



Automobile-dependency as a barrier to vision zero, evidence from the states in the USA



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ABSTRACT

With a traffic fatality rate of 10.6 per 100,000 as of 2013—more than triple that in the UK, the Netherlands, and Sweden—the United States has the worst traffic safety performance of all developed countries. Statewide variations are even more pronounced. North Dakota registers more than twice the national average and five times the rate of Massachusetts. We used panel models and annual data from 1997 to 2013 to capture the effect of seven separate sets of factors that influence traffic safety: exposure, travel behavior, socioeconomics, macroeconomics, safety policies, and mitigating factors such as health care. The results of our panel models and supplementary analysis of state effects show that two variables — Vehicle Miles Traveled and Vehicles per Capita—have the strongest impact on traffic fatality rates. This is closely followed by Infant Mortality Rates, the proxy that we used to represent the quality of health care. Policy levers such as Graduated Driver's Licenses (GDL) have improved safety, but to a limited extent. We also found that states with higher urban density and more walking are associated with lower traffic fatality rates. Taken as a whole, our findings suggest that if additional progress is to be made in reducing traffic fatalities, emphasis needs to move beyond simply focusing on policies such as GDL and seat belt laws, which have already been adopted by almost all jurisdictions across the United States. We need to also consider factors that focus on the type of urban form that we are creating to ensure that we are fostering environments that encourage multi-modal transportation such as walking to reduce the VMT and Vehicles per Capita, the two strongest predictors of traffic fatalities.

1. Introduction

Road traffic injuries are one of the leading causes of death globally. Each year, over 1.2 million people die on the world's roads, and millions more have to live with the long-term adverse consequences of serious injuries sustained in crashes (WHO, 2013). Perhaps more important are the intangible impacts—pain, grief, and suffering—of those incidents that spill out well beyond the individual to families and communities. With traffic fatalities now understood as being both predictable and preventable, considerable efforts are being made to improve safety globally. The World Health Organization has designated 2011–2020 as “The Decade of Action for Road Safety” advocating the application of a holistic safe systems approach (World Health Organization, 2013). This initiative is supported by a burgeoning body of research from academia and beyond that has sought to identify the factors responsible for road traffic fatalities and to understand the effectiveness of policies directed at improving safety in both developed

and developing world settings (Ahangari et al., 2014; Leonard, 2014; Sauber-Schatz, 2016).

Traffic safety patterns and their rates of change over time vary considerably between countries (Ahangari et al., 2014). While distinctions are typically drawn between developed and developing countries, traffic safety patterns tend to follow a “Kuznets curve” (Law, 2015). According to this curve, traffic fatalities increase with level of development (usually measured in terms of GDP per capita), reach a turning point at a particular (as yet unspecified) level of development, and then decline (Law, 2015). This somewhat simplistic conceptualization of the trajectory of traffic fatalities does not take into consideration the huge variation in traffic safety records that exist across the developed world. In 2013, the United States had road fatality rates (measured in terms of deaths per 100,000 population) of 10.6, more than triple that of the safest countries in the developed world (the UK, Sweden, and the Netherlands). From a global perspective, understanding the factors shaping traffic safety in the United States is especially important

* Corresponding author at: 3 Understanding the Factors that Contribute to 4 the Wide Disparity in Traffic Fatality Rates 5 between States in the USA.

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because many developing countries are reproducing the rapid motorization and suburban development patterns associated with the ‘American Dream’. From a national perspective, many jurisdictions have adopted Vision Zero goals for traffic fatalities (USDOT, 2015; Birdsall, 2016). In pursuing these goals it is important for stakeholders to understand which factors affecting traffic safety are within and also outside of the direct control of policy-makers.

Drilling down further it is evident that individual states within the U.S. exhibit considerable variation in traffic safety patterns. For example, examining data for 2012, North Dakota had the highest traffic fatality rate of all the states with 24.3 fatalities per 100,000 people—more than ten times the rate of Washington, DC (2.4 fatalities per 100,000 people), and almost five times the rate of Massachusetts (5.3 fatalities per 100,000 people). The safest jurisdictions, DC and Massachusetts, have safety records comparable to the safest countries in the world in terms of traffic fatalities—Switzerland and the Netherlands. In sharp contrast, North Dakota, Wyoming, and Montana have road fatality rates twice the level of the national average and on par with developing countries like Sudan, Somalia, Ghana, Zambia, and Vietnam (World Health Organization, 2013). Some variation in traffic safety records for states within the same country should be expected given the differences in geography and demography. However, the orders of magnitude variations between states are unexpectedly high and remain unexplained in the literature. A more detailed understanding of variations in traffic safety patterns across individual states and how they have evolved over time will help to inform stakeholders both within and beyond the United States. The relative performance of individual states has changed over time. For example, in 1997, the fatality rate in North Dakota was close to the national average but after 15 years it had a rate that was almost twice the national average, increasing by 35%. In contrast, some states experienced considerable improvements in traffic safety. For example, in Utah, traffic fatalities fell by 57% between 1997 and 2012 Fig. 1. Illustrates these temporal variations for a sample of states: Massachusetts, North Dakota, Utah, and Wyoming.

