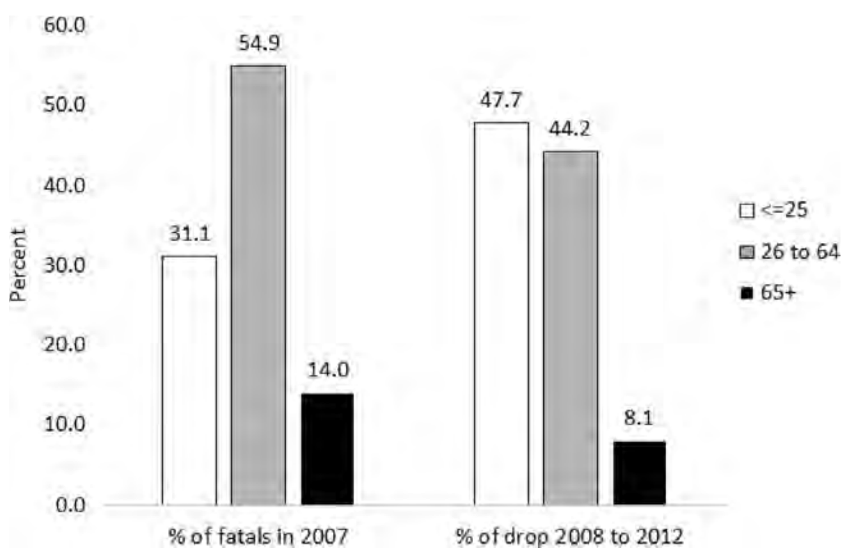


Figure 6-3. Estimated reduction in traffic fatalities, 2008–2012, by age.

6.2 Changes in Vehicles and Person Types Involved in Fatal Crashes

This section provides perspective on the distribution of vehicles and persons involved in fatal crashes. Neither was particularly important in influencing the substantial decline in fatalities 2008–2012, but both reflected long-term trends that affect the overall level of traffic safety. Personal transportation seemed to rotate away from passenger cars to light truck vehicles (LTVs), which include minivans and sport utility vehicles (SUVs). The incidence of fatalities among vulnerable road users—motorcyclists, pedestrians, bicyclists—was low relative to motor vehicle occupants, but generally trended up, though the trends varied among them.

Over the years from 2001 through 2012, the numbers of passenger vehicles involved in fatal crashes declined. The decline was reasonably steady up to 2007 and appeared to be part of a process in which LTVs gradually replaced passenger vehicles for personal travel (Figure 6-4, left axis). The number of trucks involved in fatal crashes was relatively constant up to 2007, dipped sharply in 2009, and then gradually recovered (right axis). Motorcycle involvement increased up to 2009, declined, and then recovered slowly, so that by 2012, the number was close to the pre-recession high. The number of buses involved in fatal crashes over the period was fairly stable, ranging from a low of 221 in 2009 to a high of 305 in 2001 and 2006. The "other" vehicle type consisted of a wide variety of all-terrain vehicles, snowmobiles, farm equipment, and the like. All vehicle types showed some sensitivity to the recession; trucks, the most economically sensitive type, declined the most, but there are also clear long-term trends in the rotation from passenger cars to LTVs, and the increase in motorcycle fatal involvements. Motorcycles, in fact, surpassed trucks in fatal crashes in 2007 and have been substantially greater since.

Figure 6-5 illustrates how the involvement of different motor vehicle types changed over the period. Relative to 2001, the number of passenger cars in fatal crashes declined steadily, accelerating somewhat in 2008 before leveling off and then actually increasing slightly in 2012. LTVs in fatal crashes actually increased up to 2008 and then declined through the recession and subsequent years. Trucks declined the most sharply then rebounded after 1 year. Motorcycles in fatal crashes increased each year from 2001 through 2008. In fact, in 2008, there were about 60% more motorcycles in fatal crashes than in 2001. The number decreased sharply in 2009, leveled off for a year and then increased again.

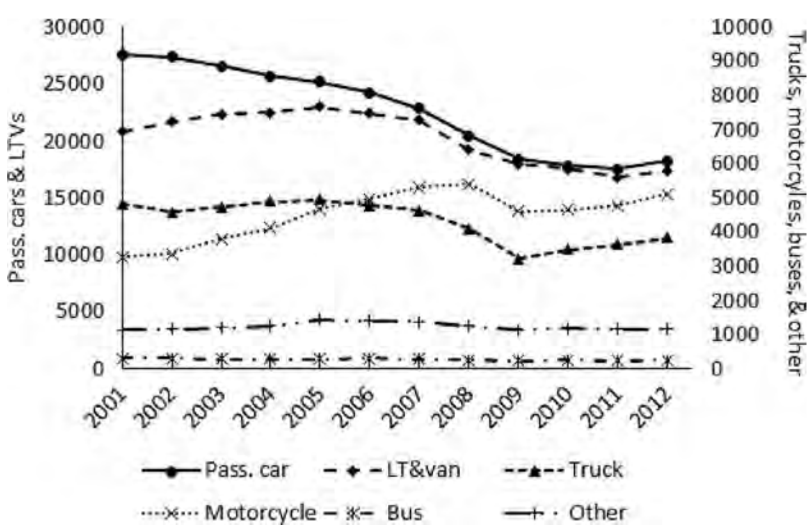


Figure 6-4. Passenger car, LTV, truck, motorcycle, bus, and other motor vehicle involvements in fatal crashes, 2001–2012.

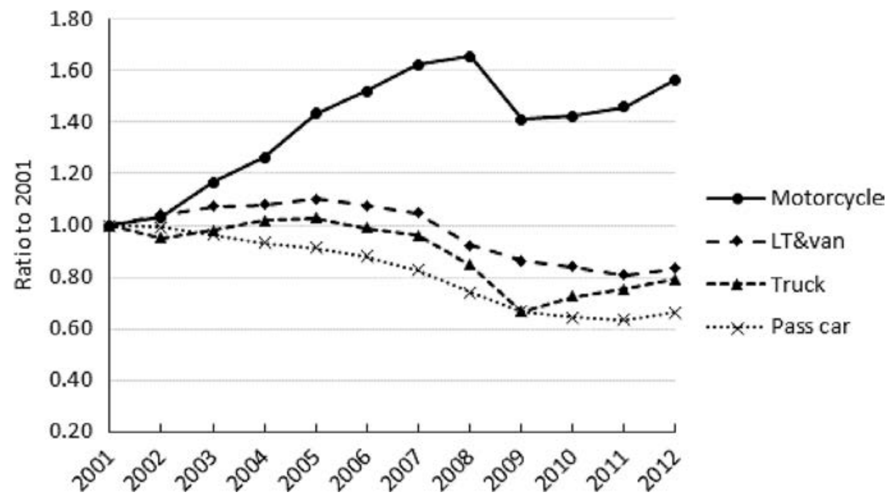


Figure 6-5. Trends in vehicle involvements in fatal crashes, 2001–2012.

Most fatalities in traffic crashes are drivers of motor vehicles, and that did not change over the study period (Figure 6-6). The percentage of drivers rose from about 61% of fatalities in 2001 to about 64% in 2012. The most significant decline was in the proportion of passengers, from about 25% in 2001 to 20% in 2012. The proportion of pedestrians and bicyclists actually increased, going from about 13% combined in 2001 to more than 16% in 2012. These trends could reflect changing modal shares (more pedestrian and bicycle travel) or improvements to occupant protection through seat belts, air bags, and improved crashworthiness of light vehicles.

Figure 6-7 illustrates more clearly how the number of fatalities by crash role changed over the period. The decline in passenger fatalities started before the beginning of the recession in December 2007, and the decline accelerated with the recession. The number of drivers killed actually increased somewhat prior, and then dropped sharply. Counts of pedestrian fatalities were relatively stable prior to the recession, then dropped in 2008 and 2009 before trending back up. Bicycle fatalities were comparatively few (averaging 805 over the period) and fluctuated within a band of about ±10%, declining during the recession before increasing at the end of the period. The increases in numbers of pedestrian and bicyclist fatalities may have reflected an increase in travel using those modes. As vulnerable road users, this would have represented upward pressure on the overall level of traffic safety. But given the relatively low share they

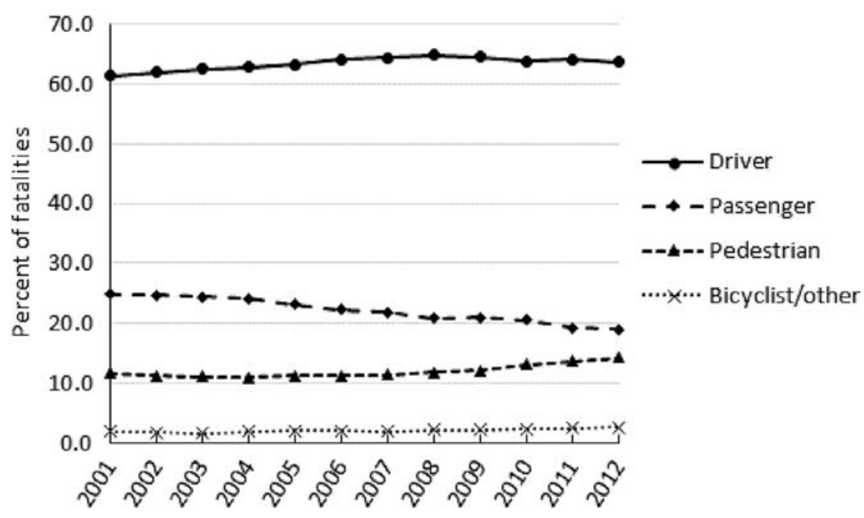


Figure 6-6. Distribution of fatalities by type of person, 2001–2012.

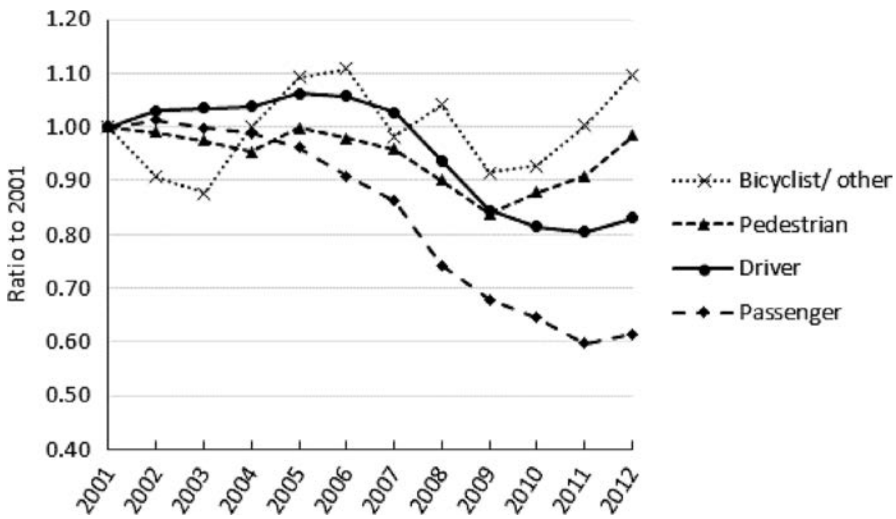


Figure 6-7. Trends in fatalities by person type, 2001–2012.

represented of the overall number of fatalities, they would not significantly mitigate the downward trend for drivers and passengers.

6.3 Roadway Class and Type

Earlier, Figure 4-2 showed that VMT generally increased each year from 2001 through 2007, dipped slightly in 2008 and then remained relatively flat through 2012. Disaggregating VMT by roadway function class and area type (urban/rural) highlights important trends that affected traffic fatality totals.

VMT tended to increase in terms of actual miles traveled over the period in urban areas and contemporaneously to decrease in rural areas (Figure 6-8). In urban areas, the VMT trend started to flatten out the year prior to the official start of the recession, while rural travel continued its decline. The effect of the recession on VMT appears to have halted the gradual increase in urban travel, while the decline in rural VMT continued. Figure 6-8 illustrates this graphically; all lines above the trend for all VMT are urban roads and all below are rural. Overall, the proportion of VMT in rural areas declined from about 39.7% in 2001 to 32.9% in 2012. This shift was important because rural VMT tended to have higher fatality rates than urban, so a shift to urban travel

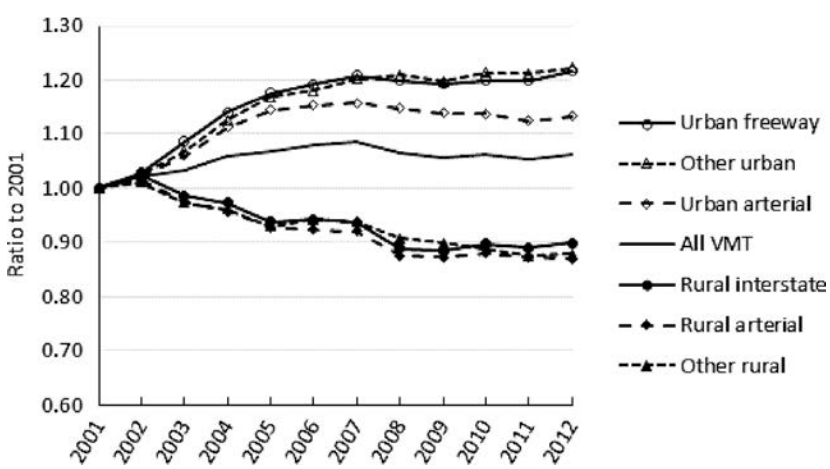


Figure 6-8. Trends in VMT by area and road type, 2001–2012.

Table 6-1. Fatality rates per 100 million VMT, by roadway function class, 2001–2012.

Year	Rural interstate	Rural arterial	Other rural	Rural total	Urban freeway	Urban arterial	Other urban	Urban total	All roads
2001	1.15	2.17	3.12	2.27	0.68	1.16	1.22	1.01	1.51
2002	1.18	2.16	3.21	2.30	0.67	1.11	1.23	0.98	1.51
2003	1.17	2.33	3.04	2.30	0.65	1.13	1.24	0.98	1.48
2004	1.21	2.49	2.99	2.36	0.64	1.04	1.17	0.93	1.44
2005	1.27	2.35	3.17	2.38	0.65	1.10	1.14	0.95	1.46
2006	1.12	2.26	3.08	2.28	0.63	1.10	1.18	0.95	1.42
2007	1.04	2.28	3.03	2.25	0.59	1.02	1.14	0.90	1.36
2008	1.00	2.11	2.88	2.12	0.55	0.91	1.05	0.82	1.26
2009	0.84	2.04	2.63	1.97	0.48	0.82	0.96	0.73	1.15
2010	0.86	1.86	2.48	1.84	0.48	0.87	0.90	0.74	1.11
2011	0.81	1.89	2.45	1.82	0.49	0.85	0.92	0.74	1.10
2012	0.75	2.07	2.46	1.88	0.47	0.92	0.98	0.77	1.14

would result in lower fatality rates per VMT overall. In addition, travel on Interstate-quality roads had significantly lower fatality rates than lower road classes in both urban and rural areas (Table 6-1).

The result of the shift of travel from rural to urban roads, in combination with lower fatal crash risk on urban roads, was that rural roads, particularly rural Interstate highways and rural roads designated "other" in Figure 6-8, accounted for a somewhat disproportionate share of the reduction in traffic fatalities from 2008 through 2012. In 2007, about 6.5% of traffic fatalities occurred on rural Interstate highways, 21.7% on rural arterials, and 28.1% on other rural roads. However, about 8.4% of the decrease in fatalities 2008–2012 was accounted for by fewer traffic fatalities on rural Interstate highways, and 31.1% of the reduction was accounted for by rural other roads (Figure 6-9). The difference between road types was not huge, but it was substantial and consistent with the change in travel patterns illustrated in Figure 6-8.

Aggregating across road types to urban/rural, traffic fatalities in rural areas fell persistently over the period. The decline began before the official start of the recession in December 2007, beginning in 2006–2007. In urban areas, the number of traffic fatalities trended up prior to the

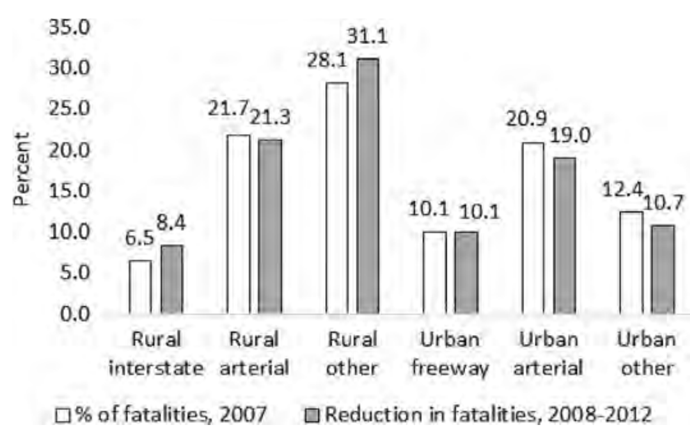


Figure 6-9. Estimated reduction in traffic fatalities 2008–2012 by road type.

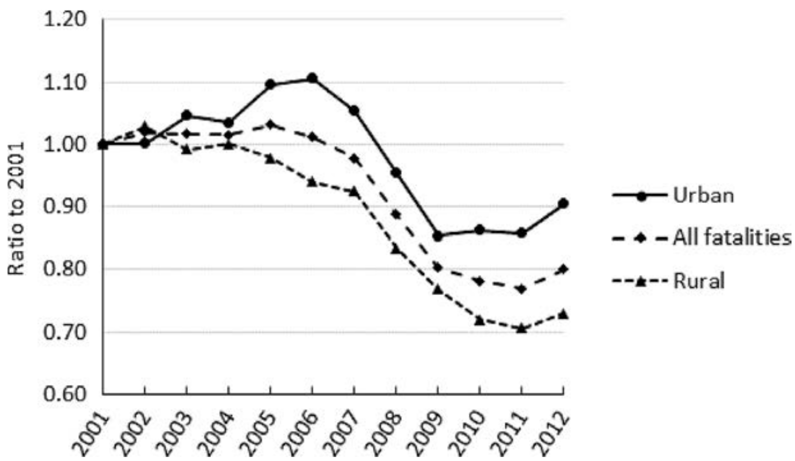


Figure 6-10. Ratio to 2001 of traffic fatalities in urban and rural areas, 2001–2012.

recession in absolute terms, as shown by a ratio to 2001 greater than 1.0 in Figure 6-10. The decline in urban areas began in 2007 and accelerated in 2008 through 2009, then stabilized before increasing slightly in 2012. In contrast, traffic fatalities in rural areas started a gradual decline in 2005 but then dropped sharply in 2008. The number continued to decline through 2011, before ticking up slightly in 2012.

The net of these trends was that rural areas contributed disproportionately to the reduction of traffic fatalities in 2008 through 2011. In 2007, about 56.4% of traffic deaths occurred in rural areas, but rural areas subsequently accounted for more than 60% of the reduction in fatalities (Figure 6-11). The difference between urban and rural areas was not overwhelming, but it was significant and consistent with changing travel patterns.

6.4 Vehicle Design and Model Year

An 81% reduction in the VMT fatality rate has been documented over the period spanning 1960 to 2012 (Kahane 2015). Kahane showed a steadily declining fatality risk related to improvements in occupant protection and crashworthiness over his study period of 1960 through 2012. The decline was related to changes in the Federal Motor Vehicle Safety Standards (FMVSS) to improve occupant protection, such as seat belts and air bags; crashworthiness, such as side impact protection, roof

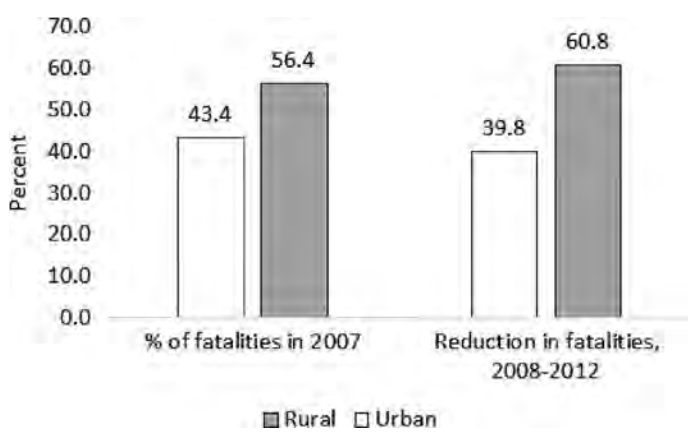


Figure 6-11. Estimated reduction in traffic fatalities 2008–2012 by area type.

crush resistance, and fuel system impact protection; and crash avoidance, such as electronic stability control (ESC). Many of the changes were implemented prior to the 2001–2012 target period; however, Kahane's model showed a decline in fatality risk at a relatively constant rate throughout the period. Thus, it is assumed here that fatality risk related to vehicle design and occupant protection improved at a constant rate over the period. In effect, the continual evolution of the vehicle fleet to newer models acts as a continuing and consistent downward pressure on traffic fatalities.

Over the 2001–2012 target period, changes in the FMVSS safety standards included FMVSS No. 138 (2005) which required all new cars and LTVs built after September 1, 2007, be equipped with a tire pressure monitoring system. While this technology has likely improved fuel economy and vehicle handling for most drivers, it is unclear how much of a direct benefit in crash reduction has occurred as a consequence. Target crash reductions would be related to tire blowouts and consequent loss of vehicle control. FMVSS No. 126 required ESC in all cars and LTVs. Kahane (2014) reported that ESC was responsible for a 60% reduction of fatal single-vehicle rollovers (Kahane 2014). Similarly, Farmer and Lund (2014) reported a 41% reduction in single-vehicle crash involvement and a 56% reduction in single-vehicle fatal crash involvement. Estimates of fleet penetration over 2001 to 2013 begin at less than 1% and show a regular increase to about 42% in 2013 (Highway Loss Data Institute 2014). There is evidence that a significant decline in single-vehicle rollover crashes can be related to ESC (National Highway Traffic Safety Administration 2007; Flannagan and Leslie 2012).

Farmer and Lund (2006, 2014) reported significant declines in crash fatal injury risk related to improvements in both occupant protection and crashworthiness. The New Car Assessment Program (NCAP) was first implemented in the 1970s, establishing star ratings as a way to encourage automobile manufacturers to compete on occupant protection and safety (MacKenzie, Hoyt et al. 2003). There were some changes to the program during the target period (Hsia and Shen 2011), as well as changes to the FMVSS to improve the crashworthiness of passenger cars and light truck vehicles. Upgrades to the rear-impact standard were phased in from 2005 to 2007 to reduce post-crash fires, along with roof crush updates in 2009 and enhancements to side-door beam regulations in 2010 (Kahane 2015).

Figure 6-12 presents the distribution of the age of motor vehicles in fatal crashes over the period. The right axis shows the percentages of vehicle cohorts aggregated into groups representing

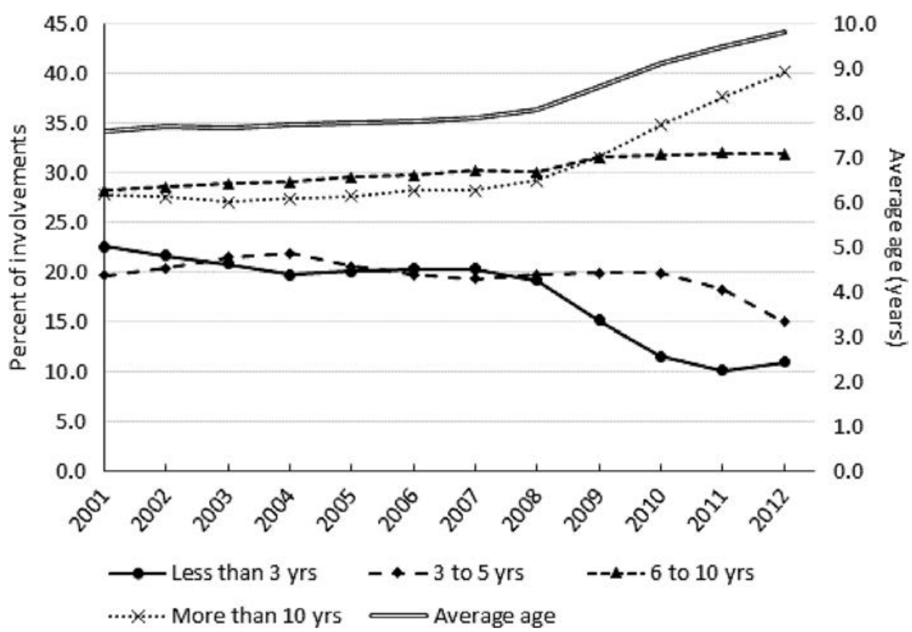


Figure 6-12. Age of vehicles in fatal crashes, 2001–2012.

vehicles less than 3 years old, 3 to 5 years, 6 to 10 years, and more than 10 years old. The right axis shows the overall average age of the vehicles. Before 2008, the share of different age cohorts remained relatively stable. Vehicles 6 to 10 years and more than 10 years old accounted for about 27% to 30% of vehicles involved in fatal crashes. Vehicles 3 to 5 years and less than 3 years old accounted for 20% to 23%. However, beginning in 2009 there was a sharp drop in the percentage of newer models and a corresponding increase in the share of the oldest age cohort. Some fraction in the drop in the proportion of newer models after 2010 may be attributed to the fact that the cutoff in the series is 2012. However, the mean age of vehicles involved followed the same pattern (right axis). Between 2008 and 2012, the mean age of motor vehicles involved in fatal crashes increased by almost 2 full years.

The pattern may be partly explained by the penetration of ESC-equipped vehicles. ESC is particularly effective against "untripped" rollovers (rollovers due to lateral acceleration rather than impact with objects) and crashes precipitated by loss of control, both of which are overrepresented in fatal crashes. Figure 6-13 shows the estimated penetration of ESC (left axis) into the registered vehicle fleet by calendar year. The data were extracted from the Highway Loss Data Institute (2014). These data are available only at the national level and were used in the statistical modeling, below, to capture the effect of ESC on the number of motor vehicle fatalities.

