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In-depth Investigation of Factors That Contributed to the Decline in Fatalities from 2008 to 2012 in the United States

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ABSTRACT

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. Most of the dramatic decline occurred from 2008 to 2012 which also coincided with the great economic recession and aftermath. The objective of this study is to provide a multidisciplinary analysis of the relative influence of the types of factors that contributed to this decline in the number of highway fatalities and fatality rates from 2008 to 2012. Two basic approaches were used to analyze the factors that were associated with the drop in traffic fatalities. The first approach developed a set of count models, using negative binomial models to examine the associations between predictors and raw fatality counts. The second approach, which is used to validate the first approach, used a log-change regression model, to examine the association between the change in predictor variables in one year with the change in the outcome variable (traffic fatalities) in the following year. The most significant contributors to the drop in traffic fatalities were the substantial increase in teen and young adult unemployment, decreased in beer consumption, and reduction in GDP/capita income. Vehicle design improvements also contributed to the decline significantly, as did the decline in rural vehicle-miles traveled (VMT) and increased strictness of DUI laws. 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 because they did not change much over the period.

Keywords: Fatalities, recession, economy, negative binomial model

INTRODUCTION

Between 2005 and 2011, peak to trough, the number of traffic fatalities in the U.S. 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 shows counts of annual traffic deaths from 2001 through 2012. The pattern in Figure 1 suggests two trends. 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. The number of fatalities has climbed to 35,092 in 2015 (*1*).

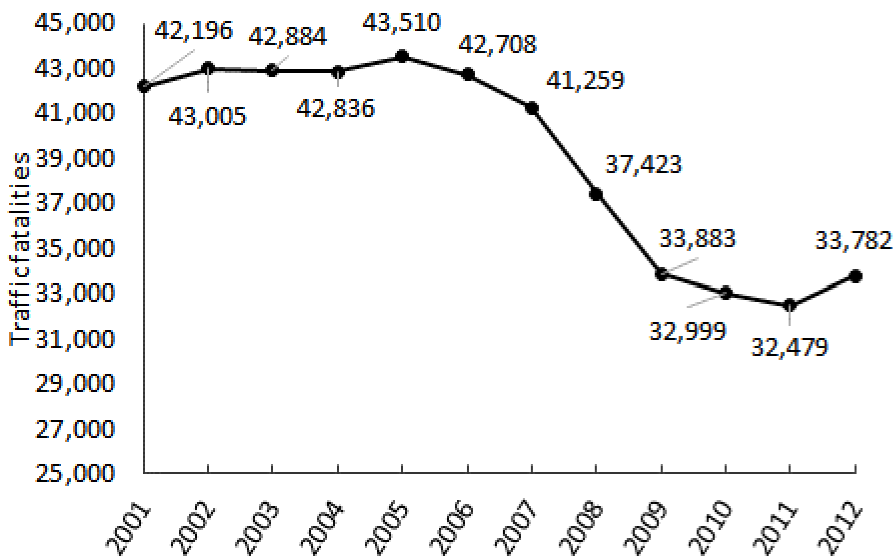

Figure 1 Traffic fatalities, 2001-2012

Fundamentally, two processes were at work over the period, from 2008 to 2012. 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 2008-2012. The major event that occurred in this period was the recession that started in December 2007 and ended in June 2009 (*2*). 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 from 2008 and 2012 was a major goal of the study, but the explanation was undertaken within the context of overall trends in traffic safety over the period.

The next section provides a brief review of studies that investigated the economic factors contributed to the decline in fatalities. The third section discusses the data sources used in the analysis. The fourth section provides the results of statistical modeling to understand the contribution of different factors to the drop in traffic fatalities, 2008 to 2012, while the fifth section provides a complete discussion of the results. The final section presents concluding remarks.

LITERATURE REVIEW

Elvik (*3*) (largely summarized in Wegman, et al. (*4*)) studied the remarkable drop in traffic fatalities in the countries of the Organization for Economic Cooperation and Development (OECD). Traffic fatalities in the countries studied dropped by a combined 12.6% from 2008 through 2010. Elvik attributed 65% of the reduction to the recession. Decreases in vehicle-miles traveled (VMT) accounted for relatively little of the decline, implying that a decline in fatal crash *risk* as such was the primary factor. Although data were not available to test directly, he suggested the risk reduction may be explained by a reduction in travel by high-risk groups (e.g., young people) or more cautious driving including reduced leisure travel (*3*).