In this paper, we present an empirical study to quantify the impact of a wide range of variables on traffic fatality rates (defined as deaths per 100,000 people) for the fifty states, along with DC, using annual data from 1997 to 2013. The period of analysis was chosen to correspond to data availability for important explanatory variables. We use panel models to evaluate both spatial and temporal variations in safety patterns with the overarching objective of understanding what factors explain variations in traffic fatalities. We then go on to consider the effect of two important variables—urban density and mode share (as a proxy for infrastructure provision). This additional step of analysis was necessary because both of these two important variables were not

available on an annual basis and thus could not be included in the original panel model.

The starting point for our empirical approach is a conceptual framework that we developed which builds on a schema from the World Health Organization (WHO). This conceptual framework is designed in order to capture a more complete set of factors that could potentially explain traffic fatalities. The expanded conceptual framework that we use in this paper has previously been used to study the evolution of traffic fatality patterns over time in 16 OECD countries (Ahangari et al., 2014). Switching to the statewide unit of analysis as we do in this current paper allows for additional variables to be taken into consideration.

2. Literature review

The literature on transportation safety is vast and growing because of the severity of this public health issue. In the interests of space, the very brief overview of the literature that we cover here will focus on studies that compare traffic fatalities in the United States to other countries, and studies that have investigated differences between states.

Comparisons of road safety records at the national or state level have attracted considerable attention over the last several decades (Ahangari et al., 2014; Siem, 1989; Simon et al., 1991; Brüde Ulf. and Brüde, 2015). Several studies have focused on documenting and explaining the large gap between the US and other developed countries in terms of road safety. In 2013, Oste et al. sought to understand why the US was lagging other countries in highway safety improvements (Oster and John, 2013). They decomposed road fatalities into groups based upon age, user, and road infrastructure. They found that the 2013 death rate on urban roads in America was 72 percent lower than that in 1980. In addition, they investigated the effect of variations in demographic factors and found that drivers in the 16–20 years old age group and the 21–24 years old age group had the highest fatality rates of any age group. In 2014, Evans, compared different road fatality measures such as fatality per population, and rate of road fatality reductions in the US and 25 other developed countries. He showed that since 1974 the road fatality improvement

in the US was about half that of other developed countries. While this study was helpful in identifying the extent to which the US was lagging other developed countries it fell short of providing insight into what factors were causing the discrepancies.

Using data for 16 developed countries from 1990 to 2010, (Ahangari et al., 2015) developed a two-step panel data model to understand the factors contributing to why the US was lagging in traffic fatality improvements compared to other developed countries. After controlling for macroeconomic conditions, gasoline price, motorization

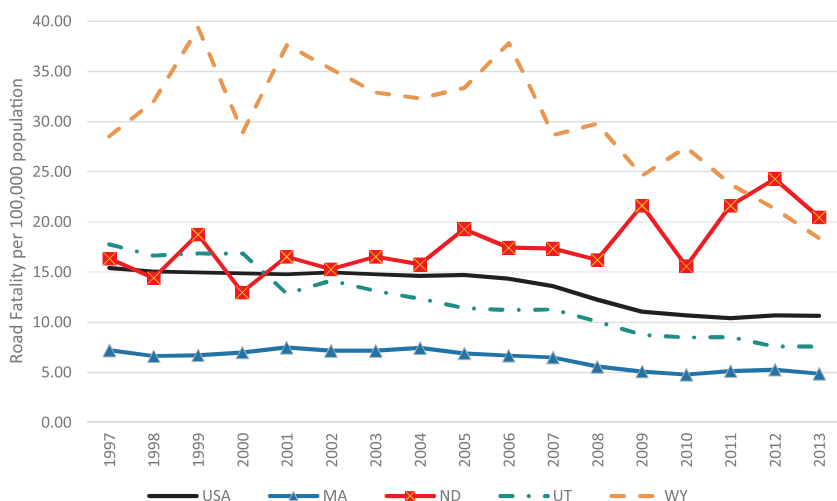


Fig. 1. Comparing Fatality per 100,000 People Nationally and in Selected States.

level, health factors, and Vehicle Miles Travelled (VMT), they hypothesized that country specific factors beyond those included in the model such as safety culture, safety policies, and infrastructure type and design explain a large fraction of the differences between countries in road traffic fatality rates. In another study, they compared the changes in traffic fatality rate in the US and 15 of its peers for different age cohorts. They reported that in the US, the safety performance of the group aged 15–24 years old improved at the same rate as the average for all countries in the study. However, the road fatality rate for children (under 15) and seniors (over 65 years) decreased at a much slower rate than most other developed countries resulting in a huge gap in traffic fatality rates for these age groups when the US is compared to the best performing countries. For example, they showed that children in the US were a stunning five times more likely to experience a road traffic fatality than their peers in the UK (Ahangari et al., 2016a).