Figure 6-13 also shows the penetration of post-1991 model year vehicles on the roadway. This metric was used as a surrogate to reflect the improvements in crashworthiness and occupant protection identified by Kahane (2015). Vehicle registration data could not be obtained over the target years to directly estimate the population of registered vehicles by model across the years of the project. Instead, an estimate was derived using quasi-induced exposure (QIE) (Chandraratna and Stamatiadis 2009; Keall and Newstead 2009).

QIE is a method for indirectly estimating exposure data from crash data. QIE assumes that in certain crash types, certain vehicles did not contribute to the crash so those vehicles are in effect a sample of vehicles on the road. Vehicles that were struck in the rear in a rear-end crash are typically assumed to have not contributed to crashes, so they are treated as an acceptable surrogate for the population of vehicles on the road. In the current case, data from the National Automotive Sampling Survey GES were used for the estimate (NHTSA 2014). The GES file is a nationally representative sample of police-reported crashes. All vehicles struck in the rear in a rear-end crash were identified in the GES data for 2001 through 2012. For each year, the proportion of

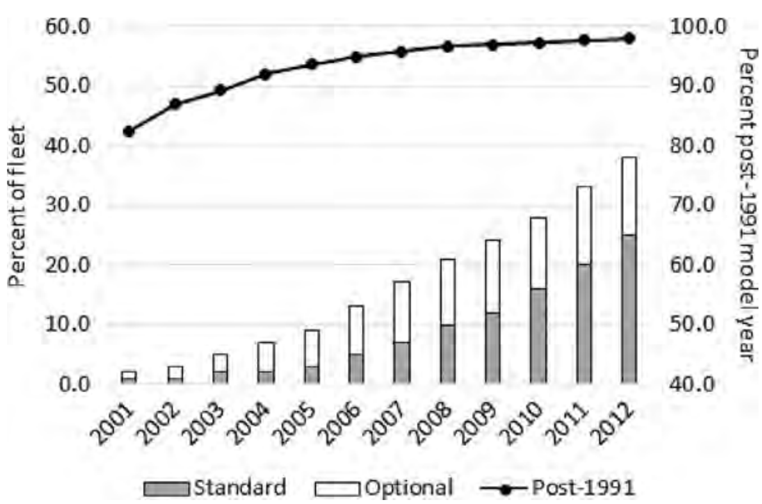


Figure 6-13. Fleet penetration of ESC and penetration of post-1991 model year. Adapted from Highway Loss Data Institute (2014).

those vehicles that were model year 2001 or later was computed. The data are displayed in Figure 6-13 (right axis). Since the vehicles were all in use on the roadway, the estimate is a measure of their exposure to crashes. The assumption that rear-end struck vehicles are a valid sample of vehicles on the road may not be true in all cases, but it seems reasonable. Moreover, the estimates are plausible. The 1991 model year was chosen to get a span of about 10 years prior to the initial year of the period being studied. Moreover, the increased penetration of the post-1991 model year occurred at about the same rate as Kahane's vehicle-based risk index, so it is considered to be a reasonable surrogate for the effect of increased safety from improvements in vehicle design.

6.5 Restraint Use

Safety belts are a primary technology in motor vehicle occupant protection. Kahane (2004) estimated that belts are responsible for 60% of lives saved by all Federal Motor Vehicle Safety Standards (FMVSS) in 2002 (14,570 of 24,561) (Kahane 2004). Updated results in 2015 estimated that seat belts saved 56% of the total lives saved by FMVSS technologies in 2012 (Kahane 2015). Again, safety belts were by far the most effective occupant protection. Evans, in a classic 1986 paper demonstrating the double-pair comparison method, estimated the effectiveness of seat belts in preventing fatalities at 43%, ±3%, compared with no belts (Evans 1986). With the exception of New Hampshire, all states have mandatory seat-belt laws. Many states have primary enforcement laws, meaning that traffic police may stop a vehicle solely to ticket occupants for non-use.

The period between 2001 and 2012 experienced a reasonably steady increase in the proportion of front-seat occupants using safety belts. Figure 6-14 shows observed belt use (top line), belt use reported for all drivers in fatal crashes (middle line), and belt use reported for fatally injured drivers in crashes. In 2001, the national average was 73% observed belt use, and by 2012, the percentage increased to 86% (Chen 2014; Pickrell and Liu 2014). Drivers in fatal crashes tended to have lower belt use, but the reported usage rate increased fairly steadily over the period. Fatally injured drivers had yet lower reported belt use, but that too increased over time. There was a slight dip in 2008, but the trend continued to increase thereafter, flattening out slightly in 2010 through 2012.

Figure 6-14 reports national-level statistics. There appears to be no discontinuity in the increasing penetration of safety-belt use in the driving population. For purposes of statistical modeling, state-level data for the observed level of safety-belt use was used. Figure 6-15 illustrates

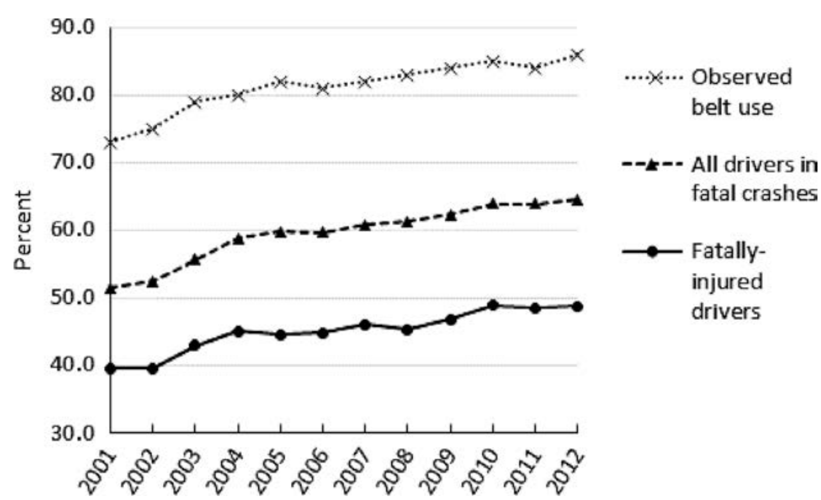


Figure 6-14. Driver safety-belt use: observed, drivers in fatal crashes, and fatally injured drivers.

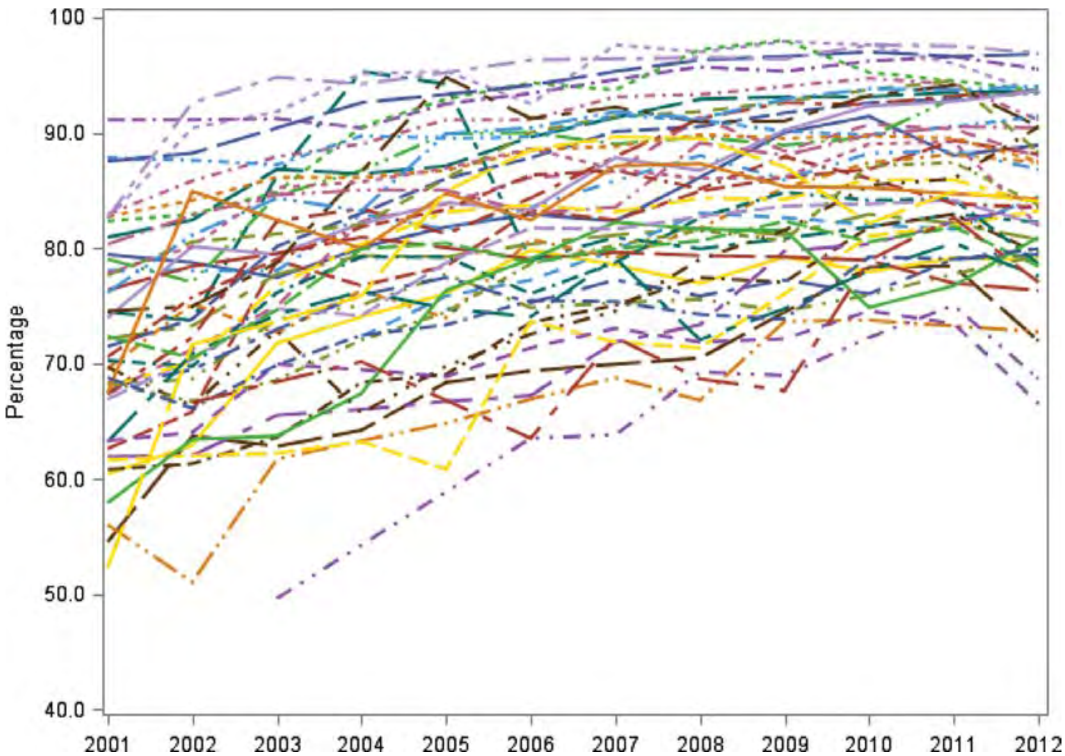


Figure 6-15. Trends in observed safety-belt use by state, 2001–2012.

the range of observed safety-belt use across the years and among the states. It is not expected that the reader will be able to discern the pattern for any set of specific states; the data are shown in this way to convey that the overall trend was toward increased observed belt use, but also that there was significant variation among states and over time. Belt-use rates ranged from a low of 49.6% in New Hampshire in 2003 to a high of 98.0% in Michigan in 2009. Individual state-level observed belt-use rate data were used in the models developed for the project.

6.6 State Regulation of Driver Behavior, Alcohol Consumption

States attempt to motivate road users to adopt behaviors that increase traffic safety. A 2013 paper from Silver, Macinko, and colleagues measured the effect of state-level traffic safety policy on traffic fatalities from 1980 to 2010. An index of state laws covering alcohol, restraints, and licensing showed a consistent increase in regulations intended to increase safety over the period. This result is analogous to Kahane's observation of a relatively steady increase in safety related to vehicle design (Kahane 2015).

Many reports and papers relate traffic safety regulation to lower crash rates and traffic fatalities. A paper by Dang (2008) showed the efficacy of alcohol-related legislation in an analysis of trends in the incidence of fatal traffic crashes (Dang 2008). Other measures related to alcohol consumption, such as beer taxes, have been shown to be associated with the incidence of traffic crashes. There is evidence that younger drivers are disproportionately affected by drunk-driving laws, higher beer taxes, and GDL laws (Silver, Macinko et al. 2013; Macinko, Silver et al. 2015), although one study showed no effect for beer taxes on 15- to 17-year-old drivers (Morrisey and Grabowski 2011). Differences in these laws regulating driver behavior have been shown to account for some state-to-state variation in fatal crashes and fatalities. Belt-use laws, typically categorized as primary or secondary enforcement laws, appeared as significant variables in state-level analyses of trends in fatal crashes and traffic fatalities. (For examples, see Grabowski and Morrisey 2004; Morrisey, Grabowski et al. 2006; Silver, Macinko et al. 2013; Ferdinand, Menachemi et al. 2014).

In the current study, safety-belt laws were rated based on whether there was primary or secondary enforcement, and whether belts were required for rear-seat positions. Primary enforcement permits vehicles to be stopped solely for violation of belt laws; secondary enforcement means enforcement only occurs secondary to some other primary offense. Figure 6-16 shows an index of the relative ratings of states over the period, with 1 being the most restrictive and 0 no requirements. All 50 states were included. Sloping vertical lines indicate states that strengthened their belt-use requirements, along with the years in which laws were tightened. As the graph illustrates, belt-use laws were strengthened in at least some states every year during the period from 2001 to 2012, except for 2008. Seven states had primary enforcement at all seating positions over the entire period. Fourteen states strengthened their safety-belt laws in the period, mainly through moving to primary from secondary enforcement. By 2012, 18 states had primary enforcement for adults for both front and back seats. Alaska had no safety-belt requirement before 2007; only New Hampshire had no safety-belt requirement throughout the period.

Motorcycle helmet laws were rated by whether adults or just youth (defined by thresholds ranging from 14 to 21) were covered, and whether all riders or just passengers were covered. Ratings ranged from 0 (no helmet use required for any rider) to 4 (universal coverage). Only two states made any changes in their coverage over the period. In 2003, Pennsylvania limited its requirement to riders 20 and younger. In 2003, Louisiana required motorcycle helmets for all riders by removing the exemption for riders 18 or older. There was wide variation between states in requirements. Three states had no motorcycle helmet requirement during the period (Iowa,

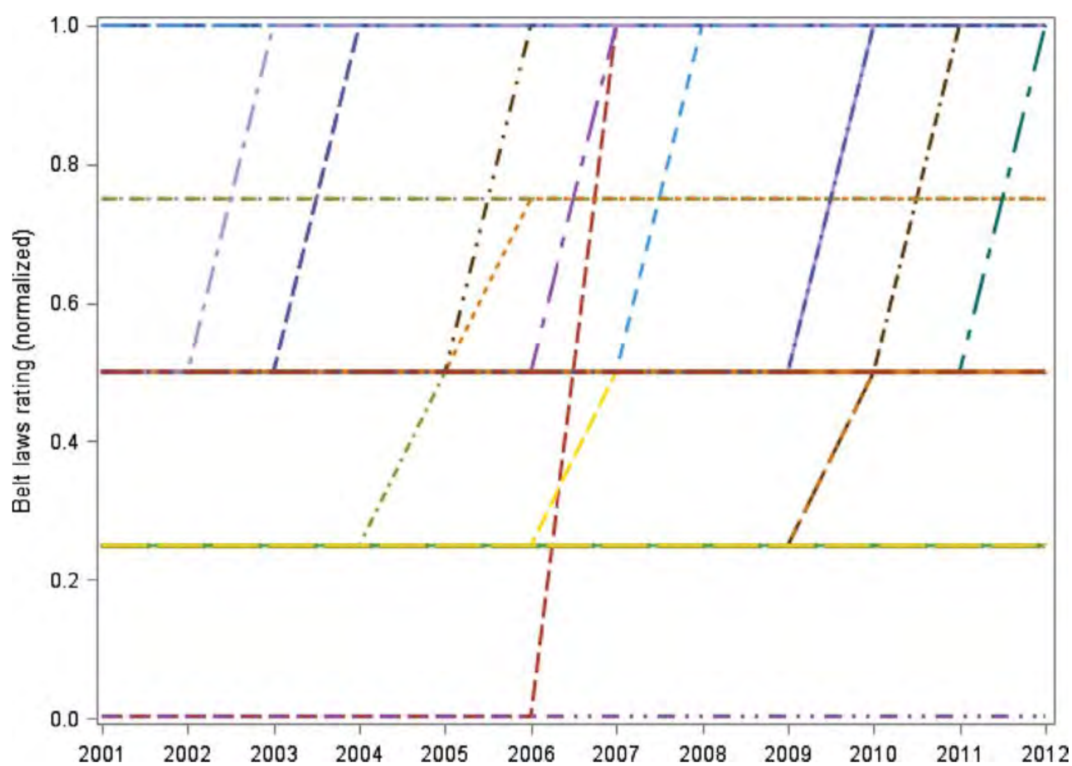


Figure 6-16. Safety-belt laws rating index by state and year, 2001–2012.

Illinois, and New Hampshire), while 19 had universal helmet laws, requiring motorcycle helmets for all riders. Other states required helmets only for passengers or only for youths, defined by a range of ages from 14 to 21. Twenty-five states required helmets only for youth, and two states required them only for passengers.

The index covering the regulation of alcohol use incorporated a number of measures. The index included BAC level, jail terms and fines for violations and multiple offenses, license suspensions, third-offense felony laws, ignition interlocks for offenders, required treatment programs, victim rights laws, and increased penalties for so-called super drunks. All states had 0.08 BAC laws by 2005, but states varied in penalties for alcohol-impaired driving, in terms of the strength of administrative license revocation rules, ignition interlock, and other related enforcement. Data on state laws prescribing allowable BAC levels and penalties for violations were supplied by Kathleen Klinich of UMTRI (Klinich 2016).

States varied in their approaches to alcohol-impaired driving over the period. For example, two states (New Hampshire and Wisconsin) had no jail time for a first offense, 18 had up to 1 year, and two (Massachusetts and Vermont) allowed up to 2 years in jail. Fines ranged from $250 for a first offense up to $10,000. Twenty-eight states had no provision for an ignition-interlock device for a first offense, but 20 did at some point over the period. In 2001, only one state (Oregon) had an ignition-interlock provision for a first offense, but by 2012, 12 states had it for a first offense, 39 for a second offense, and 41 for a third offense. Figure 6-17 shows the trend of the alcohol-laws index over the period, by state. Each state was rated each year based on its laws on 21 items related to drunk driving. For the purposes of the figure, state ratings were scaled from 0 to 1, with 1 being the strictest on all dimensions. The figure illustrates the wide range of differences from state to state as well as a trend over the period toward increasing the stringency of alcohol laws through increased fines, jail terms, license suspensions, and reduced allowable BAC levels.

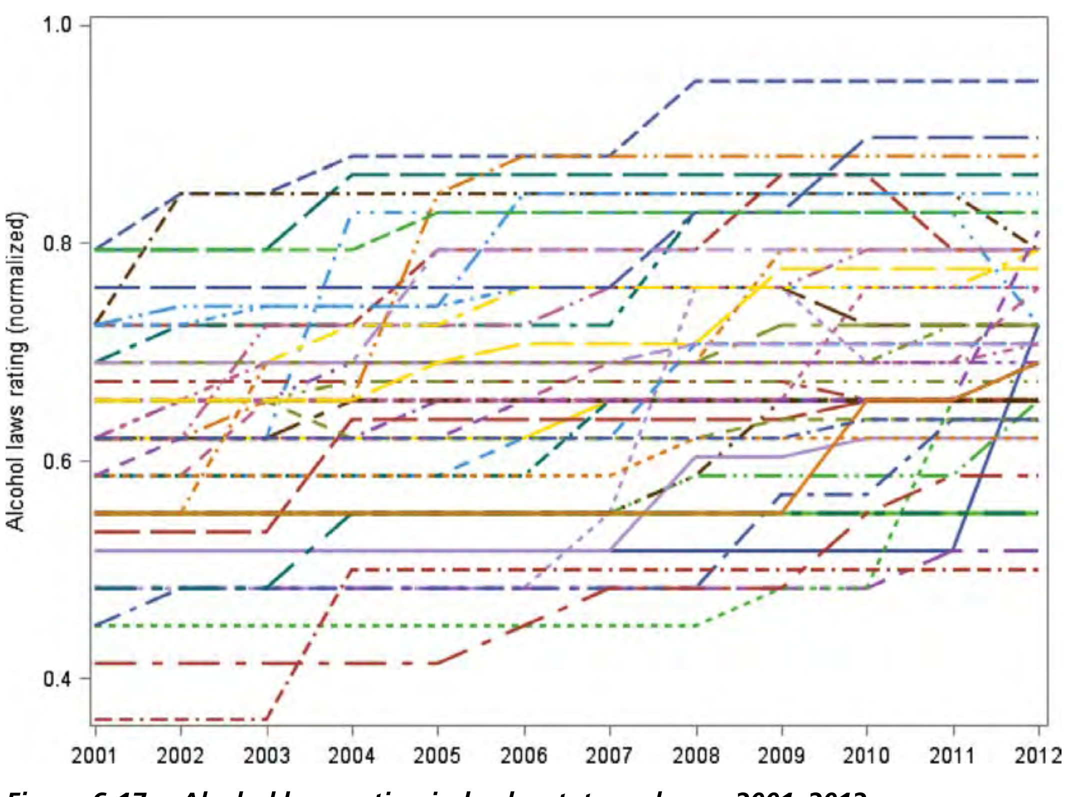


Figure 6-17. Alcohol laws rating index by state and year, 2001–2012.

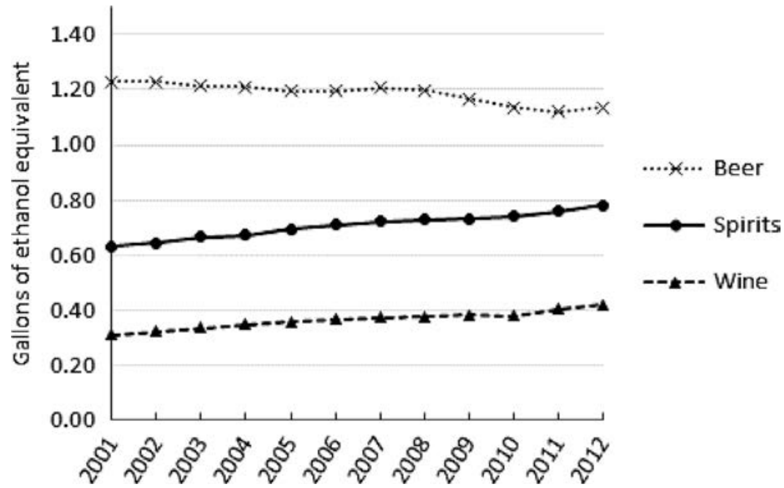


Figure 6-18. Per capita consumption of beer, spirits, and wine.

The indexes for regulation of safety-belt use, alcohol, and motorcycle helmets were incorporated into models to measure the association with the overall level of traffic safety and their contribution to the drop in traffic fatalities 2008–2012.

The models also included a measure of alcohol consumption, which directly reflects a critical element of actual driver behavior. Data on per capita alcohol consumption were compiled from Haughwout, LaVallee et al. (2015). The data were from annual surveys by the National Institute on Alcohol Abuse and Alcoholism based on sales data compiled from the states, industry, and other sources. The estimates of apparent per capita consumption were expressed by gallon of ethanol equivalent. Figure 6-18 shows national trends in beer, wine, and liquor over the period. Note that the data were for alcohol consumption at the population level, not for motor vehicle drivers. Beer was the predominate form of alcohol consumed. Per capita consumption was relatively level through 2008 and then declined slightly through 2011, with a slight increase in 2012. The consumption of wine and liquor increased steadily over the period. Wine consumption increased about 3% annually and liquor consumption increased about 2% annually. At the national level, both were apparently unaffected by the recession, but beer consumption declined by about –2.5% in 2009 and –2.7% in 2010.

6.7 Economic Factors, National Trends

Economic conditions played a major role in the decline in fatalities in traffic crashes from 2008 through 2012. Numerous papers have documented an association of various measures of economic activity with fatal crash rates and traffic fatalities. Silver, Macinko, and colleagues (2013) used the poverty rate, unemployment rates, and tax revenues per capita. Noland and Sun (2014) found significant effects for median income and the Gini coefficient (a measure of economic inequality) in some models of the decline in fatalities, 2006-2012 (Noland and Sun 2014). Kweon (2015), in an analysis of the decline associated with the recession in Virginia, found significant effects for changes in the rate of inflation as measured by the CPI, unemployment number, and unemployment rate (Kweon 2015). Grabowski and Morrisey demonstrated a connection between fuel prices and fuel taxes, VMT, and crash fatalities (Grabowski and Morrisey 2004; Grabowski and Morrisey 2006; Morrisey and Grabowski 2011).

At least three modes of change in the economic environment might affect the level of traffic fatalities and safety. The most direct is that the recession led to reduced travel demand and, in turn, decreased exposure to fatal crashes and thus the number of traffic fatalities. Figure 4-2 showed a decline in VMT over the period, but it was likely not enough to explain the decline in fatalities by pure exposure. Secondly, the recession may also have differentially affected different population groups, reducing the travel of riskier drivers or reducing travel on riskier roads. Finally, the recession may have reduced the amount of risky driving by reducing the amount of discretionary or leisure driving.

These mechanisms were tested using data on per capita gross domestic product (GDP/capita), median income, unemployment rates by age group, and net fuel costs at the pump (fuel price plus taxes). Each measure is in effect a surrogate for measures that were not obtainable. For example, it would have been desirable to have data on travel by age group over the period, or employment status of the population involved in fatal crashes. But those data do not exist. Instead, GDP/capita and median income per household were used as surrogates for the propensity to travel, assuming that reduced income also reduces the ability to drive. Median income is believed to be a useful measure of the economic condition of the less affluent, while GDP/capita was used as a measure of the overall level of economic activity normalized to a state's population. Fuel costs, including taxes, directly affect amount of driving because higher costs increase costs per mile of travel, which in turn is likely to reduce travel, and thus exposure to fatal crashes and the number of traffic fatalities.

GDP/capita increased steadily over the first part of the period, increasing from about $37,000 dollars per capita in 2001 to $48,100 in 2008, the peak prior to the recession (Figure 6-19). There was a sharp dip in 2009, which saw the depth of the recession, but then a resumption of the steady increase through the rest of the period. GDP/capita recovered to its pre-recession peak by 2010 and was $52,500 in 2012. The pattern for median income was substantially different. Median income was measured at the household level, and so can be greater than GDP/capita because of multiple-income households. Median income, again in constant 2013 dollars, fluctuated in a narrow band up to 2007, ranging from a high of $56,600 in 2001 to a low of $54,500 in 2004. Median income then began a steady decline in 2008, and by 2012 was $4,700 lower than in 2007. GDP/capita recovered from the recession, but there was no recovery reflected in median household income (US Bureau of the Census 2016; World Bank 2016).

Unemployment was relatively stable from 2001 to prior to the recession (Figure 6-20). The left axis, showing the unemployment rate, is inverted so that increases in the unemployment rate slope down and decreases in the rate slope up. For all Americans, the rate increased from 4.8% in 2001 to 6.0% in the downturn of 2003, before declining again to about 4.6% just prior

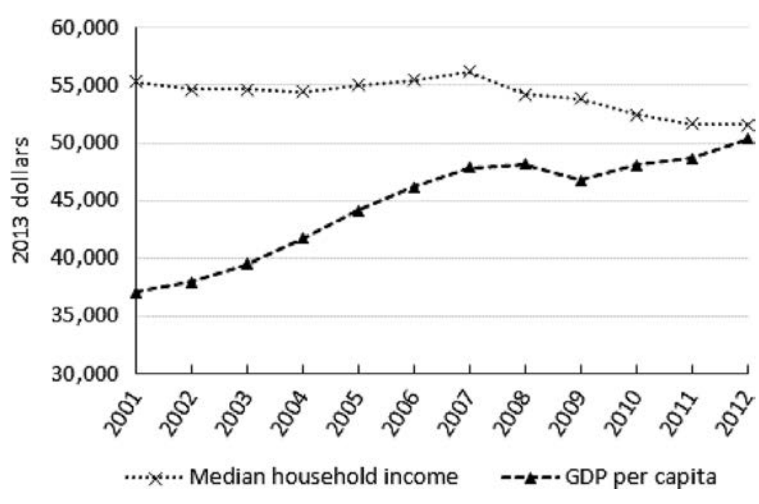


Figure 6-19. Trends in median household income and GDP/capita, 2001–2012.