Lloyd, et al. (*5*) found that changes in VMT, other than for heavy trucks, contributed relatively little to the reduction in traffic fatalities in Great Britain from 2007 through 2010. The largest drop in fatalities was for young males and females, and 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, there was a decline in crashes associated with alcohol impairment, which the authors attributed to imbibing at home rather than going out, i.e., less leisure and discretionary driving. Finally, there was a reduction in the percentage of speeders on motorways, consistent with the hypothesis that people drove more cautiously in economically-difficult times (*5*).

Elsewhere, Forsman, et al., (*6*) examined the substantial drop in traffic fatalities in Sweden during the recession years of 2008/2009. Consistent with the other studies, they found that the change in fatalities was greater than could be explained by the decline in VMT. The researchers found that periods of economic growth had higher numbers of crashes with multiple vehicles and multiple fatalities. The authors speculated that in periods of growth, there would be more vehicles on the road, increasing exposure to multiple vehicle crashes. Most of the other factors examined, include time of day, age and sex, alcohol-impaired driving and seatbelt usage, were not statistically significant, though primarily because of relatively small sample sizes. For example, the proportion of younger drivers in fatal crashes was only 15.0%, 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 (*6*). However, it is consistent with the hypothesis that the composition of VMT (e.g., less travel by young drivers) rather than the magnitude of VMT that was significant in the decline.

Silver et al. (*7*) studied the effect of state policy differences on fatal crash rates, controlling for the poverty rate, unemployment rates, tax revenues per capita, and other factors. They found that a significant effect for more comprehensive traffic safety policies. Noland and Sun (*8*) developed models of traffic fatalities for the period 1984-2011. They found significant effects for median income and the Gini coefficient (a measure of economic inequality), estimated that changes in the roadway network actually increased fatalities (by increasing the number of lanes, for example), and attributed much of the decline in traffic fatalities, 2006-2012, to graduated driver licensing laws and laws on cell phone usage. Kweon (*9*), in an analysis of the decline associated with the recession in Virginia, found significant effects for changes in the Consumer Price Index (CPI) and unemployment rate, such that increasing consumer prices and increasing unemployment was associated with significant reduction in traffic crashes and fatalities. Grabowski and Morrisey (*10*, *11*) and Morrisey and Grabowski (*12*) demonstrated a connection between fuel prices and fuel taxes, VMT, and crash fatalities. Higher fuel prices, including by increased fuel taxes, tend to decrease VMT. The consequent reduction in VMT (exposure) then tends to reduce the number of fatal traffic crashes.

DATA DESCRIPTION

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 attempt to reflect the influence of the economy on traffic safety.

The data series collected were at the state level, meaning that the observations were collected by state and year over the period 2001 through 2012. However, data were not available at that level of detail 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.

Fatality data

The National Highway Traffic Safety Administration’s (NHTSA) Fatality Analysis Reporting System (FARS) is the standard source for data on fatal traffic crashes in the U.S. The FARS data set is composed of data compiled by analysts housed within each state. Data elements cover crash-, vehicle-, and person-level information. The data are collected from police accident reports, death certificates, vehicle registration files, hospital and coroner records, emergency medical service (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 (*13*). FARS data were used for analysis in this study.

Sources of other data used

Exposure includes all types of measures that reflect the opportunity or exposure to the possibility of a crash. VMT was probably the most important measure of exposure used, because it most directly captures *exposure* to crashes. 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, as well as many other relevant data series (*14*).

Table 1 presents the list of variables used in the statistical models and their data sources. Other variables that were not used in the statistical models are not discussed here. The interested reader is referred to Blower et al. (*15*) for more details.