Some have tried to understand this underperformance of the United States in terms of traffic fatality compared to other developed countries by examining state level data. One of the first studies of traffic safety in the 50 states and DC examined the effect of violence/aggression and other societal variables on road safety measures over the period 1977–1979 (Sivak, 1983). Sivak used multiple cross-sectional models to predict the fatality rates based on 15 independent variables including demographic factors (age and gender), income, physicians per capita, unemployment and alcohol consumption. His study showed that road fatality rates are higher in states with more suicide and homicide and higher percentages of young people. The study did not consider important variables that are known to influence fatality rates such as traffic safety policy, and enforcement, and differences in the vehicle fleet and the transportation infrastructure in the different states (Loeb Peter, 1987).

Around the same time, Loeb used 1979 data for all states to assess the effect on traffic safety of policy-related variables and proxies including driving speed, vehicle emission inspection, per capita beer consumption, and the minimum drinking age. He entered gasoline price, age composition, population density and total highway miles as controls in the model. His findings indicated that beer consumption and driving speed are associated with an increase in road fatality rates while auditing policies such as vehicle emission inspection are associated with a decrease in these rates. Loeb's study was an important advancement in evaluating how policies affect safety performance but his model did not include the effects of trauma management, infrastructure and urban form. This study was conducted over 35 years ago, since then the context for traffic safety has seen many drastic alterations, therefore, there is a need to re-assess of the factors affecting traffic fatalities in the states (Sivak, 1983).

In 1991, Zlatoper provided a cross-sectional model using 1987 data to evaluate the effect of different types of infrastructure on road safety in 47 states. The study found that income, the ratio of urban to rural vehicle miles travelled, expenditures on highway police, motor vehicle inspection laws, and adult seat belt use laws are inversely related to traffic fatality rates. In addition, vehicle miles travelled, speed, speed variance (standard deviation of speed), driving density (VMT per total mile of highways in each state), and per capita alcohol consumption, were positively related to road fatality rates. Neither of these last two studies, by Loeb or Zlatoper, had a temporal component to evaluate the effects of these various factors over time (Zlatoper, 1991).

Filling the gap in terms of temporal analyses were a series of studies that considered both temporal and geographical variations in the safety performance of states using panel data models. In 2003, Noland studied the effect of road infrastructure on traffic fatalities and injuries using data from 1984 to 1997 to populate panel models for all 50 states (Noland, 2003). A suite of 14 variables considering road widths and road types were used as proxies for the variation in infrastructure between states. These variables included total lane miles, the proportion of lane miles in different road categories (interstates, arterial, and collector roads), the average number of lanes for each road category,

and lane widths for arterials and collector roads. The results showed wider travel lanes had little discernible impact on traffic safety. Instead, improvements in traffic safety over the time period of the study were attributed to a host of factors including demographic shifts and improvements in trauma care, as well as the enactment of regulations governing seat-belt use and differences in per capita alcohol consumption (Grabowski David and Morrissey, 2004).

Grabowski and Morrissey used statewide data from 1983 to 2000 in a panel model to investigate the effect of gasoline prices on road fatality rates (Grabowski David and Morrissey, 2004). They found that a 10 percent decrease in gasoline prices increased motor vehicle fatalities by 2.3 percent after controlling for income, unemployment, and laws governing seat belt use, speeding and alcohol use while driving. Absent from this model were the role of trauma management, infrastructure, and people's travel behavior. In a noteworthy advance, they later developed a model, which considered policies such as GDL and beer consumption and beer tax to explain road safety variations between different states with a specific focus on novice drivers. Using data from 1985 to 2006, they showed that GDL policy reduced fatality rates for those aged between 15 and 17 by 24%. However, they showed that beer tax was linked only to traffic fatality rate for the 18–20 and 21–24 years old groups (Morrissey and Grabowski, 2011).

In study aimed at understanding how the Great Recession of 2007–2009 affected traffic fatality rates, Cotti and Tefft examined the relationship between unemployment, income per capita and gas tax and road fatalities using quarterly data for those years for the 50 states (Cotti, 2011). They found a negative relationship between unemployment and road fatalities, and identified a 17% drop in road fatalities during the Great Recession.

Our examination of studies in the existing literature demonstrates that a wide array of factors has been shown to influence road fatalities. Many of these studies have been undertaken with a specific aim in mind—for example, uncovering the role played by road widening (), examining the effect of the Great Recession, or assessing specific policies such as Graduated Drivers Licensing (GDL). To date, there is no comprehensive analysis at the statewide level that considers the broad array of factors affecting traffic fatalities in order to help explain why traffic safety records in the states of the United States vary so dramatically.