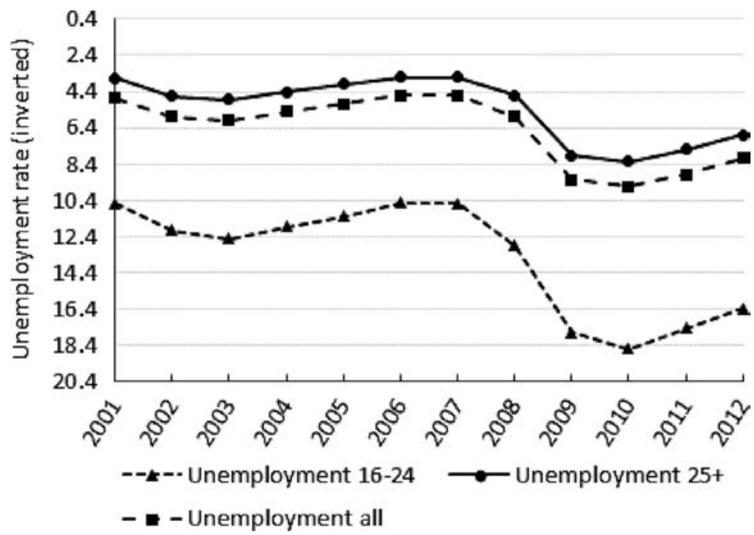


Figure 6-20. Unemployment rate by age.

to the recession that officially began in December 2007. Then the rate increased sharply to 9.6% in 2010 before declining again to 8.1% in 2012. For younger members of the labor force, 16- to 24-years-old, unemployment rates followed a similar pattern but were about double the rates of older workers. Unemployment for teens and young adults ranged from 10.6% to 12.5% in the years up to the recession, then increased to 18.6% in 2010 (Bureau of Labor Statistics 2016).

Figure 6-21 shows fuel costs, which represent the price at the pump including taxes in constant 2013 dollars. Fuel costs increased steadily from 2002 ($1.84/gallon) to 2008 ($3.46/gallon), dropped sharply in 2009 to $2.61/gallon, and then resumed the upward trend, closing the period at $3.67/gallon for 2011 and 2012 (US EIA 2016). Increasing fuel costs, other things being equal, should reduce the amount of travel and thus exposure to fatal crashes.

Unemployment rates and fuel costs by year and state were used in the models to capture variability associated with the different state economies. For example, in the recession year of 2009, the unemployment rate for 16- to 24-year-olds ranged from 8.3% in Nebraska to 22.2% in Alabama. Similarly, fuel prices varied by state. For example, in 2009, prices ranged from $2.26/gallon in Georgia to $3.07/gallon in Washington.

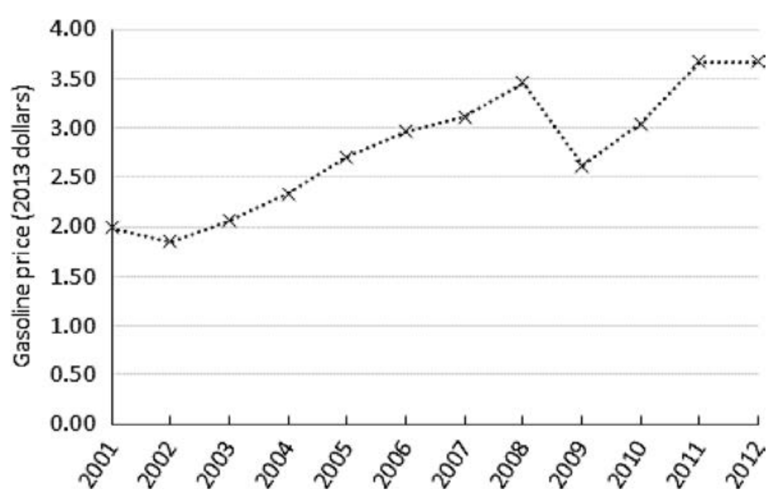


Figure 6-21. Fuel prices in constant 2013 dollars, 2001–2012.

6.8 Highway and Infrastructure

The design, condition, and level of enforcement and related safety programs on the roadway system are critical elements in the level of traffic safety. Table 6-1 illustrated the variation of fatal crash rates across different roadway function classes. Differences in fatal crash rates reflect traffic density and speed, but also include geometric design elements such as lane widths, presence and type of shoulder, degree of curvature, and protective features such as guard rails. Other safety-related roadway factors include the level of traffic safety enforcement and educational programs such as campaigns to increase seat-belt use or reduce drunk driving.

Albalate, Fernández, and colleagues (2013) used variables such as spending on construction and maintenance to capture the impact of infrastructure improvements on reducing traffic fatalities. Infrastructure improvements include widening narrow roads, installing rumble strips, road markings, signing, lighting, median separation, deployment of yield-to-pedestrian channelizing devices, providing curve warning signs, removing sight distance obstructions and fixed objects along the road, antiskid surfaces, guardrails, and wrong-way-driving countermeasures, among others (AASHTO 2010; Wunderlich 2015). These programs are generally focused on mitigating hot spots in the road network that tend to have higher crash risks. Although there is a substantial body of research to show that these programs reduce traffic fatalities, it is not possible to control explicitly for the effect of specific programs in a nationwide analysis. Moreover, by their very nature, improvements to the roadway system as a whole tend to be incremental and long term, rather than resulting in sharp, system-wide declines.

State highway fund expenditures were used to capture the safety effect of highway spending and infrastructure improvements. Comprehensive data were used in four broad areas: capital expenditures for construction; maintenance and repair; administration, research, and planning; and law enforcement and safety programs. The expenditures included funding from federal safety programs under Sections 402, 403, 405, 406, 407, 408, 410, and 411, as well as funding provided by the Motor Carrier Safety Assistance Program (Federal Highway Administration N.D.). In addition, funding under the Highway Safety Improvement Program (HSIP) was included (FHWA 2016a; FHWA 2016b). Each year, states used HSIP funds to implement low- to medium-cost safety improvements throughout the nation. The overall purpose of the HSIP program was to significantly reduce traffic fatalities and serious injuries on state roads through the implementation of medium-cost, infrastructure-related highway safety improvement projects.

State highway expenditures were classified into four areas; definitions are from Federal Highway Administration (N.D.).

Capital. All expenditures for construction, relocation, resurfacing, restoration, rehabilitation and reconstruction (3R/4R), widening, capacity improvements, restoration of failed components, additions and betterments of roads and bridges. Here and for the purposes of statistical modeling (Chapter 7), the proportion of capital spending designated by the state as safety-related was excluded from capital expenditures and added to the highway law enforcement and safety spending category.

Maintenance. The function of preserving and keeping the entire highway, including surface, shoulders, roadsides, structures, and traffic control devices, as close as possible to the original condition as designed and constructed. For improved or reconstructed facilities, subsequent maintenance work only ensures continued service as redesigned. Also include preventive maintenance activities.

Administration, research, and planning. Includes general administration, supervision and DOT overhead not directly related to specific projects, as well as expenditures for highway planning and research to support road planning and design and traffic research.

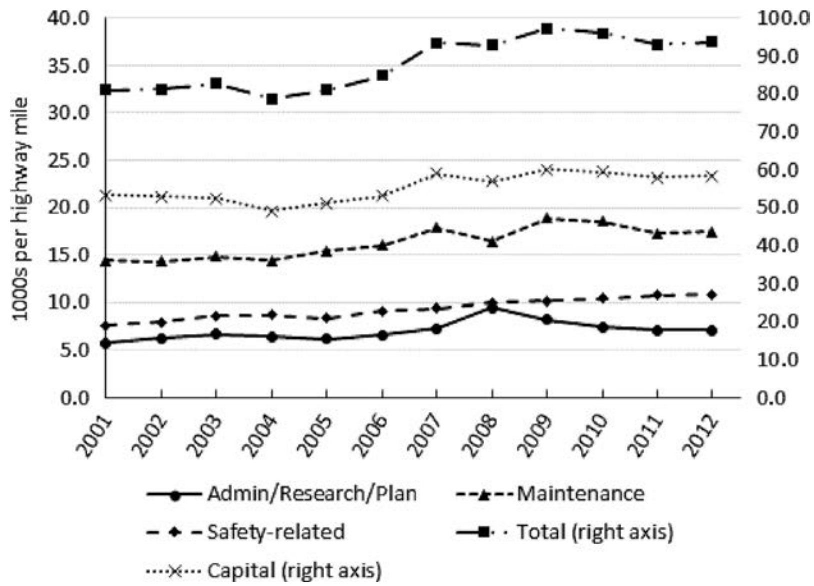


Figure 6-22. Highway spending per mile of highway, 2001–2012.

Highway law enforcement and safety. Highway law enforcement and safety expenditures by the state DOT, state police, department of public safety, traffic safety commission, and other agencies. These expenditures are classified as: (1) traffic supervision and the enforcement of state highway laws and ordinances; (2) highway, traffic, and driver safety programs; (3) motor vehicle inspection programs; and (4) enforcement of vehicle size and weight limitations. Safety also included the safety proportion, as determined by each state, of expenditures on capital improvements. HSIP funds were included as safety related. HSIP funds can be used for infrastructure programs related to safety, but also for non-infrastructure activities. Any highway safety program identified through a data-driven process may be funded under HSIP.[2]

Highway expenditures for each year were converted into 2013 dollars to control for inflation. To control for the fact that states differ in population size, area, and size of roadway system, expenditures were normalized by dividing expenditures (in constant 2013 dollars) by the number of highway miles in each state. This partially controls for the fact that states with large populations and roadway systems spent significantly more in absolute terms on highways than smaller states with smaller populations and road systems.

Expenditures on the four areas—capital, maintenance, administration, and safety—were used to examine the association with traffic fatalities over the period. Figure 6-22 shows general national trends over the entire period for the four categories, along with total. Expenditures were summed across states and then divided by the sum of highway miles to get national averages. Capital expenditures (right axis) accounted for the greatest share, ranging from an average of about $49,000/mile in 2004 to $60,000/per mile in 2009. There was a gradual increase over the period, with a slight drop in the recession year of 2008, an increase to 2009, and then relative stability thereafter. In comparison, safety-related spending, on a per-highway-mile basis, was substantially lower, although it increased fairly steadily over the period. The low was $7,600/highway mile in 2001, increasing to $10,900/highway mile in 2012.

Table 6-2 provides some descriptive state-level statistics. The amounts that states spent on a per-highway-mile basis varied substantially. On average, states spent about $64,700/highway

[2]See http://www.fhwa.dot.gov/map21/qandas/qahsip.cfm

Table 6-2. State highway expenditures per highway mile, 2010–2012, in thousands of 2013 dollars.

Highway spending per mile	Expenditure type				Total
	Capital	Maintenance	Administration, research, planning	Safety	
Average	64.7	20.7	10.2	10.9	106.6
Minimum	11.1	0.8	1.0	1.0	20.5
Maximum	282.0	266.7	150.5	60.7	459.3

mile on capital expenditures, varying from a low of $11,100/highway mile (South Dakota) to $282,000/highway mile in Delaware. Maintenance, administration/research/planning, and safety expenditures also varied materially between states and across years. State expenditures across the four categories, by year, were used in the statistical modeling to measure the association with traffic fatalities.

Part of the variation among states was likely related to geographical and demographic differences. The states that tended to rank toward the top of per mile spending were typically small and densely populated (Connecticut, Delaware, Maryland, Rhode Island). In the data used in Table 6-2, Delaware was an outlier in spending per mile of highway over the period in each category. In terms of safety spending per mile of highway, the top five states were Delaware, New Jersey, California, Massachusetts, and Maryland. States that ranked toward the bottom on a spending per mile basis tended to be large and less densely populated. The bottom five for safety spending per highway mile were South Dakota, North Dakota, Kansas, Mississippi, and Arizona.

CHAPTER 7

Modeling

This chapter describes the statistical modeling used to better characterize the relationship between fatalities and potential factors that could explain the major drop in fatalities after 2007. Given the nature of the data (i.e., random variables and unobserved heterogeneity), statistical models are needed to isolate key patterns from random noise associated with traffic fatalities. The data collected and described in Chapter 5 were used for the analyses.

The modeling approach was patterned after Elvik (2013), who reviewed a number of statistical methods for looking at predictors of fatalities over time in a group of countries. The three main methods he discussed were negative binomial models of fatalities counts, and two forms of models of year-over-year change. Two of these methods were used for the current study: a Poisson-gamma count model (equivalent to a negative binomial model) and the log-change regression model of year-over-year change.

The negative binomial model uses raw fatality counts and incorporates VMT as exposure. This means that coefficients of predictors can be interpreted as influencing fatalities per VMT, or a fatality rate in each state and year. Thus, although different factors can influence risk or exposure, in this model they are interpretable primarily as influencing risk rather than exposure.

Two key sources of variation exist in the data set of raw counts. First, differences *between* states can be thought of as generally more stable differences in environmental, population, cultural, economic, and traffic safety conditions. Second, changes over time *within* states are more transient. Some factors change very slowly and steadily (e.g., new-vehicle fleet penetration, belt-use rates) and others are more volatile (economic factors) and can have significant changes over short periods of time.

Because these factors may operate differently on travel and risk, two negative binomial regression models were developed. One uses a state fixed effect to remove the stable differences among states and focus on changes over time (model controlling for state, or MCS). The other leaves out this fixed effect, allowing differences between states to be captured by the measured predictors (model not controlling for state, or MNCS). When the effect of a predictor is different in these two models, it can indicate that differences in that variable between states have a different effect than change over time (i.e., the effect is relative). When the effect of the predictor is the same in these two models, it can indicate that the predictor has a general effect on risk that transcends local experience. The difference in these mechanisms can be informative.

The data set for the change model is a set of differences from one year to the next within a state, expressed as a percentage of the previous year. Thus, all state-to-state variation is removed, as is the magnitude of each variable within a state. The remaining information is simply the percent change from year to year within a state. Here, predictors can influence exposure and/or risk.

Before any modeling can begin, it is useful to address the high level of correlation among the variables assembled for this project. This is done using an analysis tool known as factor analysis, a data-reduction technique that helps identify patterns of correlation among many variables (as opposed to two at a time). The final predictor set chosen by this method captures the array of different factors of interest but with substantially less multi-collinearity that can create problems in interpretation of regression models.

The analyses were separated into two parts. In the first part, an exploratory analysis of the data was conducted to identify trends and factors that seem to influence fatalities at the national level. This part also included a factor analysis, which was used to rank the magnitude of the correlation between independent and dependent variables. Using the results obtained from the exploratory analysis of the data and the factor analysis, the second part focused on the two more advanced statistical analyses.

By looking at the problem from different angles, a clearer picture emerges of the most significant influences on traffic fatalities in the United States over this time frame. The following sections provide details on the choice of predictors, the modeling approaches, and the results. Section 7.1 describes the results of the exploratory and factor analyses. Section 7.2 summarizes the results of the modeling effort for the two approaches.

7.1 Factor Analysis to Identify Parameters for the Models

A significant challenge of working with this type of data set is that many of the variables in the data set are correlated. While modeling can be done with some collinearity among predictors, it tends to fail when those relationships are very strong. For example, population and VMT within a state are very closely related ($r = 0.98$), so it is not feasible to include both as predictors.

A related issue is that when predictors are correlated, it is not possible to assign responsibility statistically for the effect of the shared variance on the outcome. In other words, the analysis itself cannot point to whether VMT or population is responsible for differences in fatalities. In essence, these are the same thing. Instead, a sensible mechanistic argument must be made. In this case, the larger the population, the more people there are to drive, thus producing greater VMT. However, it is the VMT itself that exposes those people to the risk of being fatally injured in a crash. Hypothetically, if there were an entire state that had no roads or cars, it could have any size population and there would be no traffic fatalities. In contrast, if a state had 100 people who each drove 30,000 miles per year, they would have the same risk and the same expected number of fatalities (all other things being equal) as a state with 300 people who drive 10,000 miles a year. Note, however, that because population and VMT are so closely related in the real world, these types of inferences must be made by argument rather than through statistical results. This kind of argument will be made throughout the discussion of results, as analysis of these observational data cannot, in itself, address the causality of relationships among variables.

To address the collinearity problem and understand the collective relationship among these variables, a series of factor analyses was conducted. Factor analysis is a method of data reduction that produces a smaller number of dimensions, each of which is a linear combination of the original variables. For this purpose, it is best to think of factor analysis as a way of identifying a subset of the original variables that should be used as predictors of fatality. Factor analysis helps us identify patterns of covariation and select a good predictor subset. (Note that factor analysis as applied here does not evaluate the relationship between any of the predictors and fatalities; that is done in a later step.) Factor analyses were done in groups of similar variables: expenditures, economic measures, population, and VMT. Details of the factor analyses are provided in Appendix A.

Based on the results of the factor analysis, as well as some univariate exploration of the relationship between each predictor and fatalities, the following variables were used as the predictor set for modeling. General size of population is represented by total VMT. This is correlated with GDP, total VMT, urban road miles, total population, law enforcement safety expenditures, and total capital expenditures. "Ruralness" is represented by the proportion of VMT that is rural. This is also related to total rural road miles. The variables used to represent economic factors were unemployment for the 16–24 age group, unemployment for everyone else, and median income. Across the model's time span, these are related to all other economic factors, including employment and unemployment for different age groups. State expenditures are represented by safety spending (safety plus HSIP) and capital spending. Occupant protection is represented by belt-use rates, strength of belt laws, strength of motorcycle laws, and the proportion of vehicles on the road that are model year 1991 or later. Alcohol-related causation is represented by total beer consumption and the strength of DUI laws. Finally, pump price was included as a unique predictor that did not fall into other categories. These variables and the variables with which they are most correlated are summarized in Table 7-1.

7.2 Regression Models

This section describes a series of regression models that were fit. The first was a model to identify the factors that predicted VMT. Next is a set of negative binomial regression models to identify the factors affecting the risk of traffic fatalities. Finally, a log-change model is developed and discussed. This model relates year-over-year changes in predictor variables to changes in the number of traffic fatalities.

Appendix B provides descriptive statistics on the variables used in the models.

Table 7-1. Summary of predictors and correlations.

Variable group (high-level concept)	Variable(s) chosen for analysis	Other correlated* predictors
Overall size (of state)	Total VMT	GDP, capital expenditures, …
Ruralness	Rural VMT proportion	Total VMT, capital and safety expenditures, median household income, beer consumption per capita
Economy	GDP/capita, median household income, unemployment 16 to 24	Rural VMT prop., capital and safety expenditures
Occupant protection	Belt use, belt laws, motorcycle helmet laws, post-1991 model year penetration	Unemployment 16 to 24, pump price
State roadway 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 penetration
*correlation coefficients > ±0.3		

7.2.1 Regression of Factors on VMT

During the period from 2007 to 2012, changes in VMT coincided with the change in fatalities. It is therefore logical to first identify the factors that influenced VMT, especially the factors that reflected economic performance. Separate linear regression models were developed for total VMT, urban VMT, and rural VMT. Prior to developing the regression models, a correlation analysis was performed to identify the factors that were correlated with VMT. Table 7-2 presents the results of correlation analysis. A value of +1 means the variable was perfectly positively correlated with VMT. A value of –1 means the variable was perfectly negatively correlated with VMT. A value of 0 means the variable had no linear relationship to VMT. The correlation coefficients suggest that population was the most influential factor, followed by the unemployment rate, in determining VMT.

Population was most strongly correlated with VMT, measured both as total VMT and urban VMT. It is interesting that the correlation between rural VMT and total population was strong, but in practical terms much less than total or urban VMT. States with larger populations almost invariably had larger total VMT and urban VMT. However, the association with rural VMT was less strong, likely because some states with lower populations were also more rural. Note also that there were weak associations between unemployment for the two age groups considered and the different measures of VMT. There was some tendency for states with higher rates of unemployment to also have higher amounts of VMT. Big states in terms of population (and therefore VMT) also may have had higher rates of unemployment. The correlation of the different measures of VMT with pump price was almost nonexistent, though there was a weak, negative association with rural VMT; similarly, there was a moderate, weak correlation between rural VMT and median income. States with more rural VMT tended to have lower median incomes and lower GDP per capita.

7.2.1.1 Total VMT

A linear regression model was developed with total VMT in millions as the dependent variable and population and unemployment rate as independent variables. Other variables were not considered because the correlation coefficients shown in Table 7-2 were almost 0. Given the strong correlation between the unemployment rates for the two age groups, each one was included independently, and the one that gave the best fit to the data was chosen for inclusion in the model. In the total VMT model, unemployment rate of age 25 and above provided a better fit. The variables with corresponding p-values less than 0.1 can be considered statistically significant (at the significance level $\alpha = 0.1$). The R^2 statistic for the total VMT model was 0.97, which shows that the model was able to predict the VMT almost perfectly. The negative coefficient of the unemployment rate in Table 7-3 shows that as the unemployment rate increased, total VMT decreased. The primary factors determining total VMT were population and the state of the economy, as reflected by the unemployment rate.

Table 7-2. Correlation of VMT with different variables.

	Total population	Unemployment of age 16 to 24	Unemployment of age 25 and above	Pump price	GDP per capita	Median income
Total VMT	0.98	0.19	0.22	–0.04	0.07	–0.02
Urban VMT	0.98	0.17	0.23	0.00	0.12	0.07
Rural VMT	0.81	0.19	0.15	–0.14	–0.12	–0.27

Table 7-3. Parameter estimates for the total VMT model.

Variable	Estimate	Standard error	P-value
Intercept	7075.39	1210.30	<.0001
Total population	0.00898	0.0001	<.0001
Unemployment rate of age 25 and above	−425.43	235.21	0.071
R^2 statistic	0.97		

Figure 7-1 shows the comparison of the total VMT predicted by the model with the reported VMT from 2001 to 2012. Each of the circles in the graph represents one observation, i.e., one state in one year.

7.2.1.2 Urban VMT

To capture the effect of the economic variables by area type, a linear regression model was developed with urban VMT in millions as the dependent variable and population, unemployment rate, and GDP per capita as independent variables. Other variables were not considered because the correlation coefficients shown in Table 7-2 were almost 0. In the urban VMT model, unemployment rate of age 16 to 24 provided better fit. The R^2 statistic for the urban VMT model was 0.97, which shows that the model was able to predict the VMT almost perfectly. The negative coefficient of the unemployment rate in Table 7-4 shows that as the unemployment rate increased, the urban VMT decreased. Although statistically insignificant at the 10% level, the positive coefficient for the GDP per capita shows that the states with higher GDP tended to have more urban travel than states with lower GDP per capita. As with total VMT, the primary determinants of urban VMT were total population and the state of the economy, as measured by the unemployment rate and GDP per capita.

Figure 7-2 shows the comparison of the urban VMT predicted by the model with the reported urban VMT from 2001 to 2012.

7.2.1.3 Rural VMT

More factors were found to contribute to the amount of rural VMT, and the model was less strong. The correlation coefficients in Table 7-2 showed that almost all variables had some

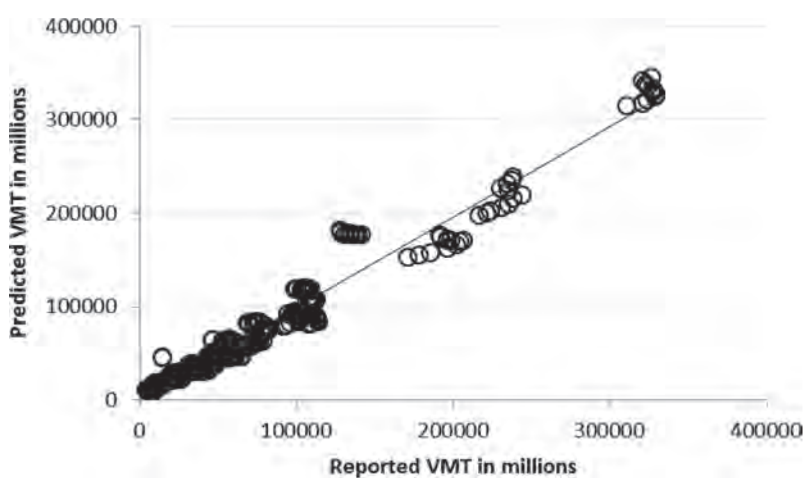


Figure 7-1. Predicted total VMT versus reported total VMT, 2001–2012.

Table 7-4. Parameter estimates for the urban VMT model.

Variable	Chapter 8 Estimate	Chapter 9 Standard error	Chapter 10 P-value
Intercept	−2588.33	2609.50	0.322
Total population	0.00705	0.0001	<.0001
Unemployment rate of age 16 to 24	−179.40	100.70	0.075
GDP per capita in 2013 dollars	0.0140	0.0328	0.670
R^2 statistic	0.97		

correlation with the amount of rural VMT. A linear regression model was developed with rural VMT in millions as the dependent variable and population, unemployment rate, pump price (total gasoline price, including tax, in 2013 dollars), GDP per capita, and median income as independent variables. In the rural VMT model, unemployment rate of age 25 and above provided better fit. The R^2 statistic for the rural VMT model was 0.77, which shows that although the model predicted VMT accurately, the model did not account for all the variation in rural VMT. The negative coefficients for the unemployment rate and pump price in Table 7-5 imply that as the quantity of these variables increased, rural VMT decreased. The negative coefficient for GDP per capita and median income showed that states with lower GDP and median income tended to have more rural travel than other states. This may imply that states with more constrained economies and lower median incomes tended to be more rural.

Figure 7-3 shows the comparison of the rural VMT predicted by the model with the reported rural VMT from 2001 to 2012.