Table 1 Data series

Variables	Data	Source
Economic	Employment, total counts of employed by state, month, & year	Bureau of Labor Statistics, Current Population Survey, Local Area Unemployment Statistics.
	Labor force, by state, month & year	Bureau of Labor Statistics, Current Population Survey
	Unemployment rate, by state, month, & year	Bureau of Labor Statistics, Current Population Survey
	State GDP by year	US Department of Commerce, Bureau of Economic Analysis, Regional Economic Accounts: Download
	State median household income by year	US Census Bureau, Current Population Survey, Annual Social and Economic Supplements.
	Fuel tax by state by year	*Highway Statistics*, FHWA. Table MF-205.
	Fuel costs	US Energy Information, State Energy Data System, prices for regular gasoline, data are converted from prices per million BTUs.
Driver- and vehicle-related	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, reported in Chen (*16*) and Chen and Ye (*17*)
	BAC limit, per se, other alcohol related laws and penalties, by state by year	Compiled from state laws, index developed from Klinich (*18*)
	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, (*19*)
	Post1991 model year	Estimated from GES, using a quasi-induced exposure technique.
Highway expenditure	Capital expenditures	Compiled from *Highway Statistics,* FHWA, Table SF-2, includes construction, relocation, resurfacing, restoration, rehabilitation and reconstruction, widening, capacity improvements, restoration of failed components, additions and betterments of roads and bridges. See (Federal Highway Administration N.D.)
	Maintenance	Compiled from *Highway Statistics,* FHWA, Table SF-2, includes preserving the entire highway, including surface, shoulders, roadsides, structures, and traffic control devices, as close as possible to the original condition as designed and constructed.
	Administration, research, planning	Compiled from *Highway Statistics,* FHWA, Table SF-2, including all general and miscellaneous expenditures not related to a specific project, expenditures for highway planning, research, and planning

	Law enforcement and safety	Compiled from *Highway Statistics,* FHWA, Table SF-2, including all relevant Federal Safety programs, sections 402, 403, 405,406, 407, 408, 410, and 411 of Title 23 of the United State Code, as well as MCSAP. Also includes capital expenditures designated by states as safety-related.
	Highway Safety Improvement Program	Compiled from FHWA funding tables under SAFETEA-LU and MAP-21, available from https://www.fhwa.dot.gov/safetealu/fundtables.htm and https://www.fhwa.dot.gov/map21/funding.cfm

Data series on employment, the labor force, and unemployment were obtained from the Bureau of Labor Statistics, extracted from the Current Population Survey (CPS). CPS 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 which includes the 12th day of the month. Unemployed persons were defined as all persons 16 or older who were not employed, were available for work, and had made specific efforts to obtain employment. The labor force includes all persons either employed or unemployed according to those definitions.

Gross domestic product (GDP) estimates by state and year were obtained from the US Department of Commerce. GDP measures the gross productive output, and was used as a gross estimate of economic activity. The estimates were divided by population estimates to obtain GDP per capita estimates. Median household income estimates were obtained from the Bureau of Census Current Population Survey. The estimates available were for two- to three-year periods. Estimates for individual years were obtain 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/capita is on a per person basis. All monetary estimates were converted to 2013 dollars using the CPI (Consumer Price Index) calculator at the Bureau of Labor Statistics (*20*).

Fuel prices were obtained from the US Energy Information Administration, State Energy Data System. Prices for regular-grade gasoline were used, as the most common grade of fuel. The prices were converted from prices per million BTUs to gallons, and then converted to 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 2013 dollars and added to fuel costs to produce an estimate of prices at the pump.

Indexes on the strength of state belt laws and motorcycle helmet requirements were developed from the valuable set of digests of state laws maintained by the Insurance Institute for Highway Safety (IIHS). Belt use rates are available from the continuing National Occupant Protection Use Survey (NOPUS), published annually by NHTSA. 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. Klinich (*18*) has been compiling state laws related to drunk driving and kindly shared data that were used to develop on index of state penalties and regulations. 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 and the strengthening of the Federal Motor Vehicle Safety Standards.

Data series on state highway expenditures are available in the FHWA's *Highway Statistics* series. 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.

Highway spending was used in the statistical models to capture the effect 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 it is the best currently available aggregate surrogate for the safety effect of changes in infrastructure. There are evaluations of specific projects, and crash modification factors (CMF) have been developed for different types of projects, (e.g. Part D of Highway Safety Manual (*21*)). But there are no comprehensive data to translate CMFs into variables that capture the system-wide effect of such modifications. For example, there is an 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. 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 identified as safety-related. Finally, it was assumed that state departments of transportation attempted to deploy their resources optimally. There are no doubt variations in effectiveness, but in light of currently available data, highway spending should be a reasonable approximation.