3. Conceptual framework and methodology

The starting place for this project is a conceptual framework for characterizing the factors affecting traffic fatalities that we pioneered for a comparative study of traffic fatality in developed countries. This framework was initially inspired by a World Health Organization model and was developed based on an extensive review of the literature on traffic safety at the macro scale. The goal for developing this framework was in providing a systematic and holistic sense of all the potential determinant of road safety.

The framework includes eight sets of factors that either directly or indirectly influence road safety (Ahangari et al., 2014). The eight sets of factors in the framework are illustrated in Fig. 2. Three of these factors – socioeconomic factors, technological changes, and exposure factors (such as motorization level) – are indirectly related to road deaths. While the other factors – urban form, infrastructure conditions, travel behavior, and moderating (policy and enforcement) along with mitigation (health and emergency response) – are directly related to road deaths. As is shown in the following section the framework is used as a guide in selecting the most relevant variables to be used in statistical analysis of traffic fatality and in analyzing the results from the statistical model.

3.1. Data

To develop a reliable model based on the above conceptual

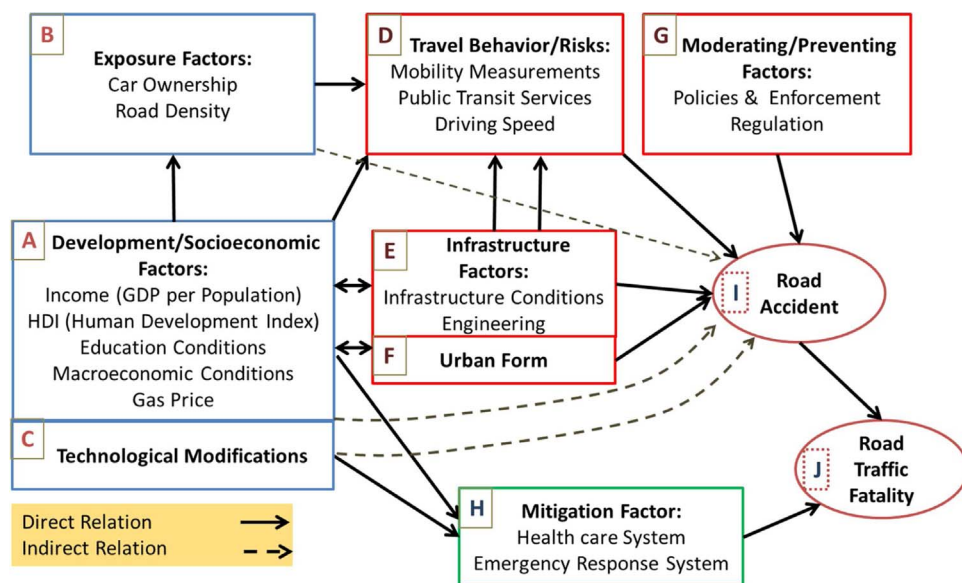


Fig. 2. Comprehensive conceptual framework.

framework, we need to select appropriate variables for both dependent and independent variables. The dependent variable selected for this study is road fatality per 100,000 population which represents the impact of road fatalities on the population as a whole. As the above comprehensive conceptual model shows, the independent variables are generally divided into two groups depending upon whether they have a direct or indirect influence on road fatality. The individual variables that we selected, the factors that they represent, the source of the data, and the maximum and minimum values of the variables across the states in the study period are shown in Table 1. A more detailed description of the factors is given in Table 1 and the variables available to characterize each factor is discussed below:

A. Socio-Economic Factors: The amount of wealth (usually expressed in terms of GDP), along with other social and economic factors, is well established as having an impact on traffic fatalities. This set of factors was represented by (i) GDP per person; (ii) Unemployment Rate; (iii) Gasoline Prices (Adjusted by 2010\$) (iv) Percentage of Population under 15; (v) Percentage of Population Aged 15–24; (vi) Percentage of Population over 65. We do not have variables that may reflect cultural differences across states and expect the impact of this to be picked up by the state effect generated by the panel model.

The analysis of the literature showed that income per capita is frequently used to compare road safety condition between states (Loeb Peter, 1987; Zlatoper, 1991; Morrisey and Grabowski, 2011; Cotti, 2011). But this factor is highly correlated with the GDP per capita. However, we chose to use GDP per capita over income for two main reasons. First, GDP is a more inclusive measure of economic activities than is income measures. In fact, GDP is more likely to capture sectoral differences between the economies in each state. In addition, GDP might also be a good proxy for such factors as fleet composition for which we do not have reliable data available.

A. Exposure Factors: We chose vehicle ownership per capita as a proxy for exposure to road travel. This does not directly capture whether or not those vehicles are actually used and/or whether people use public transit instead. Given the lack of a good metric for public transit use at the statewide level on an annual basis, we were unable to include this variable in the model. Any variation in public transit use versus vehicle use will therefore be picked up by the state and time effects in the panel model.