7.2.2 Regression of Factors on Fatalities

The models estimated in this part of the work were based on count data regression methodologies (Cameron and Trivedi 1998; Hilbe 2014). The most basic count data models are the Poisson and Poisson-gamma (also known as the negative binomial, or NB). Both models belong to the family of generalized linear models. For the Poisson model to be appropriate for a

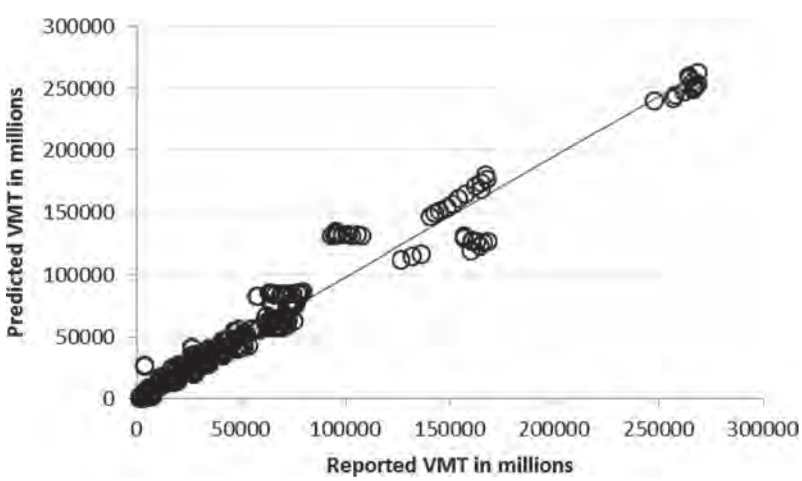


Figure 7-2. Predicted urban VMT versus reported urban VMT, 2001–2012.

Table 7-5. Parameter estimates for the rural VMT model.

Variable	Estimate	Standard error	P-value
Intercept	54822	2661.66	<.0001
Total population	0.00201	0.0001	<.0001
Unemployment rate of age 25 and above	-674.35	174.33	<.0001
Pump price	-3541.08	522.25	<.0001
GDP per capita in 2013 dollars	-0.140	0.039	0.0004
Median income	-0.458	0.053	<.0001
R^2 statistic	0.77		

given data set, the mean has to equal the variance. However, in practice, it has been found that count data often exhibit overdispersion, meaning that the variance is larger than the mean (Lord, Washington et al. 2005). On rare occasions, the data or modeling output may show characteristics of underdispersion (Oh, Washington et al. 2006; Lord, Geedipally et al. 2010). To overcome the problem related to the overdispersion, the Poisson-gamma model has been proposed as a viable alternative to the Poisson model (Hilbe 2011). The Poisson-gamma model has become very popular because it has a closed-form equation (i.e., the mathematical manipulations can be done by hand; for example, it can be shown that the Poisson-gamma mixture leads to the NB distribution), and the mathematics to manipulate the relationship between the mean and the variance are relatively simple (Lord and Mannering 2010). Furthermore, most statistical software packages have incorporated an NB function that simplifies the analysis of count data.

The Poisson-gamma model in highway safety applications has been shown to have the following probabilistic structure: the number of crashes at the i-th entity (state) and t-th time period, Y_{it}, when conditional on its mean, θ_{it}, is assumed to be Poisson distributed and independent over all entities and time periods as follows (Miaou and Lord 2003):

$$Y_{it}|\theta_{it} \sim Po(\theta_{it}) \qquad i = 1, 2, \ldots, I \text{ and } t = 1, 2, \ldots, T \qquad \text{Eq. 2}$$

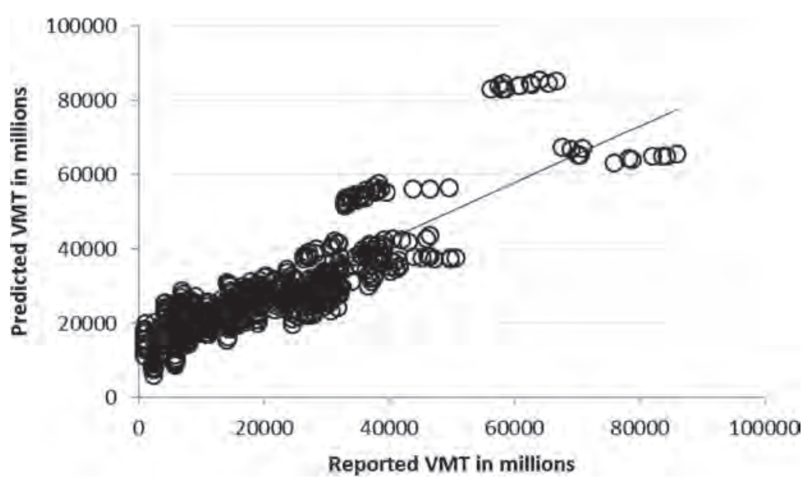


Figure 7-3. Predicted rural VMT versus reported rural VMT, 2001–2012.

The mean of the Poisson is structured as:

$$\theta_{it} = \mu_{it} \exp(\varepsilon_{it}) \qquad \text{Eq. 3}$$

Where

μ_{it} = a function of the covariates (X) (e.g., $\mu_{it} = \exp(\beta_0 + \beta_1 X_{it1} + \beta_2 X_{it2} + \cdots + \beta_p X_{itp})$ where p is the number of covariates);
β = a vector of unknown coefficients;
ε_{it} = the model error independent of all the covariates.

It is usually assumed that $\exp(\varepsilon_{it})$ is independent and gamma distributed with a mean equal to 1 and a variance $1/\phi$ for all i and t (here ϕ is the inverse dispersion parameter, with $\phi > 0$). With this characteristic, it can be shown that Y_{it}, conditional on μ_{it} and ϕ, is distributed as a Poisson-gamma random variable with a mean μ_{it} and a variance $\mu_{it}\,(1 + \mu_{it} / \phi)$, respectively.

In this modeling work, each year for every state was considered a distinct observation. As discussed by Lord and Persaud (2000), analyzing time-series or panel data in this manner can create temporal or serial correlation. Random effects models and those estimated using the generalized estimating equations can be used for handling serial correlation (Lord and Persaud 2000). However, after further investigation it was determined that the serial correlation had a minimal impact on the modeling results. To simplify the modeling effort, the models were estimated using the generalized linear models (GLMs).

Two types of regression models were estimated: (1) models not controlling for state (MNCS) (i.e., no state fixed effect in the model), and (2) MCS (i.e., state is considered as a fixed effect in the model). Further, MCS models were developed using two different types of exposure: one with VMT as exposure and the other with population as exposure. For the MCS models, each state has its own intercept. For MNCS, the model tries to establish the general relationship between the number of fatalities and various risk factors without taking into account differences between states that were not captured in the predictor variables. This model captured less of the total variation, but may better explain certain variables that have a direct influence on fatalities on a national scale, independent of each state. The MCS model type removes overall differences in fatality rates between states and focuses on accounting for how factors influence each state's fatality rate over time relative to the state's base rate. To accomplish this, each state had its own intercept, which captures the effect of variables that were unobserved as well as some that were observed. If the state-specific term was significantly different between states then there is variation between states that is not captured by the variables in the model. When model predictors differ between MNCS and MCS models, this indicates that the effect of a variable over time may be different than its effect between states. The latter is a more stable, long-term pattern, whereas the former is shorter-term and generally has a relative effect for residents of a given state.

The functional form used for the MNCS is the following:

$$\mu = \text{VMT} \times e^{\beta_0 + \Sigma_i \beta_i X_i} \qquad \text{Eq. 4}$$

Where

μ = the estimated number of fatalities per year (for each state);
VMT = the number of vehicle-miles traveled in millions (for each state);
X_i = variable i; and
β_0, β_i = estimated coefficients.

The functional form used for the MCS model is the following:

$$\text{Model 1}: \mu = \text{VMT} \times e^{(\beta_0+\gamma_s)+\Sigma_i\beta_i X_i} \qquad \text{Eq. 5}$$

$$\text{Model 2}: \mu = \text{POP} \times e^{(\beta_0+\gamma_s)+\Sigma_i\beta_i X_i} \qquad \text{Eq. 6}$$

Where

γ_s = state-specific parameter for state *s*; and
POP = population in millions (for each state).

As shown above, two measures of exposure were used. In addition, the exposure variables were used as an offset in the models. What this means in practice is that the dependent variable in the models, the variable that the models were attempting to predict, was a rate, either fatalities per VMT or fatalities per population, depending on whether VMT or population was used as the offset.

The two measures of exposure were the VMT for each state and the population of the state. Both have advantages and disadvantages. For VMT, the variable is a more direct measure of the exposure to crashes of vehicles traveling on the road network. On the other hand, the VMT values themselves are estimated values and, like many estimates, the VMT values may be prone to errors or could be unreliable in some cases. The state population variable is usually better estimated, because it is based on decennial censuses with intercensal surveys, but it may not represent the number of vehicles traveling on the network. Population is not immediately affected by economic conditions or differences in the amount of travel due to the physical size of states, population density, and other factors that may influence the amount of travel, as shown in the VMT models in Section 7.2.1. Noland and Sun (2014) preferred using population as the measure of exposure because they believe that the population estimates were generally more accurate than VMT estimates. However, the current study also estimated a model with VMT as exposure.

All models consider the following variables in each state:

1. Rural VMT as a percentage of total VMT;
2. Capital expenditures spent per highway mile, excluding capital safety expenditures, in the prior year (2013 dollars);
3. Safety expenditures (capital expenditures related to safety, law enforcement, education, and HSIP obligations) per highway mile spent in the prior year (in 2013 dollars);
4. State GDP per capita;
5. Percent unemployment for 16–24 year olds;
6. Total gasoline price (in 2013 dollars);
7. Beer consumption per capita;
8. DUI law rating;
9. Motorcycle helmet law rating;
10. Safety-belt law rating;
11. Safety-belt usage rates;
12. Median income (2013 dollars); and
13. Percent of the vehicle fleet with a model year of 1991 or newer.

These variables represent different cells in the Haddon Matrix. Capital and safety spending fall into the Environment domain and affect both the pre-crash (e.g., spending on infrastructure to reduce crash occurrence) and crash levels (e.g., spending on infrastructure features that reduce the severity of crashes). Elements of the safety expenditure variable also fall into the Human domain at the pre-crash level, insofar as law enforcement and educational programs affect who drives and how they drive. State GDP/capita, percent unemployed, median income, fuel prices, and beer consumption all are located in the pre-crash level of the Human domain, since the presumed mechanisms by which they are linked to safety are to affect decisions to drive and how (riskiness) to drive. Belt use, state belt rating, and motorcycle helmet rating fall into the Human domain at the crash level, insofar as they reflect and constrain the choices individuals make to protect themselves in crashes. Similarly, the variable to capture fleet penetration of crashworthiness features captures the pre-crash and crash levels of the Vehicle domain of the Haddon Matrix. Post-crash levels of the Haddon Matrix could not be incorporated, as it was not possible to obtain comprehensive data series on the factors represented there, such as representing advances in crash notification and post-crash medical care.

The goodness-of-fit (GOF) of the models was assessed using the Akaike information criterion (AIC), and the error-based mean absolute deviation (MAD) and mean squared prediction error (MSPE). Additional information about how the GOF criteria work can be found in Lord and Park (2013). In general, the model with smaller AIC, MAD, and MSPE values is considered superior to other models.

The modeling results are summarized further later in this chapter. In this section, the general characteristics of the results are discussed, including coefficient estimates, standard errors of the estimates, and p-values. P-values show the level of significance, in this case, the probability of obtaining the observed or more extreme results if the true value was 0, given the sample data. In observational studies, a p-value of 0.1 or below is often used as the threshold of statistical significance, meaning only a 10% (or less) chance of the obtained results if the true effect was 0, given the sample data. High p-values do not mean the parameter had no effect, just that the data were not sufficient to exclude that the parameter had no effect, at some reasonable level of confidence. With more data, a non-significant parameter may become significant. "Non-significant" parameters were left in the models to measure the effect of all factors of interest, regardless of statistical significance. The detailed effects of each variable are discussed in Section 8.1.

7.2.2.1 MNCS Model

Table 7-6 shows the modeling results for the MNCS model. As noted above, VMT was used as the exposure. For this model, three variables (DUI rating, belt rating, and motorcycle helmet rating) were found to be not statistically significant, even at the 10% level.

7.2.2.2 MCS Models

Table 7-7 shows the modeling results for the MCS model with the VMT used as an exposure. For this model, four variables (capital spending, safety spending, pump price, and belt rating) were found to be not statistically significant, even at the 0.1 level.

Table 7-8 shows the modeling results for the MCS model with population as an exposure. For this model, three variables (rural VMT proportion, safety spending, and pump price) were found to be not statistically significant, even at the 0.1 level.

7.2.2.3 Model Comparisons

The GOF statistics presented from Table 7-6 to Table 7-8 show that the MCS model with VMT as exposure provides the best fit to the data. Figure 7-4 depicts how each model compared to the actual number of fatalities observed across the United States from 2007 to 2012. The model values were derived by running the parameter values for each state and summing them to the total found in the United States. The highest level of fidelity was provided by the MCS model with VMT as the exposure, which tracked fatalities quite closely. The MCS model with population as the exposure also tracked fatalities well, but did not reflect the continued decrease in fatalities in 2011 or the rise in fatalities in 2012. Given the underperformance when compared to the MCS

Table 7-6. Parameter estimates for the MNCS model, VMT offset.

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	11.7179	0.4082	<.0001	
Rural VMT proportion	**0.2228**	**0.0667**	**0.0008**	**1.250**
Capital spending (in $1,000)	**0.0009**	**0.0003**	**0.0007**	**1.001**
Safety spending (in $1,000)	**−0.0033**	**0.0013**	**0.0124**	**0.997**
GDP per capital (in $10,000)	**0.024**	**0.0106**	**0.0241**	**1.024**
Unemployment for age 16 to 24 (%)	**−0.0132**	**0.0025**	**<.0001**	**0.987**
Pump price ($ per gallon)	**−0.0475**	**0.0258**	**0.0651**	**0.954**
Beer (gallons)	**0.2769**	**0.0425**	**<.0001**	**1.319**
DUI rating	−0.0032	0.0026	0.22	0.997
Belt rating	0.0008	0.007	0.9061	1.001
Motorcycle helmet rating	0.0065	0.0073	0.3732	1.007
Median income (in $10,000)	**−0.2149**	**0.0148**	**<.0001**	**0.807**
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	**−0.0138**	**0.0047**	**0.0033**	**0.986**
Dispersion parameter	0.0277	0.0019	--	--
AIC*	6537			
MAD*	93.07			
MSPE*	21185.56			

* Smaller values are preferred.
Bold font denotes p-values <=0.1.

model using VMT, the population model will not be discussed in greater detail. Although population estimates may be generally more accurate than VMT estimates, as argued by Noland and Sun (2014), the results here show that VMT provides a better fit to the data. The MNCS model reflected the trend of crashes, but it is clear that the combined effects of the parameters did not capture all the variation in fatalities over the focus period. The model generally under-predicted the number of traffic fatalities, indicating that other influential factors were not accounted for in the model. However, this model is still valuable because it may be able to better explain certain variables that had a direct influence on fatalities on a national scale, independent of each state.

7.2.3 Model of Annual Change in Factor Levels on the Annual Change in Fatalities

An alternative approach suggested by Elvik (2013) was also used. This approach, referred to as the “change model,” translates the data into percent change from year to year within each state. The data begin with 2002, for which each independent and dependent variable is represented by its percent change compared to the previous year (Eq. 7):

$$z_t = \frac{x_t}{x_{t-1}} \qquad \text{Eq. 7}$$

Table 7-7. Parameter estimates for the MCS model with VMT as exposure.

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	10.6995	0.302	<.0001	
Rural VMT proportion	**−0.1916**	**0.0972**	**0.0486**	**0.826**
Capital spending (in $1,000 per mile)	−0.0002	0.0002	0.2255	1.000
Safety spending (in $1,000 per mile)	−0.0006	0.001	0.5176	0.999
GDP per capita (in $10,000)	**0.046**	**0.0117**	**<.0001**	**1.047**
Unemployment for age 16 to 24 (%)	**−0.0118**	**0.0015**	**<.0001**	**0.988**
Pump price ($ per gallon)	0.0065	0.0125	0.6034	1.007
Beer per capita (gallons)	**0.4022**	**0.0747**	**<.0001**	**1.495**
DUI rating	**−0.0074**	**0.003**	**0.0119**	**0.993**
Belt rating	−0.0058	0.0073	0.4274	0.994
Motorcycle helmet rating	**−0.0347**	**0.0156**	**0.0261**	**0.966**
Median income (in $10,000)	**0.0375**	**0.0188**	**0.0459**	**1.038**
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	**−0.0177**	**0.0026**	**<.0001**	**0.982**
Dispersion parameter	0.0025	0.0003	--	--
AIC*	5643			
MAD*	35.80			
MSPE*	3165.32			

* Smaller values are preferred.
Bold font denotes p-values <=0.1.
Note: State fixed effect parameters are presented in Appendix C.

Where

x = any original variable in the model;
z = is the transformed change variable;
x_t = is the value of x in a given year; and
x_{t-1} = is the value in the prior year.

Taking the log to convert to a linear model, which is mathematically more straightforward (Eq. 8):

$$ln(y_t) - ln(y_{t-1}) = \beta_0 + \sum_{j=1}^{k} \beta_j z_t = \beta_0 + \sum_{j=1}^{k} \beta_j (ln(x_t) - ln(x_{t-1})) \qquad \text{Eq. 8}$$

Where

y_t = number of traffic fatalities in year t;
y_{t-1} = number of traffic fatalities in year $t-1$;
z_t = transformed change variable; and
β_0, β_j = estimated coefficients.

Table 7-8. Parameter estimates for the MCS model with population as exposure.

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	5.3846	0.3306	<.0001	
Rural VMT proportion	−0.0249	0.1068	0.8157	0.975
Capital spending (in $1,000 per mile)	**−0.0006**	**0.0002**	**0.0043**	**0.999**
Safety spending (in $1,000 per mile)	−0.0015	0.0011	0.156	0.999
GDP per capita (in $10,000)	**0.1815**	**0.0124**	**<.0001**	**1.199**
Unemployment for age 16 to 24 (%)	**−0.0122**	**0.0016**	**<.0001**	**0.988**
Pump price ($ per gallon)	0.0039	0.0137	0.7759	1.004
Beer per capita (gallons)	**0.2376**	**0.0813**	**0.0035**	**1.268**
DUI rating	**−0.0154**	**0.0032**	**<.0001**	**0.985**
Belt rating	**−0.0254**	**0.008**	**0.0015**	**0.975**
Motorcycle helmet rating	**−0.0466**	**0.0174**	**0.0075**	**0.954**
Median income (in $10,000)	**−0.0393**	**0.0205**	**0.0553**	**0.961**
Post-1991 (% of vehicles manufactured after 1991 in the fleet)	**−0.0078**	**0.0028**	**0.006**	**0.992**
Dispersion parameter	0.0034	0.0004	--	--
AIC*	5785			
MAD*	38.16			
MSPE*	3673.70			

* Smaller values are preferred.
Bold font denotes p-values <=0.1.

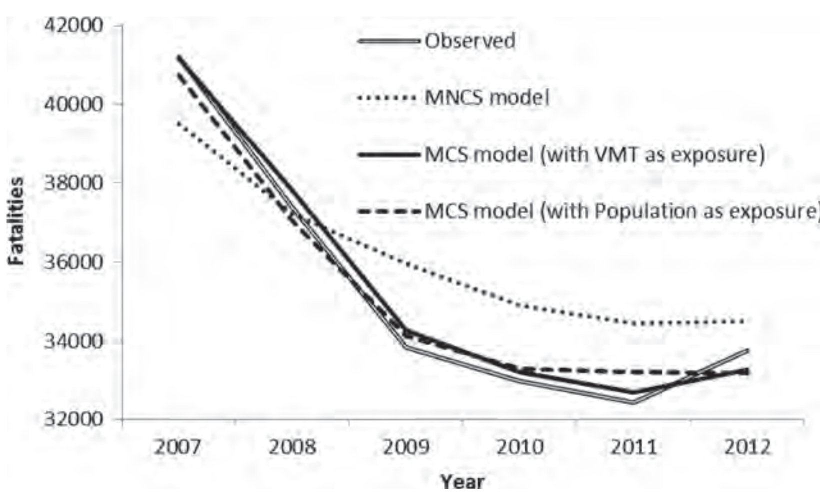


Figure 7-4. Model predictions versus actual fatalities, 2007–2012.

When exponentiated, the coefficients (βs) in this model can be interpreted as multipliers on how the rate of change in a predictor influences the rate of change in fatalities (Eq. 9):

$$\frac{y_t}{y_{t-1}} = e^{\beta_0} \prod_{j=1}^{k} e^{\beta_i} \frac{x_t}{x_{t-1}} \qquad \text{Eq. 9}$$

A key quality of the change model is that it removes overall differences between states on all variables. Large states may have larger numbers of fatalities, larger expenditures, and larger numbers of miles driven, but change in those states is proportional. Small states do, however, produce more volatile change values because of the smaller samples.

The predictors in this model were slightly different from those in the count models, but they capture the same basic sources of variance and represent the same dimensions of the Haddon Matrix. The predictors were selected to include change in total VMT, change in proportion of rural VMT out of all VMT, change in pump price, change in GDP per capita, change in median income, change in unemployment for 16- to 24-year-olds, change in capital spending per mile (lagged one year), change in safety spending per mile (lagged one year), change in belt-use rate, change in DUI law rating, change in motorcycle helmet law rating, change in beer consumption, change in wine consumption, and change in the proportion of vehicles on the road with model year newer than 1991.

Multiple linear regression was run using SAS 9.4 PROC GLM to predict change in fatalities based on change in the predictors. Parameter estimates are shown in Table 7-9, along with standard errors of the estimates and p-values.

Table 7-9. Parameter estimates for change model.

Variable	Estimate	Standard error	P-value	Exponentiated parameter
Intercept	−0.011	0.008	0.1719	
Total VMT chng	**0.540**	**0.188**	**0.0042**	**1.716**
Proportion rural VMT chng	0.022	0.061	0.7171	1.022
Pump price chng	−0.024	0.040	0.5597	0.976
GDP per cap chng	**0.128**	**0.067**	**0.0552**	**1.137**
Median income chng	**0.505**	**0.155**	**0.0012**	**1.657**
16-24 Unemp chng	**−0.138**	**0.026**	**<.0001**	**0.871**
Cap spend/mile (lag) chng	−0.008	0.022	0.7084	0.992
Safety spend/mile (lag) chng	0.011	0.014	0.4071	1.011
Belt-use rate chng	−0.051	0.122	0.6748	0.950
DUI law rating chng	**−0.181**	**0.093**	**0.0521**	**0.834**
Motorcycle helmet law rating chng	−0.013	0.100	0.8986	0.987
Beer consumption chng	0.170	0.141	0.2304	1.185
Wine consumption chng	−0.029	0.087	0.7385	0.971
MY>1991 chng	0.057	0.550	0.9179	1.059
R^2	0.168			
Adj. R^2	0.144			

Bold font denotes p-values <=0.1.

Table 7-10. Effects of change-model predictors for 2007–2011.

Variable	Parameter	2007 Mean	2011 Mean	Percent change in predictor 2007–2011	Percent change in predicted fatalities 2007–2011
Intercept	−0.011				
Total VMT	0.540	3,031,124	2,962,740	−2.3%	−1.2%
Proportion rural VMT	0.022	0.33	0.32	−1.6%	−0.1%
Pump price change	−0.024	3.11	3.20	2.6%	−0.1%
GDP per cap change	0.128	59,687	54,519	−7.5%	−1.2%
Median income change	0.505	56,081	53,621	−4.3%	−2.2%
16-24 Unemp change	−0.138	10.59	16.69	55.7%	−6.1%
Capital spend/mile (lag) change	−0.008	73.69	81.27	7.9%	−0.1%
Safety spend/mile (lag) change	0.011	13.61	14.68	9.3%	0.1%
Belt-use rate change	−0.051	85.77	88.10	2.4%	−0.1%
DUI law rating change	−0.181	19.77	20.50	4.0%	−0.7%
Motorcycle helmet law rating change	−0.013	2.91	2.91	0.0%	0.0%
Beer consumption change	0.170	1.21	1.15	−3.5%	−0.7%
Wine consumption change	−0.029	0.37	0.39	5.0%	−0.1%
MY>1991 change	0.057	95.80	97.11	1.4%	0.1%

Model diagnostics indicated that the assumptions of linear regression were generally met. However, overall R^2 was relatively low with only 16.8% of the total variance accounted for. This indicates that additional processes beyond those included influenced the specific change observed. However, these processes are not likely to have been captured in any measures available to the researchers.

To interpret the coefficients, the effect of change in each predictor was observed over the period of interest: 2007–2011. Holding all other variables constant, the parameter estimates were used to calculate the percent change in fatalities associated with each predictor individually across the range of change seen in that time period. The results are in Table 7-10.

CHAPTER 8

Discussion of Results

The Haddon Matrix was used initially to ensure that a comprehensive set of factors would be considered in studying the dramatic drop in traffic fatalities in the United States after 2007. The results showed that not all elements of the matrix—vehicle, driver, and environment—contributed equally. In addition, factors that might be considered indirectly related to elements of the matrix, i.e., the state of the economy, were most strongly associated with the decline. One of the complicating aspects of identifying and understanding the factors that influenced the number of traffic fatalities was that the number of fatalities is the product of risk and exposure, and changes in either or both can affect the number of fatalities (see Eq. 1 in Chapter 2). During the period from 2007 to 2012, both risk (the number of fatalities per VMT) and exposure (VMT) changed. This section discusses the relative importance of each in the reduction of fatalities.

Figure 8-1 is a graph of the observed number of U.S. traffic fatalities from 2007 to 2012 plotted against two lines that represent:

A. The number of fatalities that would have occurred if the level of exposure (VMT) had stayed constant at 2007 levels throughout the period and only risk varied.
B. The number of fatalities that would have occurred if the level of risk had stayed constant at the 2007 level throughout the period and only exposure varied.

Figure 8-1 illustrates that most of the variation in traffic fatalities was due to changes in risk, although some portion can also be attributed to the change in exposure. Relatively speaking, fatalities due to changes in risk declined greatly in the first 2 years, accompanied by a moderate decrease due to reductions in traffic volume. From 2010 to 2012, fatalities continued to decline moderately due to further modest reductions in risk while the influence of traffic volume was relatively stable. To understand the reduction in fatalities, it is important to focus on the factors that influenced risk during this period.