MODELING

The modeling approach was patterned after Elvik (*3*), who reviewed a number of statistical methods for evaluating predictors of traffic fatalities over time in a group of countries. The three primary methods discussed were negative binomial models of fatalities counts, and two forms of models of year-over-year change. A Poisson-gamma count model, equivalent to a negative binomial model, was used in the present study. The log-change regression model of year-over-year change was developed to validate the results of the count model.

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, though different factors can influence risk or exposure, in this model they are interpretable primarily as influencing risk rather than exposure.

There are two key sources of variation in the dataset 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), while others are more volatile (economic factors) and can have significant effects 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 between states and focus on changes over time (model controlling for state, referred to below as MCS). The other leaves out this fixed effect, allowing differences between states to be captured by the measured predictors (model not controlling for state, referred to as MNCS in the analyses below). 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 state experience. The difference in these mechanisms can be informative.

Factor analysis

A significant challenge of working with this type of dataset is that many of the variables in the dataset are correlated. While modeling can be done with some collinearity among predictors, it tends to fail when those relationships are very strong.

To address the collinearity problem and understand the collective relationship among these variables, a series of factor analyses were 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 was used to 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 related variables: expenditures, economic measures, population, and VMT.

Based on the results of the factor analysis and 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 was correlated with GDP, total VMT, urban road miles, total population, law enforcement safety expenditures, and total capital expenditures. "Ruralness" was represented by the proportion of VMT that was rural. This was 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 this timespan, these were related to all other economic factors, including employment for different age groups and unemployment for different age groups. State expenditures were represented by safety spending (safety plus the Highway Safety Improvement Program or HSIP) and capital spending. Occupant protection was 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 was 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.

Regression models

In this modeling work, each year for every state was considered a distinct observation. As discussed by Lord and Persaud (*22*), 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 (GEE) can be used for handling serial correlation. However, after further investigation, it was determined that the serial correlation had a minimal impact on the modeling results. Hence, to simplify the modeling effort, the models were estimated using the generalized linear models (GLMs).

The modeling results related to negative binomial count models are summarized in this section and the next section discusses the results. Due to space constraints, the results related to change model are not presented nor discussed in this paper. The interested reader is referred to Blower et al. (*15*) for details about the change model. In general, the results from the change model agreed with the count data models and thus verify the validity of count models.

The functional form used for the MNCS is the following:

$$\mu = \text{VMT} \times e^{\beta_0 + \sum_i \beta_i X_i} \quad \text{Eq. 1}$$

Where,

μ = the estimated number of fatalities per year (for each state);

VMT = the number of vehicle-mile 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:

$$\mu = \text{VMT} \times e^{(\beta_0 + \gamma_s) + \sum_i \beta_i X_i} \quad \text{Eq. 2}$$

Where,

γ_s = state-specific parameter for state *s*.

Table 2 below shows the modeling results for the MNCS and the MCS models. As noted above, VMT was used as the exposure. *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 zero, 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 zero, given the sample data. For the MNCS model, three variables (DUI rating, belt rating, and motorcycle helmet rating) were found to be not statistically significant, even at 10% level. For the MCS model, four variables (capital spending, safety spending, pump price and belt rating) were found to be not statistically significant, even at 0.1 level. 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 goodness-of-fit (GOF) of the models were 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 (*23*). In general, models with smaller AIC, MAD and MSPE values are considered superior to other models.