B. Technological Modifications: Technological improvements can affect transportation safety in multiple ways. The first impact is by having vehicles equipped with safety features such as ABS, air bags, and on-board crash notifications – these fall into the category of either

active or passive automobile technologies. The second impact is that technology could theoretically improve trauma management (this is already represented in Factor I, Mitigation). We believe that the available data on fleet mix in different states is not reliable therefore we did not include any variables for this set of factors. Technological modifications usually evolve over time and its effect should mostly be reflected in the time effect.

C. Travel Behavior/Risk: We selected VMT per vehicle to represent mobility. Four additional variables were also chosen to reflect user behavior: (i) Percent of Fatalities caused by Drivers Under the Influence (DUI); (ii) Percentage of Fatalities involving Speeding; (ii) Alcohol Consumption per capita; (iv) Seatbelt Usage.

E. Infrastructure: We could not find variables that adequately characterize at a statewide level the features of the infrastructure that needs to be captured for a traffic fatality analysis. In the literature, Noland’s work is focused on the effect of infrastructure. He used 14 variables as infrastructure factors including characterizing different type of roads (interstate, arterial, and collector) by lane width (9 feet to 12 feet). However, we did not feel that this measure adequate captures essential differences in infrastructure that might affect traffic fatality rates. For example, there is no measure available to determine the extent to which the transportation infrastructure in the state accommodates different modes of travel (private vehicle occupants, walkers, bikers, transit users etc.) and the interaction between different types of uses. In some studies, researchers have used the number of bikers or walkers as a proxy of how well the system accommodate these types of users (Ahangari et al., 2016b). In this study, we chose to use this approach. Our proxy is the% of commuters walking to work. One of the drawbacks of this proxy is that we do not have annual data; therefore, this variable cannot be included in our panel model. Instead, it is used in a supplemental analysis of the state effects from the panel modeling.

D. Urban Form and the Built Environment: We have developed two customized variables to characterize the urban form and the built environment. The first of these measures is the weighted density in which the most urbanized 10% of each state’s population lives (the density is determined at the census block level). The second measure is the percentage of the state living in census blocks with very low population density (less than 300 persons per square miles). In this study, these measures are referred to as high-density and low-density factors, respectively. Like with the% walking variable, these two variables are not available on an annual basis. Therefore, they cannot be included in the panel model. But they are used in the supplemental analysis of the state effects to see the extent to which they might explain variations in the

Table 1
Variables, data source, and descriptive statistics.

	Factors Shaping Road Safety	Representative Variables	Data Source	Range of Values	Residual Effect
A*	Development/ Socio Economic	GDP per capita (Adjusted \$) Unemployment Rate Gasoline Price (\$ per Gallon, adj. to 2010) % Population under 15 (%) % Population 15–24 (%) % Population 65+ (%) Vehicle Ownership per capita (Vehicle per 1000 population)	Bureau of Economic Analysis (US Bureau of Economic, 2017) Bureau of Labor Statistics (US Bureau of Economic, 2017) Energy Information Administration (US Energy Information Administration, 2017) Census Data (Bureau of Labor Statistics, 2017) Census Data (Bureau of Labor Statistics, 2017) Census Data (Bureau of Labor Statistics, 2017) NHTSA Annual Report (National Highway Traffic Safety Administration, 2016)	28,400–173,300 2.3–13.5 0.86–4.52 13.9–27.5 10.9–19.8 5.3–18.4 330–1517	State
B*	Exposure	None	N/A		State and Time
C*	Technological Modifications	VMT per vehicle	Highway Statistics Series (National Highway Traffic Safety Administration, 2016)	6060–30300	State
D	Travel Behavior/Risks	Percent of Fatalities caused by Drivers Under the Influence (DUI) (%) Percentage of Fatalities involving Speeding (%) Alcohol Consumption per capita (Gallon per capita)	Fatality Analysis Reporting System (FARS) Database (National Highway Traffic Safety Administration, 2016) FARS database (National Highway Traffic Safety Administration, 2016) National Institute on Alcohol Abuse and Alcoholism (National Institute on Alcohol Abuse and Alcoholism, 2017)	13–60 6–62 1.25–4.70	
E	Infrastructure	Seatbelt Usage (%)	NHTSA Annual Report (National Highway Traffic Safety Administration, 2016)	38.9–98.2	State
F	Urban Form	Walking Share	Census Data (US Census Bureau, 2017)		State
G	Moderating/ Preventing	Density GDL (Dummy variable) Seat Belt Laws (Dummy variable)	Census Data (US Census Bureau, 2017) NHTSA Annual Report (National Highway Traffic Safety Administration, 2016) NHTSA Annual Report (National Highway Traffic Safety Administration, 2016)	0–1 0–1	State
H	Mitigation	Gas Tax (\$ per Gallon, adj. to 2010)	Highway Statistics Series (Federal Highway Administration, 2017)	0.07–0.52	
-	Fatality Rate	Infant Mortality (Infant death per 1000 birth) Fatality per 100,000 population	National Center for Health Statistics (National vital statistics reports) FARS database (National Highway Traffic Safety Administration, 2016)	3.8–16.0 2.3–39.4	Dependent Var

Notes: *Indirect impact.

state effects.