Table 8-1 identifies the expected association with traffic fatalities of the various parameters in the statistical models and describes the mechanisms through which they were hypothesized to affect the number of traffic fatalities. Most of the modeling results were consistent with these expectations. Some of the model results for the data were inconsistent with these hypothetical influence mechanisms. For example, it was expected that the wine consumption parameter would be positively associated with traffic fatalities (greater wine consumption associated with more traffic fatalities), but the modeling showed a weak negative association, such that greater per capita wine consumption in a state was associated with lower traffic fatalities. However, the effect size was small and the coefficient non-significant.

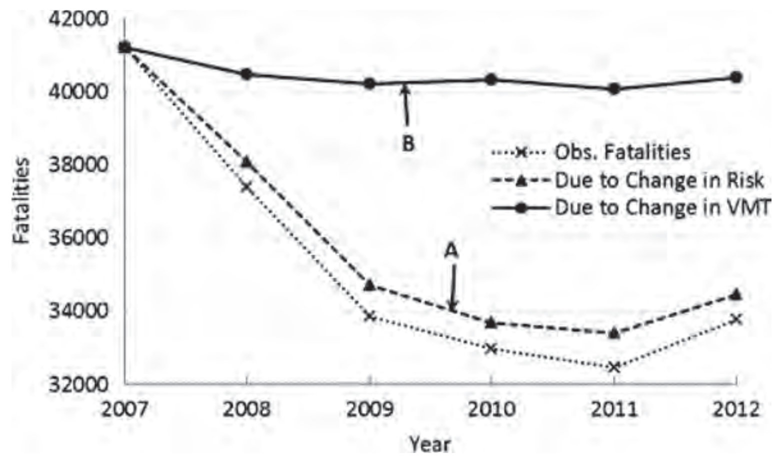


Figure 8-1. Observed traffic fatalities versus fatalities with constant exposure or risk.

8.1 Variable Influence Estimated from the Count Models

This discussion of results is based on the MNCS model (i.e., model not controlling for state) and the MCS model (model controlling for state) with VMT as exposure. In general, the MCS model provided better fit because the state fixed effect in the model is essentially a consistent adjustment that differentiates one state from another. However, the state fixed effect may be correlated with other parameters in the model and may tend to obscure the influence of those other factors. Therefore, it is instructive to review the results from models that include and exclude state fixed effects.

The variables were grouped into the categories of economic, safety, capital, regulatory, and vehicle safety factors to discuss the role each group played in determining fatalities (Table 8-2).

The influence of the variables in these groupings is shown in Table 8-3. The proportion of the decrease is based on an average of the predicted and observed fatalities for the years 2008 through 2012.

Table 8-3 compares the average percent of reduction in predicted and observed fatalities accounted for by each grouping of count model variables. The reduction of fatalities was based on the difference between the number of fatalities in 2007 and the number of fatalities actually observed predicted by each model for the years 2008 through 2012. The results indicate that economic factors had by far the largest influence on the predicted reduction in fatalities and also accounted for 73% to 80% of the observed reduction in fatalities. The next most significant contributor was improvements to vehicle safety. Regulatory changes had a much smaller impact. Safety spending had almost no influence in the MCS model and a small but not statistically significant effect in the MNCS model. Roadway capital expenditures had a mixed effect. The MCS model suggests a decrease of 1% due to capital expenditures but the MNCS model suggests that spending was associated with an increase; neither influence was statistically significant.

Figures 8-2 through 8-6 provide a visual representation of the proportion of predicted and observed fatality reductions accounted for by each of the groupings of variables (economic, safety expenditures, capital expenditures, regulatory, and vehicle effects) for each model. The top of each figure shows the predicted results from the MNCS model and the bottom from the MCS model. For example, in Figure 8-2, line segment A depicts the reduction in traffic

Table 8-1. Explanatory factors and expected mechanisms of activity.

Variable	Expected association with traffic fatalities	Expected mechanism
Total VMT	Positive	Increase in VMT increases exposure to traffic crashes and therefore fatalities.
Proportion rural VMT	Positive	Increased proportion of rural VMT increases proportion of travel on riskier roads, leading to more fatalities.
Pump price	Negative	Increased pump price raises cost of travel, reducing total travel and discretionary travel, reducing exposure to fatal crashes.
GDP per capita	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 reduces 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 model year >1991	Negative	Increased penetration of vehicles that provide more occupant protection and more safety features reduces the probability of a crash and reduces the probability of fatal injury, given a crash.

Table 8-2. Grouping of variables.

	Grouping				
	Economic	Safety expenditures	Roadway capital expenditures	Regulatory	Vehicle safety
Variables	• Rural VMT • GDP per capita percent • Unemployment % for 16- to 24-year-olds • Beer consumption • Median income	• Safety expenditures per highway mile (law enforcement, education, safety-related capital investments, HSIP obligations)	• Capital expenditures per highway mile (excluding those related to safety)	• Ratings o DUI o Helmet o Safety belts	• Percent of the vehicle fleet with a 1991 or newer model year

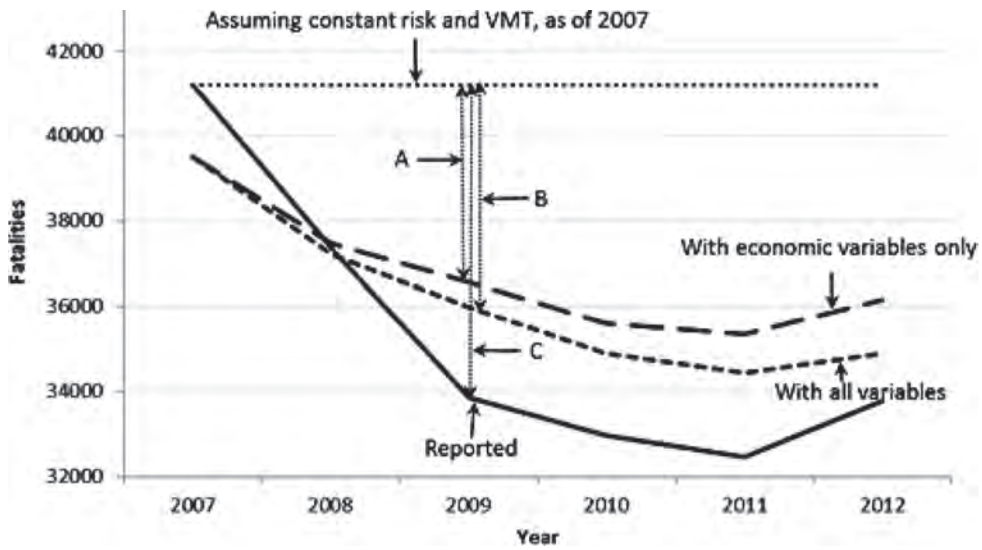
fatalities predicted by the economic variables, while line segment B depicts the predicted reduction from all variables in the model. Line segment C represents the observed drop in fatalities from 2007. The ratio of A to B expressed as a percentage gives the proportion of the total predicted fatality reduction accounted for by economic factors. The ratio of A to C, expressed as a percentage, gives the proportion of the observed drop in fatalities accounted for by economic factors. Figures 8-3 through 8-6 are interpreted similarly, however, with a minor difference for each of the respective model parameter groups. More specifically, in Figures 8-3 through 8-6, the ratio calculated as (A′ - A)/B represents the proportion of the total predicted fatality reduction.

8.1.1 Effect of Economic Variables

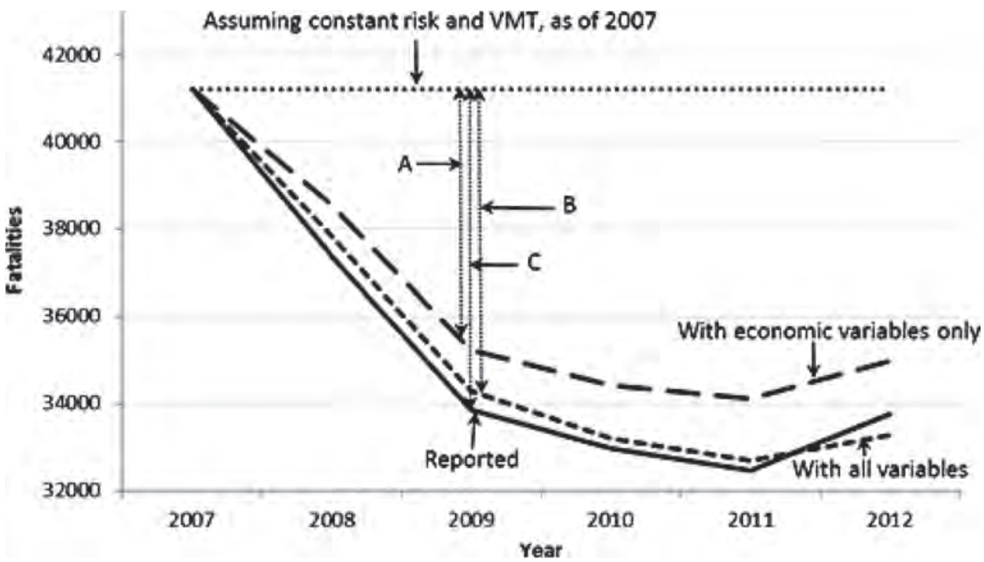
Figures 8-2 through 8-6 illustrate that both models indicated a significant portion of the drop in traffic fatalities over the period was accounted for by economic factors. According

Table 8-3. Proportion of predicted and observed reduction of fatalities accounted for by groupings of count model variables.

	MCS model		MNCS model	
Variable grouping	Reduction in predicted fatalities accounted by the variable group	Reduction in observed fatalities accounted by the variable group	Reduction in predicted fatalities accounted by the variable group	Reduction in observed fatalities accounted by the variable group
All variables	100%	−97%	100%	−83%
Economic	−82%	−80%	−88%	−73%
Safety expenditures	0%	0%	−2%	−2%
Roadway capital expenditures	−1%	−1%	+4%	+3%
Regulatory	−3%	−3%	−2%	−1%
Vehicle safety	− 13%	−13%	−12%	−10%



a) MNCS model



b) MCS model

Figure 8-2. Quantification of economics effects on fatalities.

to both models, the set of economic factors accounted for 82% to 88% of the difference between the fatality level in 2007 and the fatality level predicted by the model over the period 2008 to 2012, and 73% to 80% of the decline in observed fatalities when compared to fatalities in 2007.

8.1.2 Effect of Safety Expenditures

State safety expenditures were compiled for each state. The expenditures were normalized by miles of highway to control for differences in the size of states. Safety expenditures included law enforcement, education, safety-related capital investments, and HSIP obligations and were entered into the model the year after (lagged) the expenditure was made (because effects are not immediate, the expenditures in 2007 were evaluated in relation to fatalities in 2008). These expenditures were estimated to have made a minimal contribution to the dramatic decline in traffic fatalities over the period. According to MNCS and MCS models, on average over the

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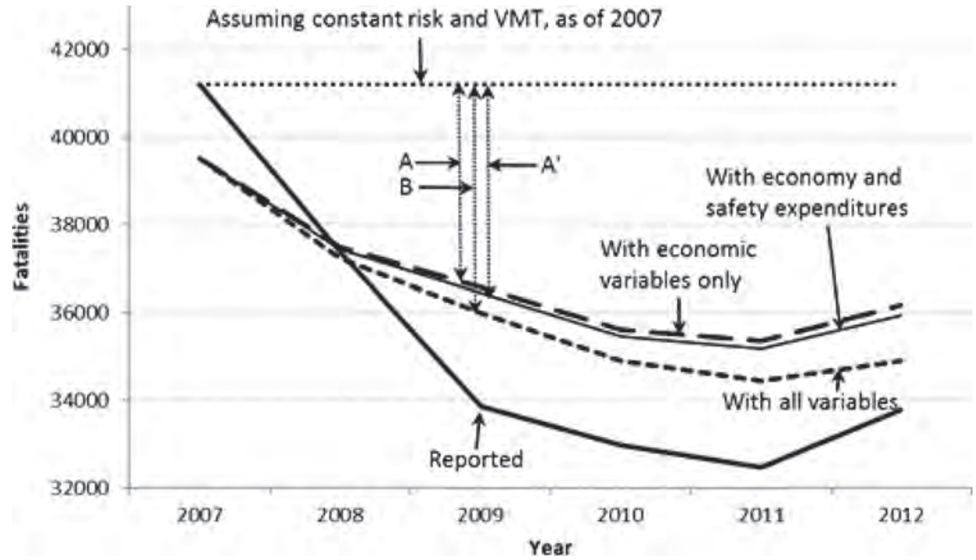
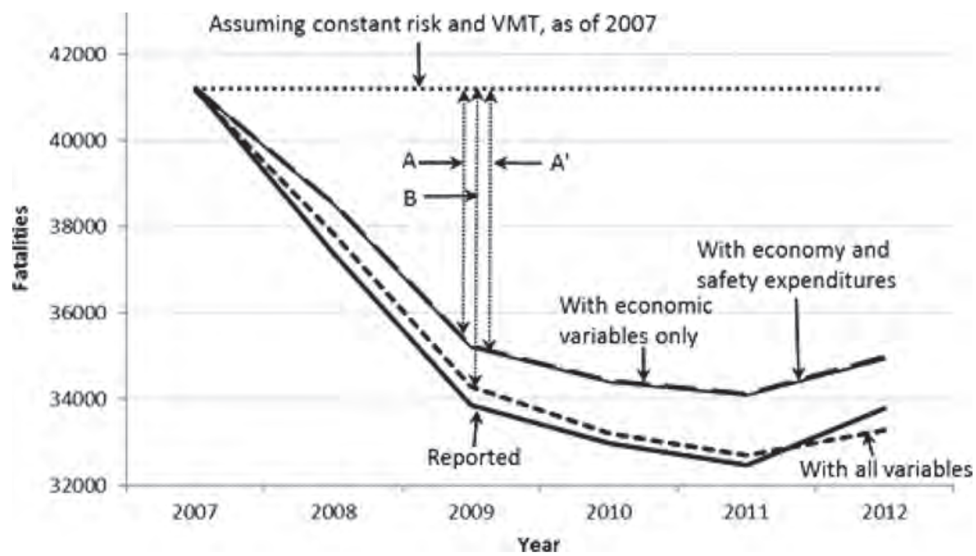


a) MNCS model



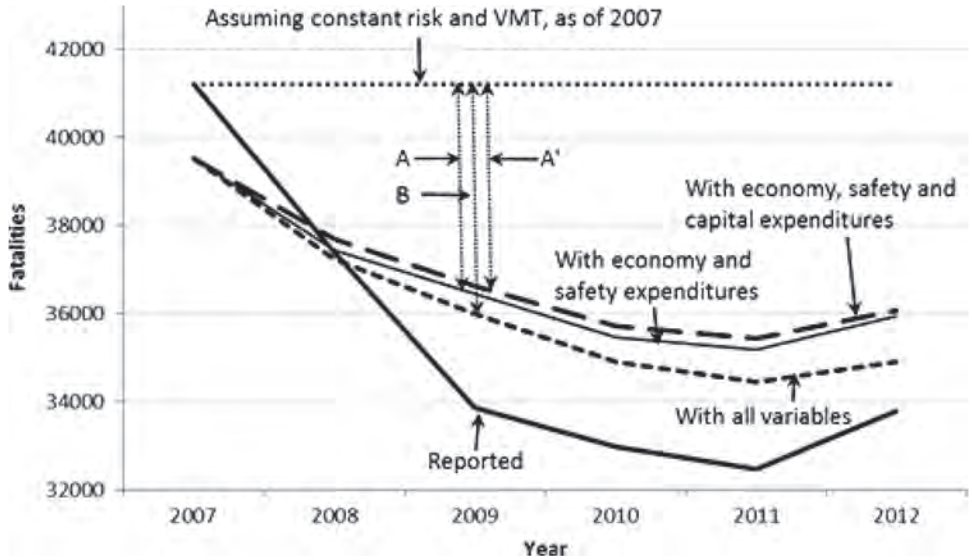
b) MCS model

Figure 8-3. Quantification of effects of safety expenditures on fatalities.

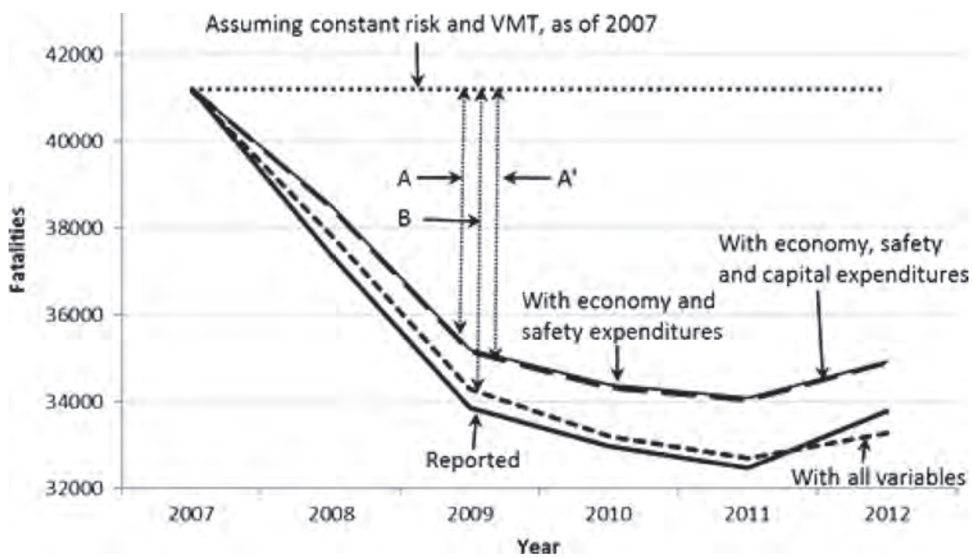
period 2008 to 2012, state safety expenditures accounted for 0% to 2% of fatalities predicted by the model. However, the effect of the lagged safety spending was not statistically significant in these data. Thus, one cannot state with confidence that there was an effect from it. There are several possible reasons for this result: (1) the effect of highway programs may tend to be more long term and cumulative, (2) short-term effects are rarely visible, (3) the effects were overwhelmed by the much larger impact of the economic recession, and (4) the effects of safety programs do not vary linearly with the amount of expenditures.

8.1.3 Effect of Roadway Capital Expenditures

Roadway capital expenditures were compiled for each state and normalized by miles of highway to control for differences in the size of states. Capital expenditures included non-safety-related capital investments and were entered into the model the year after (lagged) the expenditure was



a) MNCS model

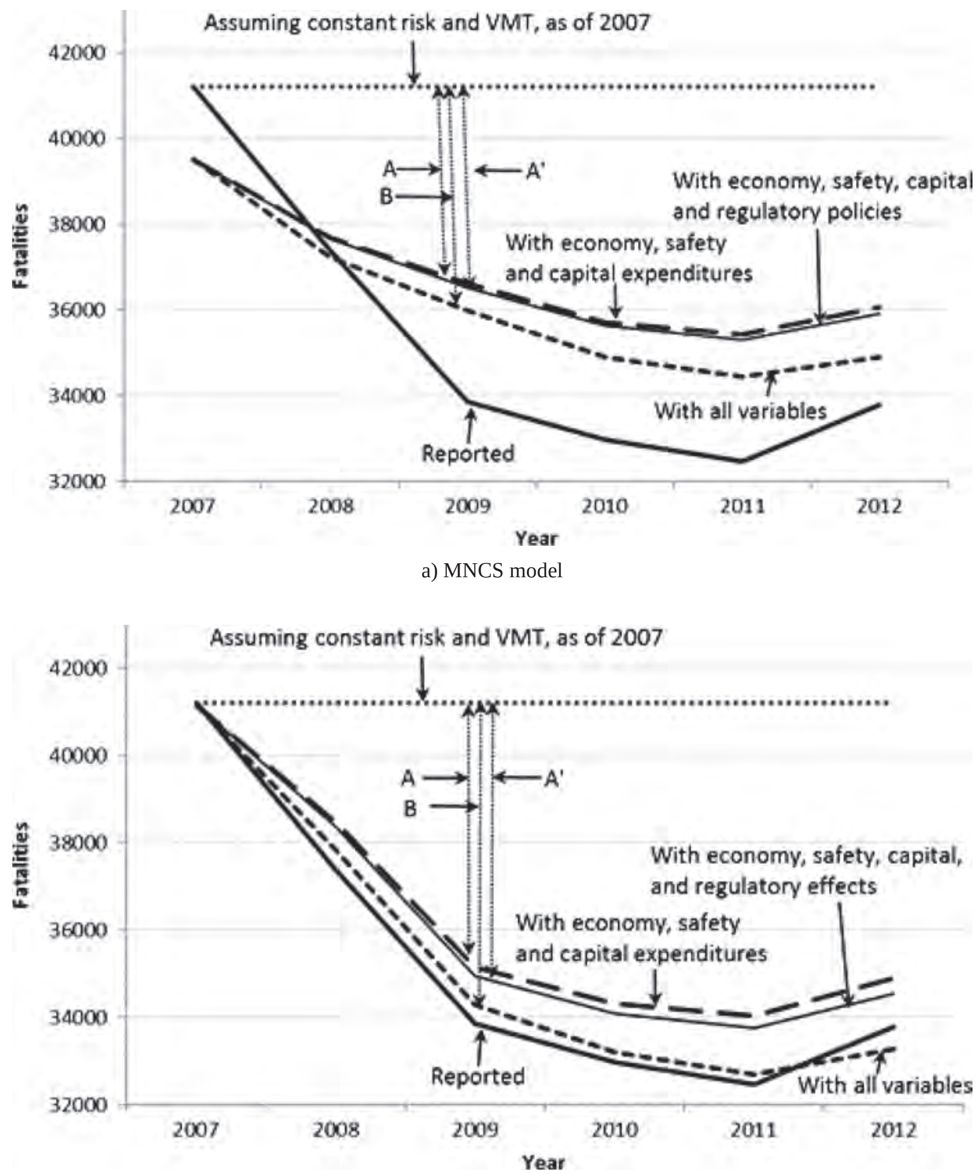


b) MCS model

Figure 8-4. Quantification of effects of capital expenditures on fatalities.

made (because the effects are not immediate, the expenditures in 2007 were evaluated in relation to fatalities in 2008). The MNCS model predicted that these expenditures were associated with an increase in fatalities. This is a surprising and somewhat counterintuitive finding, which could be attributed to the huge amount of variance in the data. In contrast, the MCS model, which fixed state effects, predicted that these expenditures were associated with a decrease in fatalities, albeit small and non-significant. In fact, the variable was not statistically significant in either model, and it cannot be said with confidence that the effect was either positive or negative.

It is possible that this result was an artifact of the modeling process and the coefficients were compensating for the effects of other related factors. It is also possible that an increase in speeds associated with improved roadways or increased travel in rural areas could contribute to an increase in fatalities. It is not possible to sort out with the current data why an increase was predicted by the model. The effect was reversed in the MCS model, which may indicate a



a) MNCS model

b) MCS model

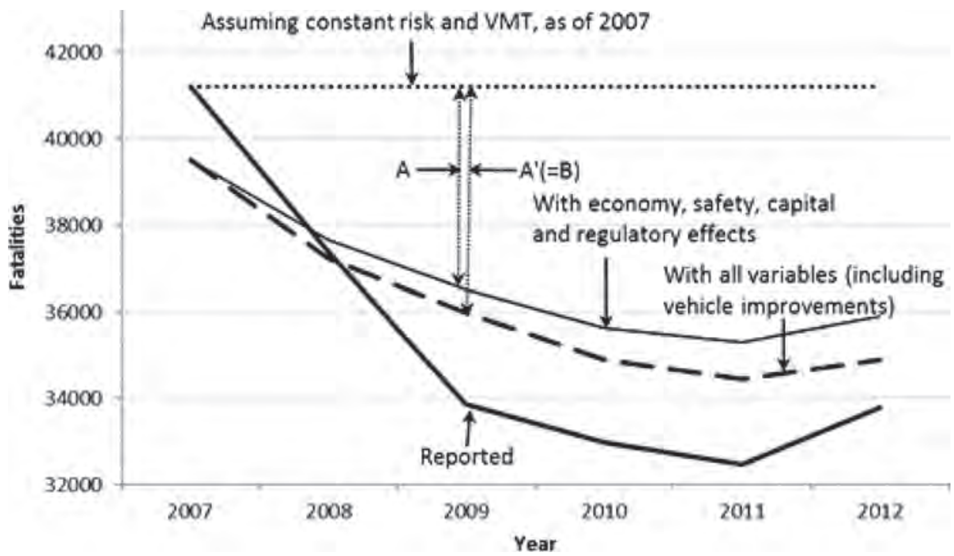
Figure 8-5. Quantification of effects of regulatory measures on fatalities.

correlation between roadway spending and state characteristics. It is possible, for instance, that capital spending was related to economic conditions within a state. Much state DOT funding comes from fuel sales. Increased fuel sales would generate more funding for capital projects but also be associated with high VMT and thus exposure to fatal crashes. The models may not be able to clearly predict the influence of roadway capital funding.

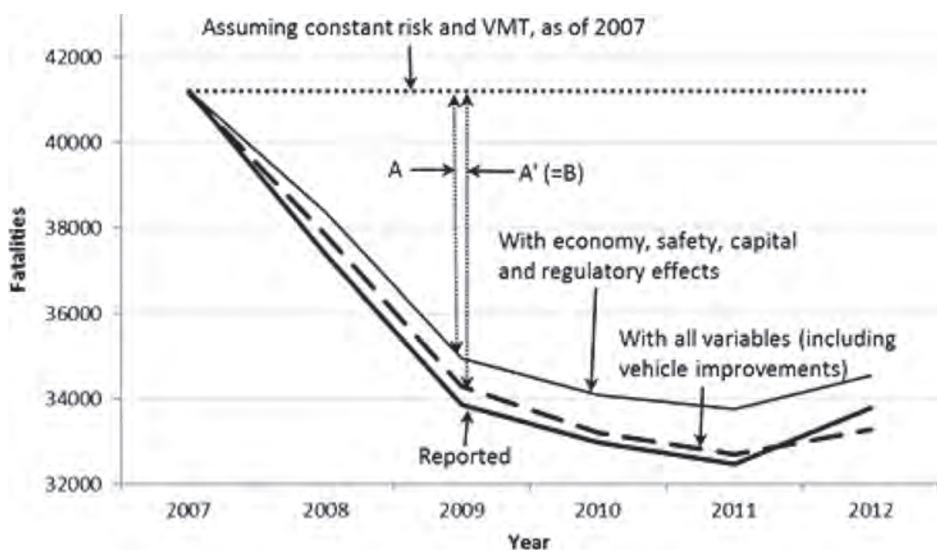
According to the MNCS and MCS models, on average over the period 2008 to 2012, the effect of roadway capital investments was not large, ranging from an increase of 4% to a decline of 1% in the predicted level of traffic fatalities.