Table 2 Parameter estimates for the count models

Variable	MNCS model			MCS model		
	Estimate	Standard error	P-value	Estimate	Standard error	P-value
Intercept	11.7179	0.4082	<.0001	10.6995	0.302	<.0001
Rural VMT proportion	**0.2228**	**0.0667**	**0.0008**	**-0.1916**	**0.0972**	**0.0486**
Capital spending (in $1000)	**0.0009**	**0.0003**	**0.0007**	-0.0002	0.0002	0.2255
Safety spending (in $1000)	**-0.0033**	**0.0013**	**0.0124**	-0.0006	0.001	0.5176
GDP per capital (in $10,000)	**0.024**	**0.0106**	**0.0241**	**0.046**	**0.0117**	**<.0001**
Unemployment for age 16 to 24 (%)	**-0.0132**	**0.0025**	**<.0001**	**-0.0118**	**0.0015**	**<.0001**
Pump price ($ per gallon)	**-0.0475**	**0.0258**	**0.0651**	0.0065	0.0125	0.6034
Beer (gallons)	**0.2769**	**0.0425**	**<.0001**	**0.4022**	**0.0747**	**<.0001**
DUI rating	-0.0032	0.0026	0.22	**-0.0074**	**0.003**	**0.0119**
Belt rating	0.0008	0.007	0.9061	-0.0058	0.0073	0.4274
Motorcycle Helmet rating	0.0065	0.0073	0.3732	**-0.0347**	**0.0156**	**0.0261**
Median Income (in $10,000)	**-0.2149**	**0.0148**	**<.0001**	**0.0375**	**0.0188**	**0.0459**
Post1991 (% of vehicles manufactured after 1991 in the fleet)	**-0.0138**	**0.0047**	**0.0033**	**-0.0177**	**0.0026**	**<.0001**
Dispersion Parameter	0.0277	0.0019	--	0.0025	0.0003	--
AIC*	6537			5643		
MAD*	93.07			35.80		
MSPE*	21185.56			3165.32		

* Smaller values are preferred.
Bold font denotes p-values <=0.1.
Note: State fixed effect parameters are not presented here for the MCS model.

DISCUSSION

The variables were grouped into the categories of Economic, Safety, Capital, Regulatory, and Vehicle Safety factors as shown in Table 3 to determine the role each grouping played in determining fatalities.

Table 3 Grouping of Variables

	Grouping				
	Economic	Safety Expenditures	Roadway Capital Expenditures	Regulatory	Vehicle Safety
Variables	• Rural VMT • GDP per Capita Percent • Unemployment % for 16-24 year olds • Beer consumption • Pump price • 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

The influence of the variables in these groupings was obtained by estimating the proportion of the decrease that was based on an average of the predicted and observed fatalities for the years 2008 through 2012.

Effect of Economic Variables

The prediction based on economic variables reveals that a significant portion of the drop in traffic fatalities over the period was accounted for by economic factors. According to both MNCS and MCS models, the set of economic factors accounted for 82% to 88% of the difference between the level of fatalities in 2007 and the level of fatalities predicted by the model over the period 2008 to 2012.

The unemployment rate for 16 to 24 year olds had the biggest effect on the decline in traffic fatalities from 2008 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., (*24*)), 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.

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, and about 13% in the state fixed effects model. The potential mechanism for this parameter to affect risk is fairly direct, as the likelihood of drunk driving would diminish as consumption of alcoholic beverages declined. The modeling indicated that a tenth of a gallon increase in per capita beer consumption would be associated with a 2.8% to 4.1% increase in fatalities.

In both models, a decrease in per capita gross domestic product was associated with a decrease in traffic fatalities. The effect was statistically significant in both models. In the MNCS model, this variable accounted for about 8% of the decline in fatalities attributed to economic factors and 15%

of the decline 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.

Pump price, median income and rural VMT had marginal or no effect on the change in fatalities. This is because either these variables do not change significantly over the period considered or they are correlated with other variables.

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 sizes 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 (e.g., because the 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 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 effect of safety programs do not vary linearly with the amount of expenditures.

Effect of Roadway Capital Expenditures

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

Effect of Regulatory Policies

In the model, the effect 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 laws become stricter. Each category—DUI, Safety Belt, and Motorcycle Helmet Laws—were considered separately in the model 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 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 were statistically significant in the MNCS model. However, DUI and motorcycle helmet law ratings were statistically significant in the MCS model.

Both models indicated that an increase in DUI ratings (stronger laws) was associated with a decline in fatalities. Although DUI rating accounted for almost all of the effect of the regulatory grouping, it only predicted some 2% of the 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 one 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.

During the period from 2008 to 2012, only a slight increase in seal belt rating and no overall change in the motorcycle helmet rating occurred, which explains why they were not associated with the decline in traffic fatalities

Effect of Changes in Vehicle Fleet Safety

The effect of the influence of improved safety (more crashworthy designs, improved occupant protection, stability control, etc.) in vehicles was incorporated into the model 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 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.

CONCLUSIONS

This study found that the changes in the economy were the primary factors in the substantial drop in traffic fatalities from 2008 through 2012. 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 economic constraints reduced 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 (*25*). We believe 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 of the factors in the model likely were that their contribution was small relative to the other factors in the model, and their effect on traffic safety was more stable and long-term.

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