G. Moderating/Prevention: These factors can be interpreted as the regulation and enforcement regime in each state. Two safety policies emerge from the literature as being especially important: Graduated Driver's Licensing Policy (GDL) and seat belt laws. Beginning in mid-1990's, some states implemented GDL program that restrict when and with whom novices can drive. We used a dummy variable to represent whether a GDL policy was in effect in a state in any given year, setting the variable to 1 if there is a policy and 0 otherwise. Currently, in 18 of the 50 states, the seat belt infraction is considered a secondary offense, which means that a police officer cannot stop and ticket a driver for the sole offense of not wearing a seatbelt. Otherwise the seat belt law is referred to as a primary law. We used a dummy variable to study the effect of this law on fatality rate; we set a value of 1 for all states with primary seat belt law in different years and a value of 0 otherwise. A final policy that states can use to influence traffic safety (via travel behavior) is gas tax. We adjusted this variable to 2010 values to correct for inflation.

E. Mitigation Factors: Whether or not a result in a fatality may depend on the quality of the health care system, specifically trauma management and emergency response times. We could not find any direct measurement or reliable data for the emergency response and mitigation at the state level analysis. Accordingly, a proxy that we chose to represent this at the state scale is infant mortality, which has been used extensively in other studies (Noland Robert, 2003).

3.2. Two steps panel modeling specification

In the section following, we explain the specifications of a two-step modeling process, which we used to address the research question. First, we introduce the specifications of the panel model and then we discuss a supplemental model that is used to better understand the effect of factors that we could not be entered directly into the model because of issues with data availability.

We used a panel data approach to assess the main determinant of the road fatality rate over time and between states, a similar framework has also been used in the past by Grabowski and Ahangari et al. (Ahangari et al., 2014; Grabowski David and Morrissey, 2004). Our data encompasses 857 observations (51 states over 17 years). Because our dependent variable, fatality per population, has no discrete values, we used a natural-log transformed normal regression panel model, specified as follows:

$$\log(\text{fatpop}_{st}) = \beta \log(X_{st}) + (\text{State}X = F) + (\text{Time}X = F) + \varepsilon_{st} \quad (1)$$

Where: *fatpop*, refers to road fatality per 100,000 population;

X includes the set of all explanatory and control variables;

β refers coefficients of X;

ε is the error term for state *s* at time *t*;

(StateX = F) represents the fixed effect for each state;

and (TimeX = F) represents the fixed effect for each year;

The proposed model can be used to give insights concerning variables that we have not been able to represent in the model – so called omitted variables. Omitted variables generally fall into one of two categories: those omitted variables related to state-specific factors and those related to time-specific factors (Green, 2012). The conceptual framework and data section suggested that in this research omitted variables largely reflect the built environment as well as technology. The omitted variables can be in the form of fixed-effect or random-effect. In theory, if the omitted variables correlate with the independent variables a fixed-effect model should be used. We hypothesized that a fixed-effect model would be appropriate in this study because omitted variables like the density factors are likely to be correlated with independent variables in the model such as VMT per capita. The Hausman test can also be used to assess when the appropriateness of our assumption concerning whether or not to use a fixed-effect model (Green, 2012).

In this study, we also develop a supplement analysis to understand the effect of factors that were not available for all years of analysis. The factors that are being tested with this approach are the percentage of commuters walking and two other measures representing the population density and distribution in the state. One outcome of the panel model is the estimated state-effect factor for each state. We hypothesize that the variable we are testing with this supplemental analysis are contributing to the estimated state-effect values. To test this hypothesis, we use a simple multiple regression model in which the state-effect values are the dependent variable and the variables of interest are the independent variables which was available for 2010.

3.3. Collinearity and factor analysis

In the data section above we discussed the 17 independent variables that are available to be entered into the panel data model. Before, running the panel model, we conducted a number of correlation tests designed to ensure that we did not include in the panel model variables that were highly correlated. A simple correlation test showed that the correlation between *Percent of Population under 15* and *Percent of Population over 65* is more than 0.60, while the correlation value between all other pairs of variables was lower than 0.5. We also conducted a factor analysis to identify potential factors that have effect on road fatality as a group. The factor analysis suggests that the demographic factors are all in the same group. In other words, *Percent of Population under 15* and *Percent of Population over 65* are in one group and, thus, we need enter only one of them in the panel model. Overall, based on the correlation and factor analysis we decided not to include *Percent of Population over 65* and *gas tax* in our initial panel model, and we entered 15 of 17 variables in the initial panel model.