8.1.4 Effect of Regulatory Policies

In the models, the effects of DUI, safety-belt, and motorcycle helmet laws were taken into consideration using rating indexes developed for each state. The rating indexes increased as the



a) MNCS model



b) MCS model

Figure 8-6. Quantification of effects of vehicle improvements on fatalities.

laws become stricter. Each category—DUI, safety-belt, and motorcycle helmet laws—was considered separately in the models, and a combined effect was evaluated to assess the effectiveness of regulatory policies. Both models show a marginal change in the prediction through the inclusion of these ratings. According to both models, on an average over the period 2008 to 2012, the influence was not large, and ranged from 2% to 3% decline in fatalities. None of the effects of the individual parameters was statistically significant in the MNCS model. However, DUI and motorcycle helmet law ratings were statistically significant in the MCS model.

8.1.5 Effect of Changes in Vehicle Fleet Safety

The effect of the influence of improved safety (more crashworthy designs, improved occupant protection, stability control, and the like) in vehicles was incorporated into the models as the proportion of the U.S. vehicle fleet that was model year 1991 or newer. Because data on fleet penetration could not be obtained for each state, this value was assumed to be the same across

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all the states. The proportion of the predicted reduction in fatalities that can be attributed to vehicle fleet safety, on average over the period 2008 to 2012, was 13% for the MCS model and 12% for the MNCS model.

8.1.6 Effects of Individual Factors within the Economic Grouping

Table 8-4 lists the economic factors, the change in each parameter between 2007 and 2011, and the associated fatality effect in the MNCS and MCS models. The effects of individual factors were determined by calculating the average value of the variable in the period from 2008 through 2012 and using the difference between that average and the value in 2007 to determine the resulting impact of that change on fatalities.

8.1.6.1 Unemployment Rate for Ages 16 to 24

The unemployment rate for 16- to 24-year-olds had the biggest effect on the decline in traffic fatalities from 2007 through 2012. In both models, the overall magnitude of the effect was similar, and both were statistically significant. In both models, the effect of the increase in teen and young adult unemployment accounted for between 50% and 52% of the total reduction predicted by the set of economic factors. Because unemployment itself is not a traffic risk in and of itself, there has to be a mechanism that acts upon risk. It is suggested that the increase in teen and young adult unemployment led to reduced driving by this group, and because this group tends to have higher crash rates (risk) (see, e.g., Massie, Campbell et al. 1995), reduced the risk per unit of overall VMT. Both MNCS and MCS models indicated that a 5% increase in the unemployment rate for 16- to 24-year-olds resulted in a 5.7% to 6.4% decrease in fatalities.

8.1.6.2 Pump Price

Increases in the pump price of gasoline were associated with reductions in fatalities in the model without state-fixed effects (MNCS). However, when state fixed effects were considered, the influence of pump price was reversed and reductions were associated with an increase in fatalities. This may be because the state fixed effect was correlated with pump price and in some way tended to overestimate without an adjustment. The effect of pump price was not significant

Table 8-4. Effects of individual economic factors.

Variable	Change in parameter value from 2007 to 2011	MNCS model		MCS model	
		Predicted change in fatalities	Statistically significant at 5% level?	Predicted change in fatalities	Statistically significant at 5% level?
Rural VMT proportion as percent of total	−0.8 %	−103	Yes	95	Yes
State GDP per capita	−$6,301 per person	−617	Yes	−1,236	Yes
Unemployment rate for 16- to 24-year-olds	+6.39%	−3,305	Yes	−3,125	Yes
Pump price	+$0.55/gallon	−877	No	127	No
Per capita beer Consumption	−0.08 Gal./person	−835	Yes	−1,312	Yes
Median income	−$3,760	2,677	Yes	−466	Yes

in the MCS model and marginally significant in the MNCS model. Accordingly, it cannot be said with certainty that the effect was not 0.

The manner in which pump price may lower risk is that higher prices may discourage driving among riskier populations, which could be young people without jobs, or older drivers with limited resources. It may also tend to discourage riskier rural driving because of the longer distances traveled and increased fuel consumption on those trips. In addition, it may reduce discretionary, leisure travel, particularly among teens and young adults, and those in the lower-income quintiles.

The average national pump price over the period from 2007 to 2012 is shown in Figure 8-7. Note that the pump price fluctuated in a manner not entirely consistent with the trend in fatalities over that time. This may contribute to the mixed results obtained in the two modeling scenarios and the lack of statistical significance of the effect of pump price. Other studies, as noted in Section 6.7, found a relationship between fuel prices and traffic fatalities (Grabowski and Morrisey 2004; Grabowski and Morrisey 2006; Morrisey and Grabowski 2011).

8.1.6.3 Beer Consumption

The models indicated a consistent relationship between a reduction in per capita beer consumption and a reduction in traffic fatalities, both of which were statistically significant. In the model without state fixed effects (MNCS), the reduction in beer consumption predicted 10% of the total reduction in fatalities due to economic factors. The MCS model predicted about a 13% reduction. The potential mechanism for this parameter to affect risk is fairly direct, as the likelihood of drunk driving was likely to diminish as consumption of alcoholic beverages declined.

The modeling indicated that one tenth of a gallon increase in per capita beer consumption would be associated with a 2.8% increase in fatalities in the model without state fixed effects and a 4.1% increase in the model that includes state fixed effects. The national trend in beer consumption from 2007 to 2012 was shown in Figure 6-18. Over the period, beer was the primary alcoholic beverage consumed and, in contrast to wine and spirits, consumption declined by 2.5% in 2009 and 2.7% in 2010.

8.1.6.4 GDP per Capita

In both models, a decrease in per capita GDP was associated with a decrease in traffic fatalities. The effect was statistically significant in both models. In the MNCS model this variable

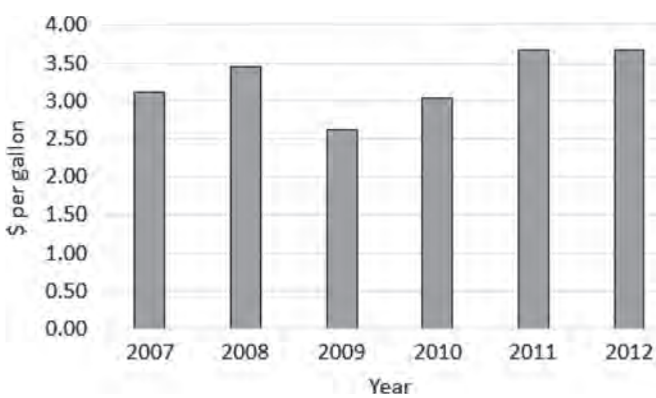


Figure 8-7. Fuel prices, constant 2013 dollars, 2007–2012.

accounted for about 8% of the decline in fatalities attributed to economic factors; the decline was 15% from economic variables in the MCS model.

Per capita GDP was likely connected to traffic fatalities by influencing the types and amounts of travel (VMT). GDP per capita is a measure of economic activity, much of which is realized through the transport of goods and services. Higher rates of economic activity may also be associated with greater leisure and discretionary driving, which may be riskier, while also allowing more travel by riskier groups (such as younger, novice drivers). Similarly, declines in GDP or reduced growth could limit or reduce riskier travel.

8.1.6.5 Rural VMT

The association of the proportion of rural travel of total VMT with traffic fatalities was not consistent across the models. Although the MNCS model suggested that a decline in rural VMT proportion was associated with a reduction in traffic fatalities, the MCS effect model suggested the reverse. The effects were statistically significant in both models.

The percentage of rural VMT in a state might be a surrogate for the degree of ruralness of that state, and therefore the parameter may be correlated with the fixed effect. In that case, the proportion of rural VMT might be "adjusting" the fixed effect and act differently than when considered without those state effects. Rural travel is riskier than urban travel, so it would be expected that a decrease in the rural proportion of travel would be associated with a decrease in fatalities. The MNCS model estimated that a 10% increase in rural VMT proportion would predict a small (2.25%) increase in fatalities. The percent of rural travel was fairly stable during the period from 2007 to 2012, declining only slightly, which may also help to explain the mixed results from the models.

8.1.6.6 Median Income

The association of median income with traffic fatalities also differed between the MCS and MNCS models. The MNCS model indicated that lower median income was associated with a greater number of traffic fatalities. The MCS model suggested the opposite. Both were statistically significant.

This result, in combination with the result for rural VMT proportion, illuminates important differences between the two models, as well as the mechanisms that connected the factors in the models with safety. The MNCS (model not controlling for state) attempted to account for variance from two primary sources: the 50 states and the 12 years of the target period. States with lower median income tended to have a higher proportion of rural VMT, tended to spend less per highway mile on safety, and had higher fatal crash rates. Thus, lower median income was associated with higher risk and thus higher fatalities. The model controlling for state (MCS) focused on changes over time (the 12-year period of the study) *within* a state. In this model, decreases in median income likely reduced the travel of a relatively riskier population and thus reduced overall risk and, therefore, traffic fatalities. This may be considered an example, in the regression context, of Simpson's Paradox, in which a trend appears in disaggregate groups of data, but disappears or is reversed when the data are aggregated. In this case, the MNCS model may capture the long-term effect of low median income and correlated factors across states, while the MCS model may capture the short-term effect of changes in median income on who drives and how much they drive.

Figure 8-8 depicts the national trend in median income from 2007 to 2012. Median income declined over the period, then grew in 2012. This trend was very similar to the national trend in traffic fatalities over the same period.

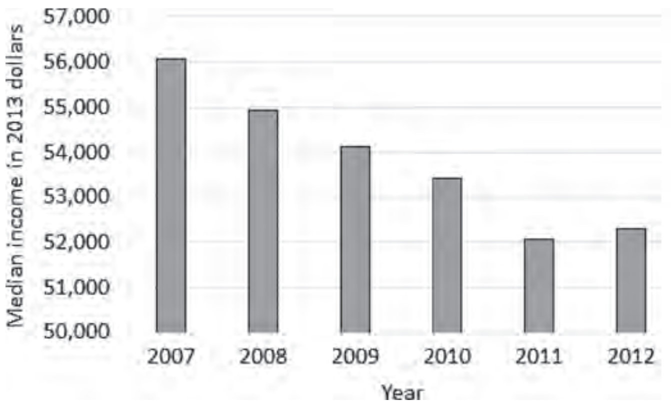


Figure 8-8. Trends in median household income, 2007–2012.

8.1.7 Effects of Individual Factors within the Regulatory Factors

Table 8-5 lists the parameters that were included in the regulatory factors grouping, the change in each parameter between 2007 and 2011, and the associated effects on traffic fatalities in the MNCS and MCS models.

8.1.8 DUI Rating

Both models indicated that an increase in DUI ratings was associated with a decline in fatalities. Although DUI ratings accounted for almost all of the effect of the regulatory grouping, it only predicted some 2% of reductions of all the parameters associated with the predicted decline in fatalities in the MNCS model, and about 3% in the MCS model. The parameter was statistically significant in the MCS model but not significant in the MNCS model. A 1-point increase in the rating (i.e., increased stringency of the laws related to drunk driving) was associated with a decrease of 0.3% in the MNCS model and 0.7% in the MCS model. The mechanism relating DUI laws to risk was to deter impaired driving through increasing the severity of consequences for driving while impaired. The rating steadily increased over the period, reflecting the adoption of stricter DUI laws.

8.1.9 Safety-Belt Rating

The models suggested a very small and inconsistent effect of changes in safety-belt ratings. A small increase in fatalities was associated with an increase in the safety-belt rating in the MNCS

Table 8-5. Effects of individual regulatory factors.

		MNCS model		MCS model	
Regulatory factor	**Change in parameter value**	**Predicted change in fatalities**	**Statistically significant?**	**Predicted change in fatalities**	**Statistically significant?**
DUI laws rating	−1.05	−120	No	−261	Yes
Safety-belt laws rating	−0.16	5	No	−28	No
Motorcycle helmet law rating	0	0	Yes	0	No

model and a small decrease in the MCS model. The parameter was not statistically significant in either model. There was only a slight increase in the rating during the period, which may help explain why the effect was not significant and inconsistent between the models.

8.1.10 Motorcycle Helmet Rating

During the period from 2007 to 2012, no overall change in the motorcycle helmet rating occurred, and therefore it is not associated with the decline in fatalities (see Section 6.6).

8.2 Variable Influence Estimated from the Change Model

Figure 8-9 illustrates the magnitude of the effect of changes in the different parameters in the change model on the number of traffic fatalities, 2007–2011. In 2007, there were 41,259 traffic fatalities. In 2011, there were 32,479 traffic fatalities, a –21.3% change from 2007. The factors in the change model accounted for about 12.4 percentage points of the decline, leaving 8.9 percentage points of the decline not accounted for.

The decline in total VMT accounted for only a modest reduction in traffic fatalities over the period. The model predicted that the 2.3% reduction in total VMT was associated with a 1.2% reduction in total fatalities. This finding aligns well with the overall expectation from Figure 4-2, which suggested the substantial drop in fatalities could not be explained by the modest drop in total VMT. Much of the reduction in VMT occurred in rural areas, while urban roads, which tended to have lower fatal crash rates, either plateaued or increased slightly (Figure 6-8), so in addition to the effect of the change in overall VMT, there was a slight shift in the distribution of travel from rural roads to urban roads. The percentage of travel on rural roads declined by 1.6%, resulting in a 0.1% decline in traffic fatalities predicted by the change model. Overall, change in VMT was not a primary contributor to the decline in traffic fatalities during the period.

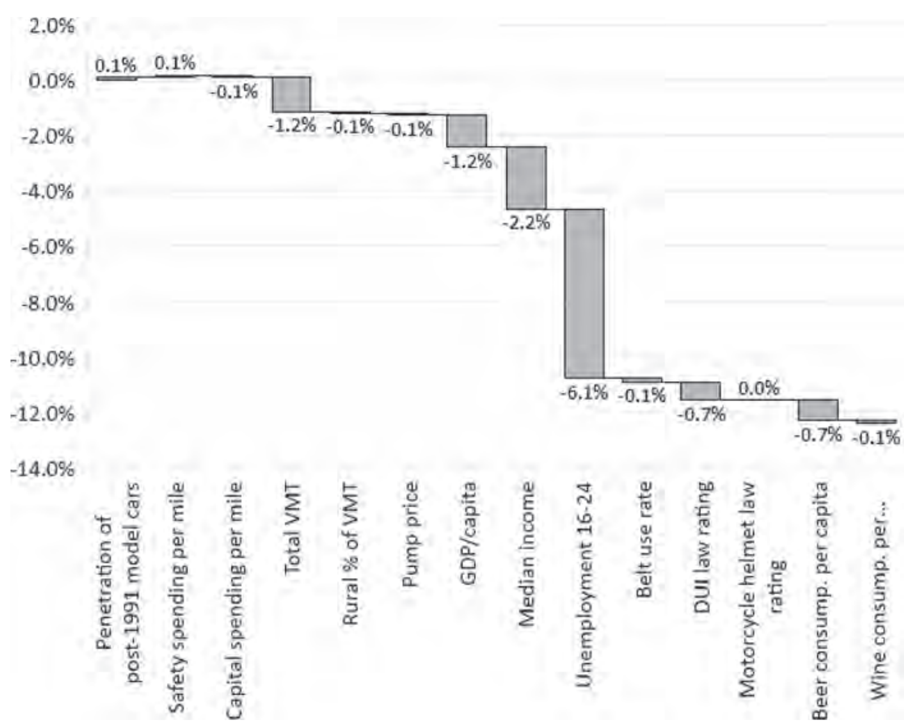


Figure 8-9. Change-model prediction of variable effect on reduction in traffic fatalities, 2007–2011.

8.2.1 Economic Factors

Economic factors explained most of the decline in traffic fatalities over the period. Economic effects were captured mainly by four measures: unemployment for teens and young adults (ages 16 to 24), GDP per capita, median household income, and the pump price of auto fuel. The primary factor in the change model was teen and young adult unemployment. There was a 55.7% increase in the teen and young adult unemployment rate during 2007 to 2011, which the change model predicted produced a 6.1% decline in the number of traffic fatalities. Declines in GDP per capita and median income also contributed significantly. The 7.5% reduction in GDP per capita was predicted to reduce fatalities by 1.2%; the 4.3% reduction in median income reduced fatalities by 2.2%. The slight increase in the pump price of gasoline (up 2.6%) was predicted to result in a decrease in traffic fatalities by only 0.1%. In total, economic factors accounted for 9.5 percentage points of the total of 12.4 predicted by the model. This result from the change model aligns well with the two count models discussed above. In those models, economic factors accounted for 80% to 90% of the total effect predicted by the models. In the change model, the set of economic factors accounted for 76.6% of the total effect predicted by the model.

Reductions in median income produced greater reductions in traffic fatalities than the larger changes in GDP per capita. GDP per capita is interpreted as characterizing the overall growth (or contraction) in the economy, normalized by population to account for population differences between the states. Median household income is interpreted as capturing the median economic status of households, and by inference the lower quintiles of the population. If median income declined, it is likely that the household income of lower quintiles also declined. Even though the decline in median income was proportionally less than GDP per capita, the change model predicted a larger effect on traffic fatalities. This suggests that lower-income households disproportionately contributed to the reduction in traffic fatalities, somewhat in the way that the increase in unemployment among teens and young adults may have contributed to teens and young adults accounting for a disproportionate share of the reduction in traffic fatalities documented in Section 6.1, especially Figure 6-3. Some studies have suggested that lower socioeconomic groups have significantly higher mortality rates in traffic crashes and may have benefited from the recession through reduced travel and reduced risky travel (Cotti and Tefft 2011; Harper, Charters et al. 2015). The finding here is of an association between declines in median income and traffic fatalities. Further research is needed to explore the mechanism through which they are connected, e.g., through reduced travel, reduced risky travel, shifts in the mode of travel, or some other means.

8.2.2 Driver and Vehicle Factors

One mechanism through which economic factors affected the number of traffic fatalities was through changing driver behavior, either by reducing the travel of riskier driver populations or inducing them to drive more safely, both for economic reasons. The change model included three other factors that may be regarded as reflecting driver behavior: safety-belt usage rates, beer consumption per capita, and wine consumption per capita. The parameters for each were not statistically significant, and the effects were small.

Safety-belt use rate increased by 2.4% over the period, resulting in a predicted 0.1% decline in traffic fatalities. Many studies have shown the relationship between safety-belt use and occupant protection. The fact that the coefficient was small and non-significant in the current study does not mean that there was no contribution from increasing belt use; instead, it points up the focus and context of the study. Safety-belt use, from observational studies, showed a slow and steady increase over the entire period. Increased belt use was among the long-term factors that operated to set the baseline level of safety over the period. The study, however, was focused on the substantial drop in traffic fatalities after 2007. There was no significant change in the rate of increase of safety-belt usage, just the continuation of the prior trend of increasing belt usage.

The penetration of more recent vehicle models into the fleet showed a similar pattern and effect. The percentage of post-1991 model year vehicles in the passenger vehicle fleet was used as a surrogate for the long-term spread of occupant protection and collision-mitigation features, as documented by Kahane (2015). These features are part of the long-term base of safety that cumulatively reduced crash risk, but because the fleet turns over slowly, the effects were incremental and long term. In these data, the effect was positive, but small and not statistically significant.

Beer consumption per capita declined over the period by 3.5%, and the change model associated that decline with a 0.7% decline in traffic fatalities. The reduction in beer consumption may have been related to the recession, as consumers had less income to spend on beer, or it may have been related to other factors (changing consumer tastes, for example). The predicted result of the decline in beer consumption per capita was in the expected direction, although the effect was small, reducing traffic fatalities by 0.7%.

The effect of wine consumption in the model, however, was somewhat counterintuitive. The change-model parameter coefficient for wine consumption was small and negative, indicating that increased wine consumption was associated with a small (0.1%) reduction in traffic fatalities. As indicated, the parameter was non-significant, meaning there was no statistical support that the coefficient differed from 0.

8.2.3 Regulatory Factors

As in the count models, the parameter for DUI laws was statistically significant and associated with a decrease in traffic fatalities. There was a 4.0% increase in the DUI rating index over the period, and the change model predicted a small, 0.7%, decline in the number of traffic fatalities associated with this change. This result aligns with the expected mechanism of DUI laws, i.e., increased stringency of laws was intended to discourage driving under the influence of alcohol and thus reduce crashes and fatalities. The result also was of similar magnitude to the effect in the count models, although it was statistically significant in only one (MCS) count model. While these laws helped set the long-term level of safety, as indicated by the modeling result here, their contribution to the substantial drop in traffic fatalities after 2007 was small and incremental.

In contrast, there was effectively no change in the index of motorcycle helmet laws; therefore, there could be no effect of a change in the index.

8.2.4 Highway Expenditures

The results of the change model for state highway expenditures on capital improvements and gross safety spending were also mixed, and paralleled the results from the two count models. The effects in the change model were small, not statistically significant, and mixed. The change in capital spending on state highways in the change model was slightly negative, but not statistically significant. The effect of gross safety spending (including capital spending related to safety, law enforcement, and safety education programs) was actually positive, meaning associated with an increase in fatalities, but also not statistically significant. It is likely that the mixed result was a statistical artifact and not meaningful, even directionally. The two variables were strongly correlated (0.78), so they overlap in explaining the variance. The effect of spending on roadways, with the exception of law enforcement, would be expected to be lagged and cumulative, not expressed over a short time period. Accordingly, it would not be expected that incremental changes in highway spending would have an immediate and dramatic effect on traffic fatalities. Improvements in infrastructure roll out incrementally and over a long period of time. The change measures were lagged by one year in the modeling, but still were both small in terms of predicted effect and statistically insignificant. Factors related to drivers can change substantially over a short period of time, as was the case for the great increase in the unemployment rate of teens and young adults. But it is very difficult to change infrastructure significantly in a short period.

8.3 Implications for Reducing Fatalities and Crash Risk

This study found that the changes in the economy were the primary factors in the substantial drop in traffic fatalities from 2008 through 2011. Details of the results suggest possible areas for interventions that may be pursued productively to reduce traffic fatalities.

- Teens and young adults accounted for almost 48% of the reduction in traffic fatalities, 2008 through 2012. It was suggested here that the mechanism was economic constraints reducing total travel and risky (discretionary and leisure) travel. The increase in teen and young adult unemployment rates was the primary economic factor in the statistical models of the decline in traffic fatalities. It has long been known that teens and young adults have disproportionately high crash risk, but the results from this study suggest that their behavior can be significantly modified over the short run, substantially reducing fatalities.
- The findings related to median household income raise the possibility of an income effect. This finding warrants further investigation to determine if lower-income groups disproportionately reduced their driving, engaged in less risky discretionary driving, or some combination of the two. There is some recent evidence that lower socioeconomic groups, as measured by educational attainment, tend to have higher traffic mortality rates (Harper, Charters et al. 2015). Further research is needed to understand the influence of changes in household income and the effect on the amount and types of travel. One goal would be to determine if safety interventions aimed at lower-income groups may have a disproportionately positive effect, similar to reducing crash risk among teens and young adults.
- DUI laws showed a significant positive effect in reducing traffic fatalities, even over the short term of this study and even within the substantial impact of the economic contraction. Reduced beer consumption similarly showed a significant, positive effect. It is clear that continuing to focus on reducing drunk driving can have a disproportionate effect on reducing traffic fatalities.
- Rural VMT bears a higher risk of fatal crashes across all road types; reduction in the proportion of rural VMT was significant in the model that controlled for state effects. Programs aimed at reducing the risk of rural travel can substantially reduce traffic fatalities.
- It may be difficult to discern in any given year the effects of safety countermeasures, due to the significant influence of other factors on traffic fatalities. There is a need to more fully assess and document safety advances from countermeasures because these other factors may obscure them.
- The results here clearly illustrate that factors outside the authority of safety professionals can have highly significant impacts on the level of highway safety. In the short term, shocks in the economy can swamp the effect of safety interventions. It is clear that exogenous factors such as economic trends should be accounted for in setting realistic goals and evaluating traffic safety programs.

Most of the factors incorporated into the models have been shown in other contexts to be effective in increasing traffic safety and reducing crashes and fatalities. That some were not statistically significant in the analysis here does not show that they are not related to safety. The specific problem at hand was explaining the sharp decline in traffic fatalities after 2007. The mixed results for some factors in the model likely resulted from their small contribution relative to the other factors in the model, and the fact that their effect on traffic safety was more stable and long term.

CHAPTER 9

Limitations

The current study established associations between the independent variables and the outcome (traffic fatalities) but not causal relationships. A series of mechanisms were suggested (see Table 8-1) linking the factors to their expected effects. Many of the findings were consistent with those mechanisms, but a truly causal linkage would require a different approach. Moreover, this was an observational, not experimental, study. Thus, there was no control over the explanatory factors to directly test their effect on the outcome (traffic fatalities). The "experiment" was, in effect, the Great Recession, which drastically affected certain of the transient variables (unemployment rates, GDP, household income), but had much less effect on more stable factors not directly connected to the economy (belt-use rates, DUI laws).

Most of the parameters used in the models were surrogates for factors that could not be directly measured. The general analytical explanatory framework was that a variety of economic pressures changed the distribution of who drives, how much they drive, and where they drive. However, there was relatively little data that bear directly on each of those points. For example, the unemployment rate, particularly for teens and young adults, was substantially associated with the decline in traffic fatalities. It was plausibly suggested that the reduction in employment caused a decline in discretionary and leisure travel by teens and young adults, but there are no comprehensive data showing that occurred over the period. There is evidence from the NHTS showing a substantial drop in self-reported travel by younger drivers, including teens, in 2009. But in the period covered, only two snapshots were available: one in 2001 at the beginning of the period and the other in 2009, which was within the recession period. In addition, it is likely that the decline in median household income constrained the driving of lower-income groups, but there is no direct evidence. However, see Maheshri and Winston (2015) who used insurance data on a sample of drivers from Ohio, showing an association between aggregate unemployment rates and reduction of VMT of individuals in their sample. There is a need for much more granular exposure data, for example, data series on VMT by driver age or VMT by household income.