4. Results of panel modelling

In this section, we present the results of each of the five sequential panel data models in turn. As explained above, we then analyzed the state-effect from the final model in order to see how they relate to the two omitted factors for which we have proxies.

4.1. Results from panel models

The results of the five panel models are shown in Table 2. Detailed discussion of the results from each model is given in the following sections.

Model 1 is a base model that takes into account all of the explanatory variables but has no time or state fixed effects. The model has an R^2 of 0.77, which means that these factors explain 77% of the variations in road fatality rates between states. All explanatory variables have statistically significant effect on road fatality rate with the exception of *percentage of population over 65*. All signs in the model are as expected. Gasoline price, GDP per capita, unemployment, GDL policy and seat belt law are inversely related to the road fatality rate while all other factors are positively related to an increase in traffic fatality rates.

Model 2, which extend Model 1 by including time effects, have exactly the same R^2 of 0.77, and all explanatory variables are statistically significant. Comparing to Model 1, the fact that we have the same R^2 value suggests that adding time effect does not add to the explanatory power of the model. This suggests that other variables in the model are adequately accounting for changes in traffic fatality over time.

Model 3 considers state effect and no time effect. With the addition of the state effect and the removal of the time effect, the R^2 value increases significantly to 0.91. It is important to note that in the panel modeling process it is not uncommon that including a place effect significantly increases the R^2 value. The reason for this is that the state effect typically accounts for variations in many of the variables that are not already included in the model. These include hard to characterized

TABLE 2
Road traffic fatality rate regressions.

Independent var	Dependent Var				
	Model 1 (fatpop)	Model 2 (fatpop)	Model 3 (fatpop)	Model 4 (fatpop)	Model 5 (fatpop)
Real Gas price	-0.034 (0.00)*	-0.011 (0.68)	-0.051 (0.00)*	-0.106 (0.00)*	-0.110 (0.00)*
Unemployment	-0.113 (0.00)*	-0.065 (0.04)**	-0.156 (0.00)*	-0.199 (0.00)*	-0.202 (0.00)*
GDP per capita	-0.465 (0.00)*	-0.469 (0.00)*	0.134 (0.13)	-0.155 (0.03)**	-0.105 (0.09)**
Vehicle per capita	1.203 (0.00)*	1.186 (0.00)*	1.073 (0.00)*	0.876 (0.00)*	0.862 (0.00)*
VMT per Vehicle	1.119 (0.00)*	1.125 (0.00)*	1.033 (0.00)*	0.853 (0.00)*	0.840 (0.00)*
Infant Mortality Rate	0.598 (0.00)*	0.587 (0.00)*	0.287 (0.00)*	0.314 (0.00)*	0.315 (0.00)*
Alcohol Consumption per Capita	0.190 (0.00)*	0.216 (0.00)*	0.04 (0.24)	0.020 (0.47)	
Percent of Population 15–24	0.417 (0.00)*	0.326 (0.00)*	0.652 (0.00)*	0.380 (0.00)*	0.420 (0.00)*
Percent of Population over 65	-0.024 (0.72)	-0.026 (0.71)	0.142 (0.12)	-0.099 (0.22)	
Graduated Drivers Licensing	-0.125 (0.00)*	-0.135 (0.00)*	-0.068 (0.00)*	-0.026 (0.00)*	-0.026 (0.00)*
Seat Belt Law (Primary, Secondary)	-0.033 (0.04)**	-0.031 (0.07)**	-0.067 (0.32)	-0.013 (0.29)	
Seat Belt Usage (%)	0.160 (0.00)*	0.123 (0.07)**	-0.139 (0.02)**	-0.159 (0.00)*	-0.170 (0.00)*
Percent of Fatality Caused by Speeding	0.038 (0.05)**	-0.034 (0.09)**	-0.011 (0.88)	0.012 (0.71)	
Percent of Fatality Caused by Under Influence Drivers	0.213 (0.00)*	0.165 (0.00)*	0.216 (0.00)*	0.184 (0.00)*	0.183 (0.00)*
State Fixed Effect	No	No	YES†	YES†	YES†
Time Fixed Effect	NO	YES†	NO	NO	NO
Adjusted-R ²	0.77	0.77	0.91	0.94	0.94

- Standard errors are presented in the parentheses.

* Significant at 1% level.

** Significant at 5% level.

*** Significant at 10% level.

† Hausman test approved that FE model is better.

factors such as differences in driving culture, in design policy and, as we shall see later in the supplemental analysis, differences in urban form. In this case for Model 3, these unobserved factors represented by the state effect can be interpreted to account for about 14% of the error in Model 1.