The data showed significant variability across states, and the independent variables in the models did not capture all the variation between states. There are clearly other variables reflective of state differences that are not in the models. The fact that many of the parameter coefficients were stable between the MNCS and MCS models shows that the operation of those variables was stable across states. However, it is clear that some state-to-state differences were not captured.

Another source of variability that complicated results was the sheer variability in size across states. The object of analysis was traffic fatalities, for which the counts ranged per year from 55 to 4,333. Extending the analysis to less-severe crash types would increase data available and reduce relative variability. However, less severe injuries are not as well defined or measured as fatalities.

Finally, there was a substantial amount of variability not accounted for in the models. Clearly, there are other factors that affected the number of traffic fatalities not included in the models. The next chapter addresses some areas of future research that may strengthen the results presented here.

CHAPTER 10

Data Needs and Future Research

10.1 Data Needs

10.1.1 Infrastructure

There is a substantial need for more detailed information on the nature and condition of infrastructure in the United States. The *Highway Safety Manual* (AASHTO 2010) has detailed information on crash reduction factors for different infrastructure components. However, there is no detailed inventory of the distribution of infrastructure-based safety features (for example, road miles with rumble strips or installation of advanced crash cushions). Nor is there an evaluation of lives saved by different infrastructure features or changes, analogous to Kahane's (2015) estimation of lives saved by improvements to occupant protection and crashworthiness of the passenger car fleet.

The current study used state highway spending per highway mile as a surrogate measure of efforts to improve safety related to the roadway, but these are relatively crude measures. The safety impact of programs can vary significantly, so the relationship between dollars spent and lives saved is not linear. A comprehensive evaluation at the system level of the effect of infrastructure changes is needed. This might take the form of a comprehensive inventory of roadway features related to safety, such as median barriers, rumble strips (centerline and shoulder), and paved shoulders. In addition, there should be a systematic evaluation of the net contribution of infrastructure spending to safety. Currently, safety evaluations have focused on specific projects or specific types of activities in specific geographic areas. There is a need for a higher-level analysis to estimate the net impact of the roadway environment on traffic safety.

10.1.2 Drivers

The relative dearth of exposure data is a continuing obstacle in traffic safety studies. The current study found evidence for the impact of variations in exposure for different populations. There is a substantial need for more granular data on exposure. Data for driver VMT by age are available only from the NHTS. The NHTS is conducted only every 5 to 8 years. It was fortunate that, within the time period covered by this study, one year was 2009, which was the depth of the recession, but the prior survey was in 2001, so it was impossible to discern any trends within the period. For example, the timing of the decline in teen and young adult VMT within the period would be of great interest, but was unavailable. Ideally, some estimate of VMT by driver age and road type could be collected. The period saw significant changes in travel patterns by road type and urban/rural. Teens and young adults may have restricted their discretionary and leisure travel more than older age groups, but the data to determine this was lacking. Because the distribution of who drives, how much they drive, and where they drive can have profound impacts on traffic safety, these characteristics—how they are influenced in the short term by economic factors and over the long term by social and demographic changes—are critical to fully understanding traffic safety and ways to improve it.

Driver licensing rates by age and state were a plausible surrogate for driving exposure for different age groups. Licensing information would have been useful to document trends at the state level in the decision to drive. Delay in licensure has been found at the national level (Tefft, Williams et al. 2013), and this likely contributed to the long-term decline in teen traffic fatalities. However, the data at the state level were too unreliable to be usable in the current project (Curry, Kim et al. 2014). These data must be improved.

The current study also identified the specific effect of changes in median household income on traffic fatalities, suggesting that the reduction in risk was related to changes in the driving of groups especially affected by the economic contraction. However, this could not be measured directly by, for example, examining changes in the income distribution of drivers involved in fatal crashes, or in travel. Gaining resolution on this question and building longitudinal data through repeated cross-sectional driver surveys would be very valuable. Linking socio-economic data such as mean household income by zip code to crash data would provide additional insights. There are mechanisms to achieve this, but pursuing them was beyond the scope of the current project.

In addition, there is a substantial need for more granular data on driver behavior, particularly as vehicles deploy more technologies for communication and entertainment, and as the connected environment becomes more inescapable. Driver attention and distraction is inherently transient and difficult to capture, but is often used to explain significant increases in crashes and fatalities. Much better data are needed on driver behavior to be able to measure changes objectively and estimate their effect on traffic safety.

10.1.3 Vehicles

Improvements in the crashworthiness of the vehicle fleet have been demonstrated by Kahane (2004, 2014, 2015) and Farmer and Lund (2006, 2014). However, researchers found it problematical when they attempted to capture that concept in the data used for statistical modeling. The penetration of post-1991 model year vehicles into the overall U.S. fleet was used as a surrogate. The usefulness of crash data would be considerably enhanced if they included information on the crash-avoidance technologies with which the vehicles were equipped. As technologies that permit increasing levels of autonomous driving are deployed, this will become increasingly salient. In some cases, information about available technologies can be derived directly from the vehicle identification number and in other cases can be inferred from the make, model, and model year. Linking the NCAP rating would also be useful in estimating the contribution of vehicle design to traffic safety.

10.2 Future Research

Trends in recent years suggest that the decline in traffic fatalities after 2007 did not establish a “new normal.” After reaching a plateau of approximately 33,000 traffic fatalities per year from 2010 to 2014, the number of deaths increased in 2015 by about 7.4%, to approximately 35,092 (NHTSA 2016b), and again in 2016 by about 7.7% to an estimated 37,700 (projected from NHTSA (2016a). Either traffic fatalities are returning to trend or new factors (texting and cell phone use have been suggested) are driving up fatal crashes.

A useful first step would be to apply the models developed for this study to the needed input data series from recent years to see how well the models predict recent trends. This may show that current models are adequate or that other factors are influencing the result and should be added. Was the recent increase in traffic fatalities related to a recovery in teen and young adult employment? What was the impact of the decline in fuel prices in 2015? Has the effect of reduced household income diminished as households, economies, and governments adjust to reduced growth? Is the decline in teen and young adult driving part of long-term trends in culture and communication or due to lack of employment and resources? Given that the reduction in novice driver and youth fatalities were a big part of the decline, this area should get a lot of attention.

How can this information help inform goal setting for safety improvements? Clearly, many elements out of the control of transportation agencies have great influence on the level of fatalities. The primary factors identified here were the impact of the economic recession on specific demographic groups. How can this be accounted for when setting goals? Estimating and tracking "lives saved" from actions (programs and projects) may be as important as tracking actual fatalities. Moreover, tracking fatalities should be put into the context of these other influential factors. To do this, better and comprehensive data are needed on safety program measures (beyond dollars spent) and safety projects. Do these measures really have a small influence, or is there a need for better input data?

The comparison of the MNCS and MCS models showed that states' experience differed significantly in some regards. The variables included in the MNCS model did not capture all the salient differences between states. Moreover, some states performed substantially better than others during the recession period, meaning that their reduction in fatalities was greater than predicted by the models, beyond what was predicted from the impact of the recession in their state. Appendix D provides a set of panel graphs that compare the trend in actual traffic fatalities and the number of traffic fatalities predicted by the models. Some states did substantially better in reducing traffic fatalities over the period, and some did less well.

A study comparing a set of states that did better than predicted with a set of states that did worse, with the objective of identifying the specific factors that contributed to the outperformance, would be very useful. These factors may be demographic or other factors that are not in the control of transportation agencies. However, there may also be specific programs that influenced the outcome. One limitation of the current study was the inability, because of the lack of data for all the states, to measure the effect of state-level safety programs, beyond the general surrogate of safety spending. A state-level study that focused on a manageable number of states would overcome that limitation. The goal would be to identify and measure the specific factors that led to the over- and underperformance, including factors related to economic performance, state demographics, and specific state traffic safety programs, both related to infrastructure and related to enforcement and education. The current study was unable to address these issues at a sufficient level of detail, but a study focused on a limited number of states should be able to. The current study has identified the major issues and a set of candidate states for an in-depth study.

References

AASHTO (2010a). An Introduction to the Highway Safety Manual. Washington, DC, American Association of State Highway and Transportation Officials.

AASHTO (2010b). *Highway Safety Manual*. Washington, DC, American Association of State Highway and Transportation Officials.

Albalate, D., L. Fernández, et al. (2013). "The road against fatalities: Infrastructure spending vs. regulation?" *Accident Analysis & Prevention* **59**: 227–239.

Antoniou, C., G. Yannis, et al. (n.d.). Improving fatalities forecasting in times of recession in Europe. Athens, Greece, National Technical University of Athens.

Bureau of Labor Statistics (2013). CPI Calculator.

Bureau of Labor Statistics (2016). Local Area Unemployment Statistics, Retrieved from http://www.bls.gov/lau/.

Cameron, A. C. and P. K. Trivedi (1998). *Regression Analysis of Count Data*. Cambridge, UK, Cambridge University Press.

Chandraratna, S. and N. Stamatiadis (2009). "Quasi-induced exposure method: Evaluation of not-at-fault assumption." *Accident Analysis & Prevention* **41**(2): 308–313.

Chen, Y. Y. (2014). Seat Belt Use in 2013—Use Rates in the States and Territories. Washington, DC, National Highway Traffic Safety Administration.

Chen, Y. Y. and T. J. Ye (2009). Seat Belt Use in 2008—Use Rates in the States and Territories. Washington, DC, National Highway Traffic Safety Administration.

Cotti, C. and N. Tefft (2011). "Decomposing the Relationship between Macroeconomic Conditions and Fatal Car Crashes during the Great Recession: Alcohol- and Non-Alcohol-Related Accidents." *B E Journal of Economic Analysis & Policy* **11**(1).

Curry, A. E., K. H. Kim, et al. (2014). "Inaccuracy of Federal Highway Administration's licensed driver data: implications on young driver trends." *Journal of Adolescent Health* **55**(3): 452–454.

Dang, J. N. (2008). Statistical analysis of alcohol-related driving trends, 1982–2005. Washington, D.C., National Highway Traffic Safety Administration.

Elvik, R. (2013). An analysis of the relationship between economic performance and the development of road safety. Oslo, Norway, Institute of Transport Economics.

Evans, L. (1986). "The effectiveness of safety belts in preventing fatalities." *Accident Analysis & Prevention* **18**(3): 229–241.

Farmer, C. M. and A. K. Lund (2006). "Trends Over Time in the Risk of Driver Death: What If Vehicle Designs Had Not Improved?" *Traffic injury prevention* **7**(4): 335–342.

Farmer, C. M. and A. K. Lund (2014). The effects of vehicle redesign on the risk of driver death. Arlington, VA, Insurance Institute for Highway Safety.

Federal Highway Administration (N.D.). A Guide to Reporting Highway Statistics. Washington, DC, US Department of Transportation.

Ferdinand, A. O., N. Menachemi, et al. (2014). "Impact of texting laws on motor vehicular fatalities in the United States." *American Journal of Public Health* **104**(8): 1370–1377.

FHWA (1992–2014). Highway Statistics Series. Office of Highway Policy Information. Washington, DC.

FHWA (2016a). Highway Funding under Extensions of SAFETEA-LU.

FHWA (2016b). MAP-21 Highway Authorizations. Washington, DC, FHWA.

Flannagan, C. A. C. and A. Leslie (2012). Analysis of Rollovers and ESC in Light Vehicles. Ann Arbor, MI, University of Michigan Transportation Research Institute.

Forsman, Å., L. Simonsson, et al. (n.d.). Analysis of fatal accidents during a period of severe economic recession. Linköping, Sweden, VTI.

Grabowski, D. C. and M. A. Morrisey (2004). "Gasoline prices and motor vehicle fatalities." *Journal of Policy Analysis and Management* **23**(3): 575–593.

Grabowski, D. C. and M. A. Morrisey (2006). "Do higher gasoline taxes save lives?" *Economics Letters* **90**(1): 51–55.

Harper, S., T. J. Charters, et al. (2015). "Trends in Socioeconomic Inequalities in Motor Vehicle Accident Deaths in the United States, 1995–2010." *Am J Epidemiol* **182**(7): 606–614.

Haughwout, S. P., R. A. LaVallee, et al. (2015). Surveillance Report #102, Apparent per capita alcohol consumption: national, state, and regional trends, 1977–2013. Arlington, VA, National Institute on Alcohol Abuse and Alcoholism**:** 61.

Highway Loss Data Institute (2014). "Predicted availability of safety features on registered vehicles – an update." *HLDI Bulletin* **31**(15).

Hilbe, J. M. (2011). *Negative Binomial Regression*. Cambridge, UK, Cambridge University Press.

Hilbe, J. M. (2014). *Modeling Count Data*. Cambridge, UK, Cambridge University Press.

Hsia, R. Y. and Y.-C. Shen (2011). "Changes in geographical access to trauma centers for vulnerable populations in the United States." *Health Affairs (Project Hope)* **30**(10): 1912.

Kahane, C. J. (2004). Lives Saved By The Federal Motor Vehicle Safety Standards and Other Vehicle Safety Technologies, 1960–2002-Passenger Cars and Light Trucks-With a Review of 19 FMVSS and Their Effectiveness in Reducing Fatalities, Injuries and Crashes. Washington, DC, National Highway Traffic Safety Administration.

Kahane, C. J. (2014). Updated Estimates of Fatality Reduction by Electronic Stability Control. Washington, DC, National Highway Traffic Safety Administration.

Kahane, C. J. (2015). Lives saved by vehicle safety technologies and associated Federal Motor Vehicle Safety Standards, 1960 to 2012 – Passenger cars and LTVs – With reviews of 26 FMVSS and the effectiveness of their associated safety technologies in reducing fatalities, injuries, and crashes. Washington, DC, National Highway Traffic Safety Administration.

Keall, M. and S. Newstead (2009). "Selection of Comparison Crash Types for Quasi-Induced Exposure Risk Estimation." *Traffic injury prevention* **10**(1): 23–29.

Klinich, K. (2016). Digest and index of state laws on alcohol for drivers. Unpublished data. University of Michigan Transportation Research Institute.

Kweon, Y. J. (2015). "What affects annual changes in traffic safety? A macroscopic perspective in Virginia." *Journal of Safety Research* **53**: 17–21.

Lloyd, L., C. Wallbank, et al. (2015). "A collection of evidence for the impact of the economic recession on road fatalities in Great Britain." *Accident Analysis & Prevention* **80**: 274–285.

Lord, D., S. Geedipally, et al. (2010). "Extension of the Application of Conway-Maxwell-Poisson Models: Analyzing Traffic Crash Data Exhibiting Under-Dispersion." *Risk Analysis* **30**(8): 8.

Lord, D. and F. Mannering (2010). "The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives." *Transportation Research Part A-Policy and Practice* **44**(5): 291–305.

Lord, D. and B. Park (2013). *CrimeStat IV: Appendix C– Negative Binomial Regression Models and Estimation Methods*. Washington, DC, Ned Levine & Associates and the National Institute of Justice

Lord, D. and B. Persaud (2000). "Accident Prediction Models With and Without Trend: Application of the Generalized Estimating Equations (GEE) Procedure." *Transportation Research Record* **1717**: 6.

Lord, D., S. P. Washington, et al. (2005). "Poisson, Poisson-gamma and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory." *Accid Anal Prev* **37**(1): 35–46.

Macinko, J., D. Silver, et al. (2015). "Age, period, and cohort effects in motor vehicle mortality in the United States, 1980–2010: The role of sex, alcohol involvement, and position in vehicle." *Journal of Safety Research* **52**: 47–57.

MacKenzie, E. J., D. B. Hoyt, et al. (2003). "National inventory of hospital trauma centers." *Journal of the American Medical Association* **289**(12): 1515–1522.

Maheshri, V. and C. Winston (2015). Did the Great Recession keep bad drivers off the road? Washington, DC, AAA Foundation for Traffic Safety**:** 37.

Massie, D. L., K. L. Campbell, et al. (1995). "Traffic accident involvement rates by driver age and gender." *Accid Anal Prev* **27**(1): 73–87.

Miaou, S.-P. and D. Lord (2003). "Modeling Traffic Crash-Flow Relationships for Intersections: Dispersion Parameter, Functional Form, and Full Bayes versus Empirical Bayes." *Transportation Research Record* **1840**(9).

Morrisey, M. A. and D. C. Grabowski (2011). "Gas prices, beer taxes and GDL programmes: effects on auto fatalities among young adults in the US." *Applied Economics* **43**(25): 3645–3654.

Morrisey, M. A., D. C. Grabowski, et al. (2006). "The strength of graduated drivers license programs and fatalities among teen drivers and passengers." *Accident Analysis & Prevention* **38**(1): 135–141.

National Highway Traffic Safety Administration (2007). The New Car Assessment Program Suggested Approaches for Future Program Enhancements. Washington, DC, National Highway Traffic Safety Administration.

NBER (2010). Statement of the Business Cycle Dating Committee, NBER, National Bureau of Economic Research.

NBER (2013) "The NBERs Recession Dating Procedure."

NCSA (2014). Fatality Analysis Reporting System (FARS) Analytical Users Manual, 1975–2013. Washington, DC, USDOT NHTSA.

NHTSA (2014). National Automotive Sampling System (NASS) General Estimates System (GES) Analytical Users Manual 1988–2014. Washington, DC.

NHTSA (2016a). Early estimate of motor vehicle traffic fatalities for the first half (Jan-Jun) of 2016. N. H. T. S. Administration. Washington, DC, National Highway Traffic Safety Administration.

NHTSA (2016b). Early Estimate of Motor Vehicle Traffic Fatalities in 2015. Washington, D.C., National Highway Traffic Safety Administration**:** 1–4.

Noland, R. and F. Sun (2014). Why have traffic fatalities dropped in the US? *Transportation Research Board 94th Annual Meeting*.

Oh, J., S. P. Washington, et al. (2006). "Accident prediction model for railway-highway interfaces." *Accident Analysis and Prevention* **38**(2): 346–356.

Pickrell, T. M. and C. Liu (2014). Seat Belt Use in 2013 – Overall Results. Washington, DC, National Highway Traffic Safety Administration.

Santos, A., N. McGuckin, et al. (2011). Summary of Travel Trends: 2009 National Household Travel Survey. Washington, DC, FHWA**:** 82.

Silver, D., J. Macinko, et al. (2013). "Variation in U.S. traffic safety policy environments and motor vehicle fatalities 1980–2010." *Public Health* **127**(12): 1117–1125.

Tefft, B. C., A. F. Williams, et al. (2013). Timing of driver's license acquisition and reasons for delay among young people in the United States, 2012. Washington, DC, AAA Foundation for Traffic Safety.

US Bureau of the Census (2016). Real Median Household Income in the United States. *Retrieved from FRED, Federal Reserve Bank of St. Louis*. St. Louis, MO.

U.S. Department of Commerce, Bureau of Economic Analysis, Regional Economic Accounts. https://www.bea.gov/data/economic-accounts/regional.

US EIA (2016). State Energy Data System. *US Energy Information Administration*, Retrieved from http://www.eia.gov/state/seds/.

Williams, A. F. (1999). *The Haddon Matrix: its contribution to injury prevention and control*. Third National Conference on Injury Prevention and Control, Brisbane, Queensland.

World Bank (2016). World development indicators. Washington, DC, World Bank.

Wunderlich, R. (2015). An Estimation of Lives Saved by Installing Guardrails, Median Barriers, and Impact Attenuators from 1982 through 2012. College Station, TX, Texas A&M University.

APPENDIX A

Factor Analysis Details

Factor analysis is a method of dimension reduction based on Principal Components Analysis (PCA). The starting point is a rectangular data set with a relatively large number of correlated variables (p) and a larger number of observations (n). The original set of variables can be thought of as dimensions in a p-dimensional space, and PCA produces a new basis for that space, where each dimension in the new space is a linear combination of the original variables. The linear combinations are selected based on variance accounted for by each dimension. The first Principal Component (PC) is the linear combination that accounts for the most total variance in all variables, followed by the PC that accounts for the most remaining variance *and is orthogonal to the first PC*, followed by the PC that accounts for the most remaining variance *and is orthogonal to the first two PCs*, and so on.

Once the PCs are determined, the next step is to select a small subset of dimensions to define a new, smaller space that accounts for a large proportion of the original variance. Note that these new dimensions (PCs) are orthogonal by definition. Factor analysis takes the reduced dimensions and rotates them in the original space to better line up with the original dimensions. The goal of the rotation is to produce a reduced but more interpretable set of dimensions.

In this application, a group of variables that are all correlated with a given PC give an indication of the “meaning” of that PC. From these groups, it is generally possible to identify a process that is being captured and to select 1–2 variables from the set that will be used in analysis of fatalities to represent that process. Factor analyses for this project were run in groups of similar variables to focus the data-reduction activities around each variable grouping (rather than trying to develop dimensions across all possible variables). The analysis is not prescriptive in which variables might be the best predictors, so we present the reasoning behind our selections in each section.

Population Variables

Population variables include overall state population for each year, as well as state population broken down by age and gender, 19 variables in total. The factor analysis resulted in only one factor, which accounted for 97.7% of the total variation in all population variables. Thus, states vary generally in population, but do not have substantially different age distributions or gender distributions. Total population will be used to represent population in analysis where appropriate.

VMT Variables

A series of VMT variables including overall state VMT for each year, as well as VMT broken down by rural and urban road types, were available for analysis. Three factors were identified, but the first one accounts for 63% of the total variance and the second and third account for 8% and 7% respectively. The first factor generally reflects the magnitude of VMT for each state with an emphasis on urban VMT. The second reflects rural VMT variables, and the third is specific to VMT on rural freeways and rural local roads. Thus, urban VMT and rural VMT vary somewhat differently across states, but variation by road type is common across states. Based on these results, we selected total VMT (to capture the overall magnitude as in Factor 1) and proportion of VMT that is rural VMT (to capture rural-specific VMT as in Factors 2 and 3).

Employment/Unemployment Variables

Employment and unemployment for different age and gender groups consisted of 20 different variables. Factor analysis on these variables produces two factors that captured 68% and 15% of the variance, respectively. After rotation, Factor 1 primarily reflected average employment and unemployment (where employment had negative coefficients) with a greater weight on unemployment. Factor 2 primarily reflected employment alone and especially employment of older portions of the population (who, if retired, would affect the employment statistics but not the unemployment statistics). Although older adults' employment varies somewhat differently from employment and unemployment across the age groups, further investigation of the relationship between employment, unemployment, and fatalities showed that unemployment among young people (ages 16–24) is more strongly associated with fatalities than for other age groups. Since unemployment in this group is correlated with other employment/unemployment statistics, it captures the overall magnitude as well as the specific variation in the younger population. Thus, we used only this statistic as the predictor representing employment and unemployment.

Expenditures

Expenditures per mile were available for the following categories: total, capital, administrative, safety, maintenance, HSIP apportioned, and HSIP obligated. The factor analysis of these variables returned a single factor explaining 74% of the variance. This factor reflected the overall magnitude of spending per mile, which varies by state but is fairly consistent across all categories. Because of the safety application of this project, we used two categories—capital expenditures and total safety expenditures including HSIP—to represent expenditures in our models.

APPENDIX B

Descriptive Statistics

Table B-1. Variables in MCS and MNCS models.

Variable	Units	Non-missing observations	Mean	Median	Std Dev	Range	10th Pctl	90th Pctl
TotalVMT	Millions of miles	600	58,855.4	46,758.5	59,853.4	324,674.0	8,994.0	110,541.0
UrbanVMT	Millions of miles	600	38,189.8	25,532.5	47,024.8	266,918.0	2,643.5	75,298.0
RuralVMT	Millions of miles	600	20,665.6	17,419.0	15,586.2	85,131.0	4,033.5	38,043.0
ruralvmt_prop	Proportion	600	0.44	0.44	0.19	0.91	0.19	0.72
cap_m_lag	1,000s dollars per highway mile (2013 dollars)	550	64.2	49.4	47.7	270.9	19.9	123.6
safe_total_m_lag	1,000s dollars per highway mile (2013 dollars)	550	10.8	8.2	10.0	58.1	2.5	23.5
gdp_cap	Constant 2013 dollars	600	57,200.7	56,367.8	11,595.9	83,060.0	43,268.3	72,262.3
MedIncome	Constant 2013 dollars	600	54,591.7	53,886.7	8,276.6	37,527.7	44,246.8	67,301.0
UnEmp_16_24	Percent	600	12.8	12.1	3.8	19.2	8.5	18.5
pump_price	Constant 2013 dollars	600	2.81	2.84	0.6	2.88	1.95	3.68
Beer	Gallons per capita	600	1.2	1.2	0.2	1.2	1.0	1.5
Wine	Gallons per capita	600	0.4	0.3	0.2	0.9	0.2	0.6
BeltUse	Percent	590	81.3	81.9	9.3	48.4	68.6	93.3
DUI_rating	Index	600	19.3	19	3.3	17	15	24
Belt_rating	Index	600	2.2	2	1.1	4	1	4
MC_hlmt_rating	Index	600	2.7	2	1.2	4	2	4
post1991	Percent	600	93.4	95.3	4.7	15.4	86.9	97.6

Table B-2. Variables in change model.

Variable	Non-missing observations	Mean	Median	Std Dev	Range	10th Pctl	90th Pctl
TotalVMT_chng	550	0.00622	0.00789	0.02562	0.35682	-0.02135	0.03286
Ruralvmt_prop_chng	550	-0.01939	-0.00265	0.07630	0.89543	-0.05241	0.01552
pump_price_chng	550	0.05467	0.09493	0.12895	0.56582	-0.10027	0.17155
gdp_cap_chng	550	-0.01966	-0.01713	0.06465	1.40280	-0.05227	0.01856
MedIncome_chng	550	-0.00553	-0.00444	0.02945	0.21803	-0.04311	0.02765
UnEmp_16_24_chng	550	0.03487	0.02442	0.19197	1.58067	-0.18368	0.30060
cap_m_chng_lag	500	0.00980	0.00442	0.19744	1.88702	-0.21202	0.23149
safe_total_m_chng_lag	500	0.02805	0.03784	0.31743	3.83360	-0.21989	0.29174
BeltUse_chng	537	0.01669	0.01056	0.04165	0.49134	-0.02260	0.06047
DUI_rating_chng	550	0.01356	0.00000	0.04602	0.47000	0.00000	0.05268
MC_hlmt_rating_chng	550	0.00000	0.00000	0.04184	1.38629	0.00000	0.00000
Beer_chng	550	-0.00591	-0.00755	0.03412	0.36229	-0.04078	0.02765
Wine_chng	550	0.02910	0.02740	0.05024	0.40705	-0.00552	0.08004
Post1991_chng	550	0.01556	0.01049	0.01463	0.04889	0.00308	0.02979

APPENDIX C

State-Specific Parameters for the MCS Model

Table C-1. State-specific parameters for the MCS model with VMT as exposure.

State	Estimate	Standard error	P-value
Alabama	0.3596	0.0641	<.0001
Alaska	0.0299	0.07	0.6695
Arizona	0.2314	0.0725	0.0014
Arkansas	0.5598	0.0593	<.0001
California	-0.1229	0.0872	0.1586
Colorado	-0.2502	0.0656	0.0001
Connecticut	-0.4656	0.0935	<.0001
Delaware	-0.1887	0.0903	0.0367
Florida	0.1176	0.0845	0.1641
Georgia	0.0791	0.0669	0.2369
Hawaii	-0.2054	0.0832	0.0136
Idaho	0.2567	0.0584	<.0001
Illinois	-0.2918	0.0822	0.0004
Indiana	-0.0912	0.0597	0.1264
Iowa	-0.1557	0.0626	0.013
Kansas	0.1342	0.0617	0.0296
Kentucky	0.4626	0.0539	<.0001
Louisiana	0.3855	0.0634	<.0001
Maine	-0.0201	0.056	0.7201
Maryland	-0.2049	0.0928	0.0272
Massachusetts	-0.6195	0.0995	<.0001
Michigan	-0.1634	0.0712	0.0218
Minnesota	-0.5554	0.0565	<.0001
Mississippi	0.5557	0.0649	<.0001
Missouri	0.1053	0.0632	0.0958

(continued on next page)

State	Estimate	Standard error	P-value
Montana	0.392	0.0577	<.0001
Nebraska	-0.1662	0.0596	0.0053
Nevada	0.0031	0.0786	0.9683
New Hampshire	-0.7107	0.085	<.0001
New Jersey	-0.345	0.1094	0.0016
New Mexico	0.228	0.0574	<.0001
New York	-0.1999	0.0804	0.013
North Carolina	0.2237	0.0662	0.0007
North Dakota	-0.1153	0.0513	0.0248
Ohio	-0.2456	0.0656	0.0002
Oklahoma	0.2174	0.0617	0.0004
Oregon	0.0114	0.0691	0.8694
Pennsylvania	-0.0609	0.063	0.3341
Rhode Island	-0.361	0.0919	<.0001
South Carolina	0.4392	0.0547	<.0001
South Dakota	0.1469	0.0513	0.0042
Tennessee	0.3403	0.0686	<.0001
Texas	0.0205	0.0688	0.766
Utah	-0.1108	0.0854	0.1944
Vermont	-0.327	0.0678	<.0001
Virginia	-0.1919	0.0781	0.014
Washington	-0.2291	0.0793	0.0039
West Virginia	0.577	0.0675	<.0001
Wisconsin	-0.2803	0.056	<.0001
Wyoming	0	0	.

Table C-2. State-specific parameters for the MCS model with population as exposure.

State	Estimate	Standard error	P-value
Alabama	0.4992	0.0699	<.0001
Alaska	-0.7208	0.0749	<.0001
Arizona	0.1407	0.0788	0.0743
Arkansas	0.5336	0.0641	<.0001
California	-0.3947	0.0957	<.0001
Colorado	-0.4884	0.0712	<.0001

State	Estimate	Standard error	P-value
Connecticut	-0.904	0.102	<.0001
Delaware	-0.4366	0.0983	<.0001
Florida	0.1446	0.0922	0.1169
Georgia	0.0714	0.0731	0.329
Hawaii	-0.5401	0.0901	<.0001
Idaho	0.1767	0.0626	0.0048
Illinois	-0.6258	0.0903	<.0001
Indiana	-0.0965	0.0648	0.1364
Iowa	-0.3045	0.0681	<.0001
Kansas	0.0277	0.0667	0.6781
Kentucky	0.3825	0.0583	<.0001
Louisiana	0.1845	0.0691	0.0076
Maine	-0.1783	0.0605	0.0032
Maryland	-0.3002	0.1017	0.0031
Massachusetts	-0.9782	0.109	<.0001
Michigan	-0.2843	0.0778	0.0003
Minnesota	-0.7161	0.061	<.0001
Mississippi	0.7983	0.0707	<.0001
Missouri	0.0992	0.069	0.1503
Montana	0.4253	0.0618	<.0001
Nebraska	-0.318	0.0646	<.0001
Nevada	-0.2593	0.0856	0.0025
New Hampshire	-0.7527	0.0919	<.0001
New Jersey	-0.625	0.1201	<.0001
New Mexico	0.3478	0.0619	<.0001
New York	-0.9236	0.0881	<.0001
North Carolina	0.1423	0.0724	0.0495
North Dakota	-0.1945	0.0543	0.0003
Ohio	-0.434	0.0712	<.0001
Oklahoma	0.3377	0.0668	<.0001
Oregon	-0.1785	0.0754	0.0179
Pennsylvania	-0.4151	0.0685	<.0001
Rhode Island	-0.7258	0.0993	<.0001
South Carolina	0.4646	0.0591	<.0001
South Dakota	-0.0059	0.0546	0.9142

(continued on next page)

State	**Estimate**	**Standard error**	**P-value**
Tennessee	0.3062	0.075	<.0001
Texas	-0.1285	0.0751	0.0871
Utah	-0.2402	0.0927	0.0096
Vermont	-0.2146	0.0724	0.003
Virginia	-0.3139	0.0854	0.0002
Washington	-0.5256	0.087	<.0001
West Virginia	0.595	0.0734	<.0001
Wisconsin	-0.3481	0.0604	<.0001
Wyoming	0	0	.

APPENDIX D

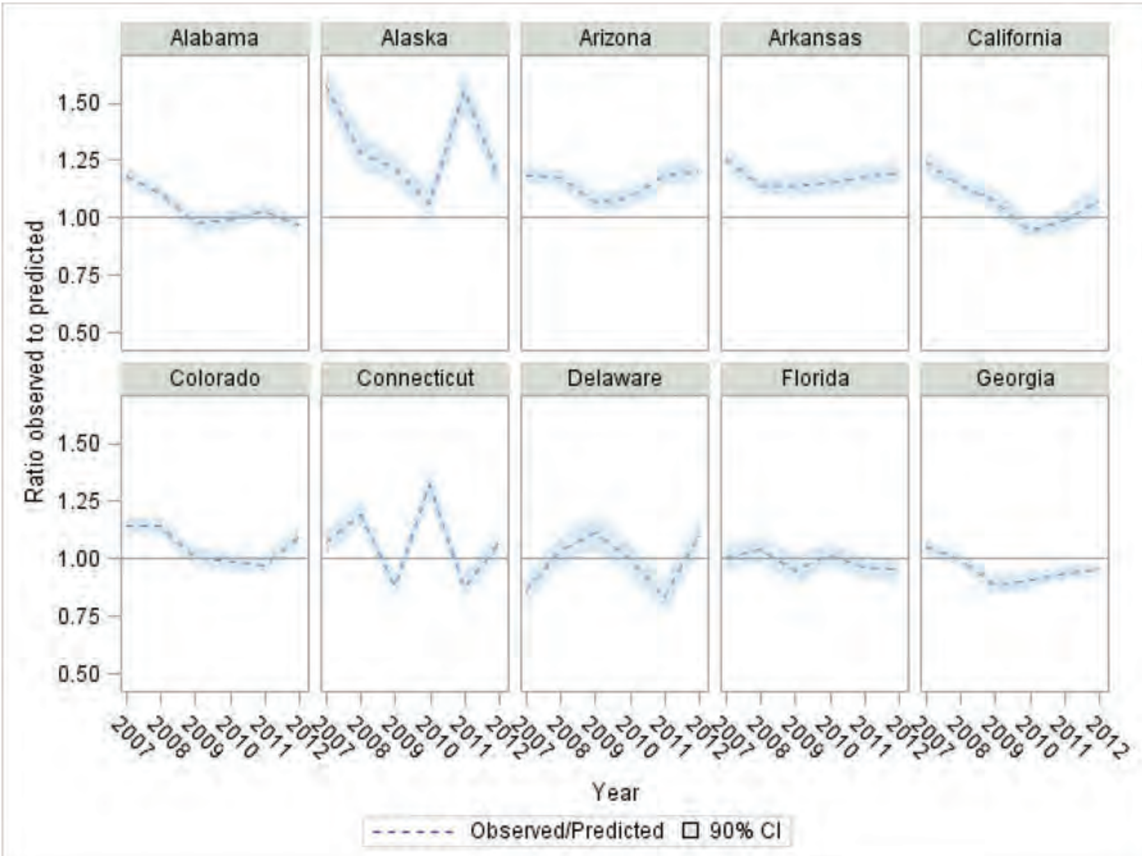
State-Level MNCS Model Prediction vs. Performance

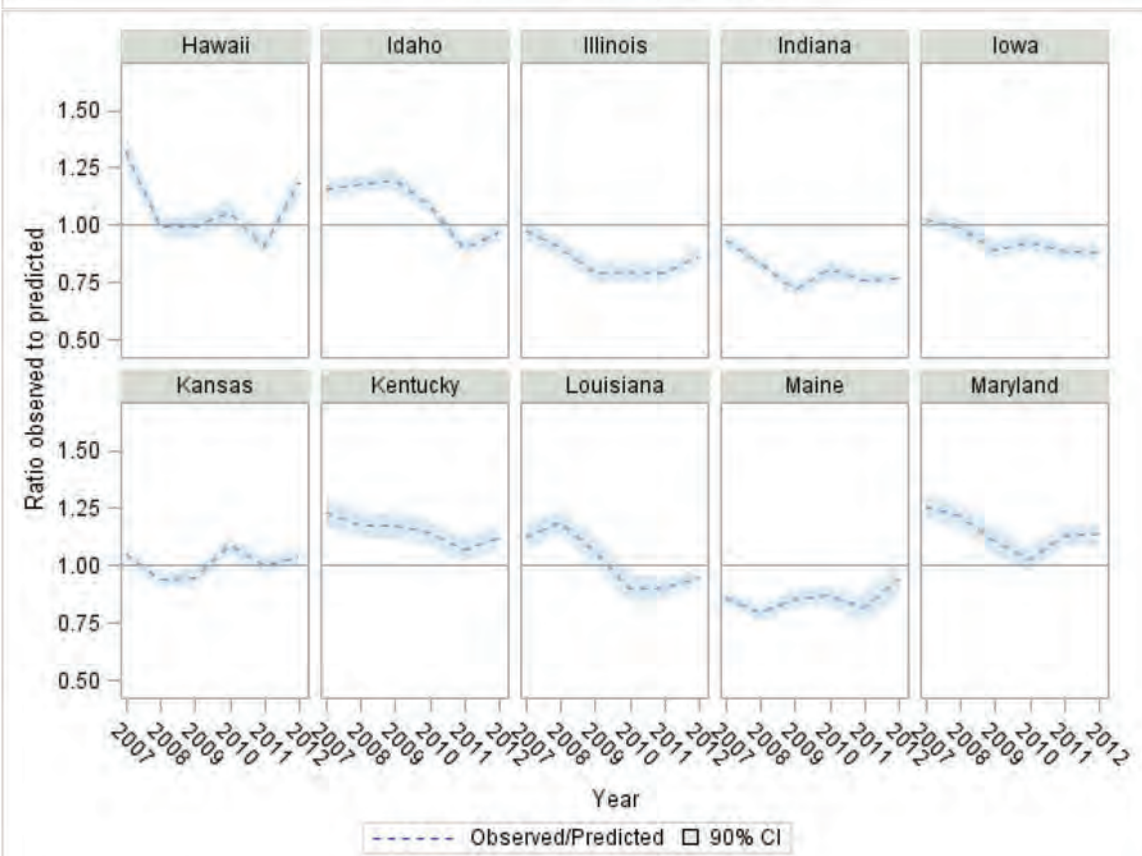
The panels in this appendix compare the predicted number of fatalities for each state with the number actually experienced, computed as the ratio between observed and predicted. The MNCS (model not considering state) model was used for the purpose, because the goal was to compare how states differed from the prediction, in order to identify states that had more or fewer traffic fatalities than predicted by the model.

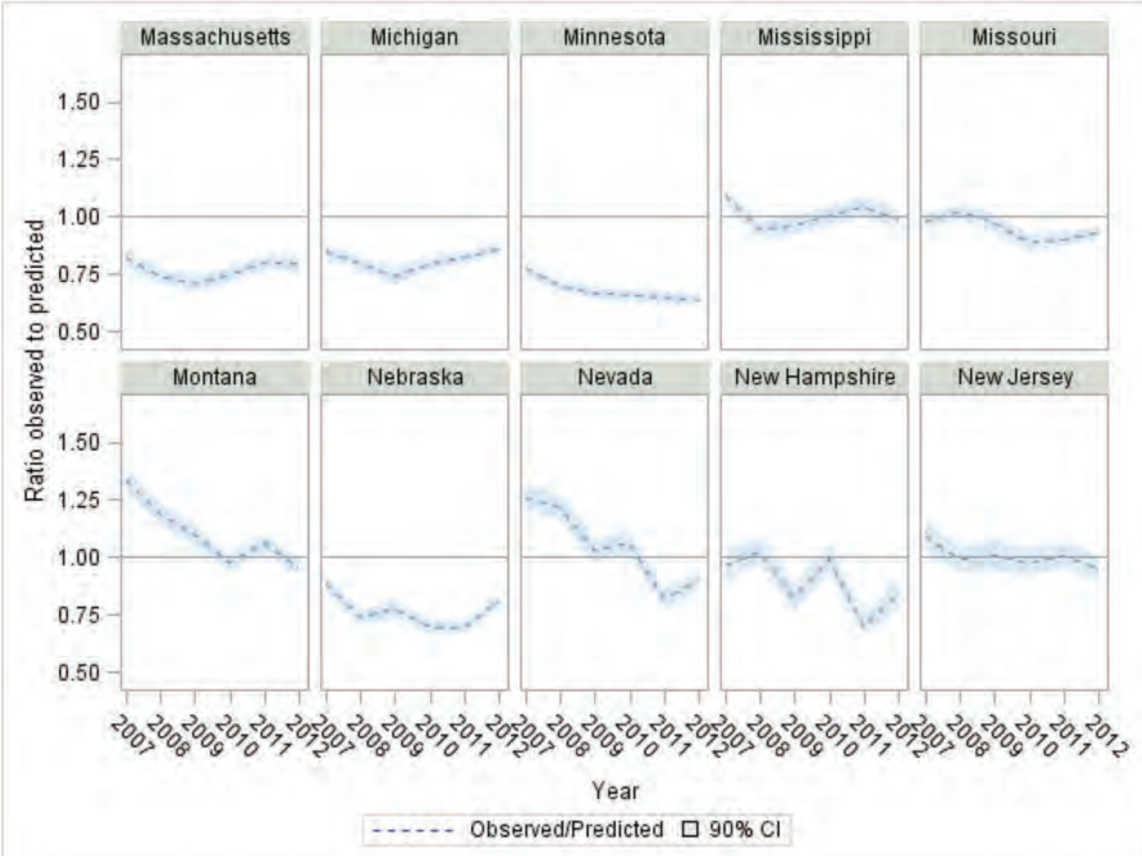
In the panels, the horizontal line represents no difference from predicted. The dashed line represents the value obtained by dividing the observed number of traffic fatalities by the number of fatalities predicted by the MNCS model. Lines above the horizontal line represent a greater number than predicted, and those below represent fewer than predicted. The grayed band represents the 90% confidence interval of the ratio. Small states with relatively few traffic fatalities tended to have more volatility in their number of traffic fatalities, so the ratios were less stable. Predictions for larger states tended to be more stable and showed less fluctuation.

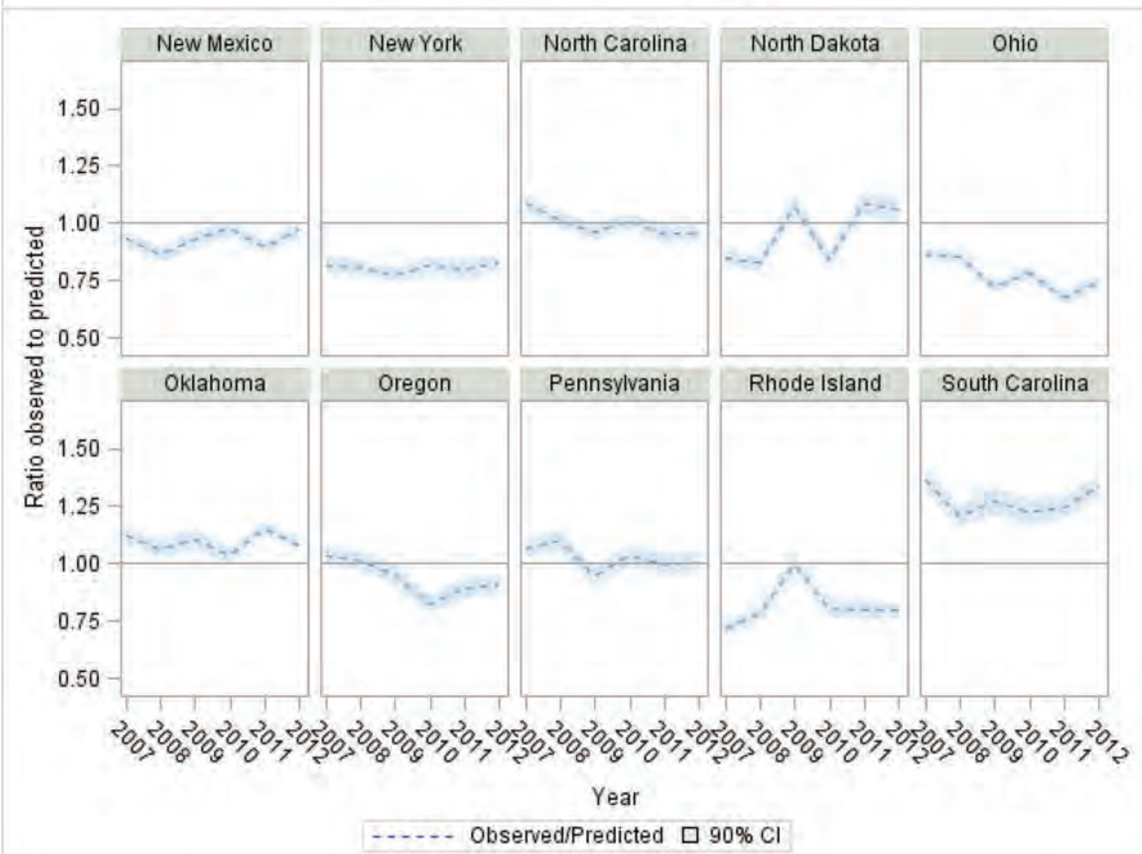
For several states, the ratio was close to the horizontal line (of no difference), showing that the MCS model prediction was close to the outcome. In these states, the model explained most of the variation. These states included Alabama, Colorado, Florida, Mississippi, North Carolina, and Pennsylvania. In other states, the ratios were persistently less than 1. These states may have some features or programs that consistently resulted in a safer traffic environment. These states include Indiana, Massachusetts, Michigan, Minnesota, New York, Ohio, and Vermont. In other states, the dashed line was consistently above the horizontal line, indicating that the number of fatalities was persistently greater than predicted by the MNCS model.

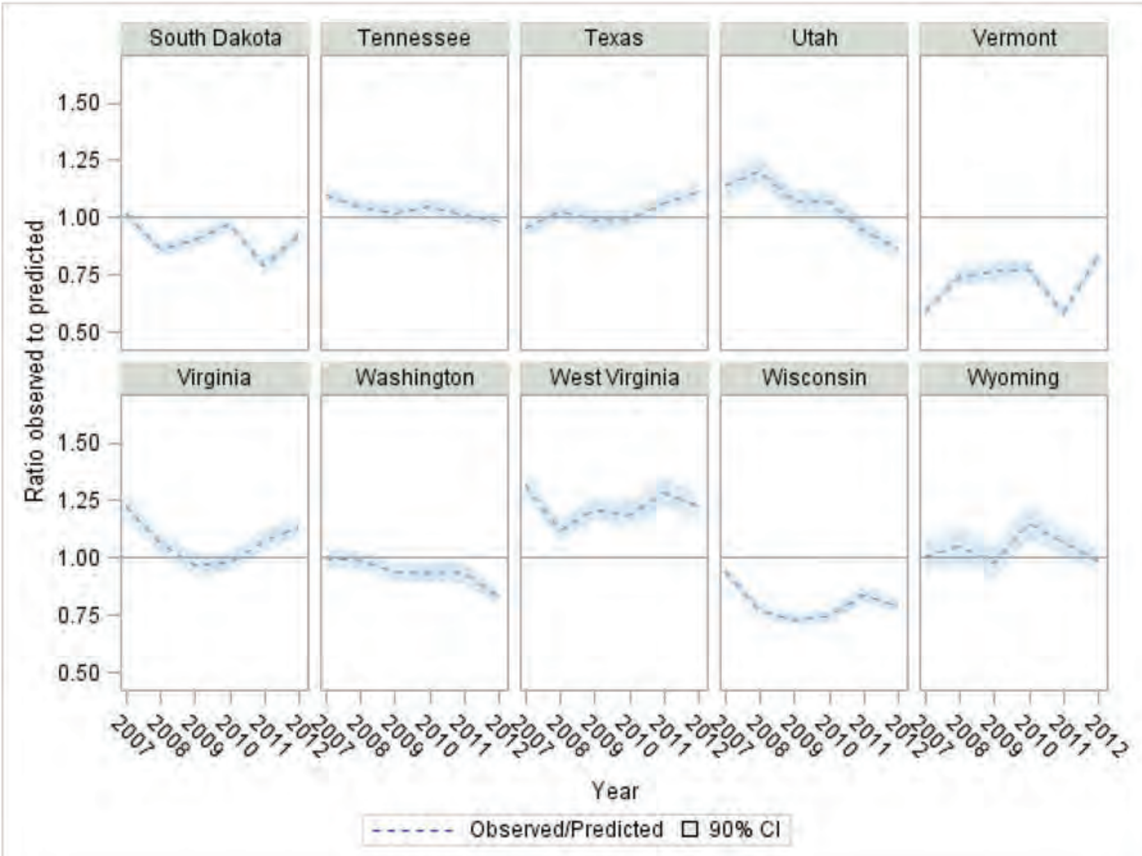
A comparison of states that had fewer traffic fatalities than predicted by the model, with the states that had more, would be useful to identify characteristics, programs, and interventions that contributed to the difference in safety environment.


Alabama
Alaska
Arizona
Arkansas
California
Colorado
Connecticut
Delaware
Florida
Georgia
Ratio observed to predicted
0.50
0.75
1.00
1.25
1.50
2007
2008
2009
2010
2011
2012
Year
Observed/Predicted
90% CI


Hawaii
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maine
Maryland
Ratio observed to predicted
0.50
0.75
1.00
1.25
1.50
2007
2008
2009
2010
2011
2012
Year
Observed/Predicted
90% CI


Massachusetts
Michigan
Minnesota
Mississippi
Missouri
Montana
Nebraska
Nevada
New Hampshire
New Jersey
Ratio observed to predicted
1.50
1.25
1.00
0.75
0.50
2007
2008
2009
2010
2011
2012
Year
Observed/Predicted
90% CI


New Mexico
New York
North Carolina
North Dakota
Ohio
Oklahoma
Oregon
Pennsylvania
Rhode Island
South Carolina
Ratio observed to predicted
1.50
1.25
1.00
0.75
0.50
2007
2008
2009
2010
2011
2012
Year
Observed/Predicted
90% CI


South Dakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
West Virginia
Wisconsin
Wyoming
Ratio observed to predicted
1.50
1.25
1.00
0.75
0.50
2007
2008
2009
2010
2011
2012
Year
Observed/Predicted
90% CI

Abbreviations and acronyms used without definitions in TRB publications:

A4A	Airlines for America
AAAE	American Association of Airport Executives
AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transportation Officials
ACI–NA	Airports Council International–North America
ACRP	Airport Cooperative Research Program
ADA	Americans with Disabilities Act
APTA	American Public Transportation Association
ASCE	American Society of Civil Engineers
ASME	American Society of Mechanical Engineers
ASTM	American Society for Testing and Materials
ATA	American Trucking Associations
CTAA	Community Transportation Association of America
CTBSSP	Commercial Truck and Bus Safety Synthesis Program
DHS	Department of Homeland Security
DOE	Department of Energy
EPA	Environmental Protection Agency
FAA	Federal Aviation Administration
FAST	Fixing America's Surface Transportation Act (2015)
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
FRA	Federal Railroad Administration
FTA	Federal Transit Administration
HMCRP	Hazardous Materials Cooperative Research Program
IEEE	Institute of Electrical and Electronics Engineers
ISTEA	Intermodal Surface Transportation Efficiency Act of 1991
ITE	Institute of Transportation Engineers
MAP-21	Moving Ahead for Progress in the 21st Century Act (2012)
NASA	National Aeronautics and Space Administration
NASAO	National Association of State Aviation Officials
NCFRP	National Cooperative Freight Research Program
NCHRP	National Cooperative Highway Research Program
NHTSA	National Highway Traffic Safety Administration
NTSB	National Transportation Safety Board
PHMSA	Pipeline and Hazardous Materials Safety Administration
RITA	Research and Innovative Technology Administration
SAE	Society of Automotive Engineers
SAFETEA-LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (2005)
TCRP	Transit Cooperative Research Program
TDC	Transit Development Corporation
TEA-21	Transportation Equity Act for the 21st Century (1998)
TRB	Transportation Research Board
TSA	Transportation Security Administration
U.S. DOT	United States Department of Transportation

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