With the addition of the state effect we now have four explanatory factors – alcohol consumption per capita, seat belt law, population over 65, and percent of fatality caused by speeding– that are statistically insignificant. One explanation why these variables are not statistically significant once we include the state effect might be due to the fact that how these variables are characterized and governed varies from state to state. For example, the percentage of fatality caused by speeding is determined by the threshold that is selected to define speeding. How this threshold is defined will vary from state to state or even from jurisdiction to jurisdiction in the same state. All of these factors combined limit the extent to which these variables may represent actual behavior.

The analysis of error term for Model 3 reveals that the variances of the residuals are correlated with the calculated value for road fatality rate, a condition that is referred to as heteroscedasticity. This requires that the model be rerun with a relaxation of the homoscedasticity assumption. Model 4 therefore uses a robust GLS (Generalized Least Square) approach to estimate the coefficients under condition of a relaxation of the homoscedasticity assumption. As in Model 3, we released the time effect and kept the state effect. The results showed that the R² is 0.94. The findings of Model 4 are similarly to Model 2, but all variables show a higher level of statistically significant.

In the fifth and final model, we removed alcohol consumption per capita, percentage of population over 65, seat belt law, and percentage of fatality caused by speeding, which were the statistically insignificant variables in Model 4. The findings of Model 5 are similar to Model 4, but we obtain more statistically significant relationship for all variables.

4.2. Supplementary analysis: assessing the state effect

In this section, we analyzed the state-effect coefficients from Model 5. The state-effect is an estimated value for each state, which represents the effect of state specific factors that are not represented by variables in the panel model Fig. 3. Shows the estimated value of the state-effect for all 50 states and DC. As the figure shows, the highest state-effect

coefficients are for Montana, Wyoming and Kentucky at 0.407, 0.341, and 0.300, respectively. Conversely, Massachusetts, Rhode Island, Connecticut at -0.545, -0.397 and -0.310, respectively, had the lowest values of state-effect coefficients. These results can be interpreted to mean that the state specific omitted varies are contributing to higher fatalities in states like Montana and lower fatality in states like Massachusetts. The purpose of the analysis in the rests of this section is to attempt to better understand some of these omitted state specific factors.

In the data section we stated that infrastructure design and availability, along with urban form and the built environment, are the two important groups of factors that were not represented in the panel model. As we discussed, we do not have any readily available data for characterizing the features of the transportation infrastructure that affect traffic safety. Instead, we use% of commuters walking as a proxy to represent how well the system accommodate multimodal travel. For the urban form, we developed two custom measures of density: a high density factor (weighted density in which the most urbanized 10% of each state’s population lives) and a low density factor (percentage of the state living in census blocks with very low population density). In this section we used percentage of population which subscribed to wireless cell phone providers in 2010 as a proxy for the potential of distracted driving Fig. 4. Illustrates the relationship between state-effect and i) commuter walk share, ii) high density area factor, iii) and low density area factor, respectively.

As we discussed earlier, a positive value of the state effect coefficient indicates that the state specific factors are resulting in higher traffic fatality rates in that state. The results above show that all three of the variables we tested have a statistically significant relationship with the state effect coefficients. The first plot shows that the state effect decreases as walking percentage increases. In other words, the more people walk (which might be due to a better environment for walking) the lower the rate of fatality in that state. Similarly, the higher the density of the most dense part of the state, the lower the traffic fatality. Conversely, the higher proportion of people living in very low density conditions the higher the traffic fatality rate.

In order to get a better understanding of the interaction between these factors, we conducted a simple multiple regression analysis. Because the high density and the low-density factors are highly correlated we chose to enter only the low density factor in the model. The

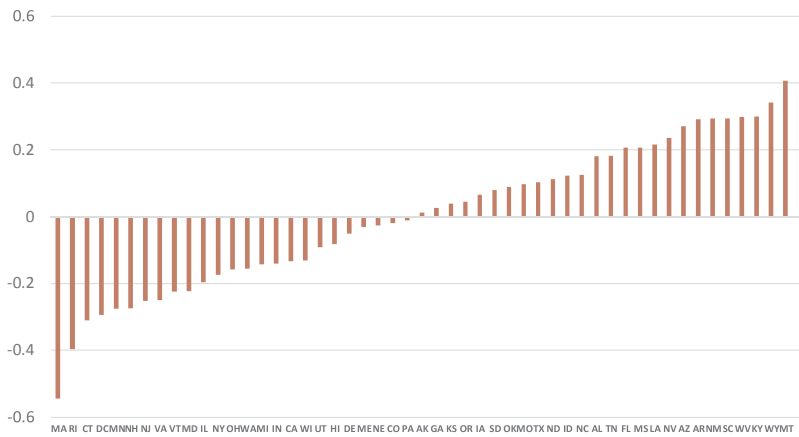


Fig. 3. Estimated State-effect Coefficient.

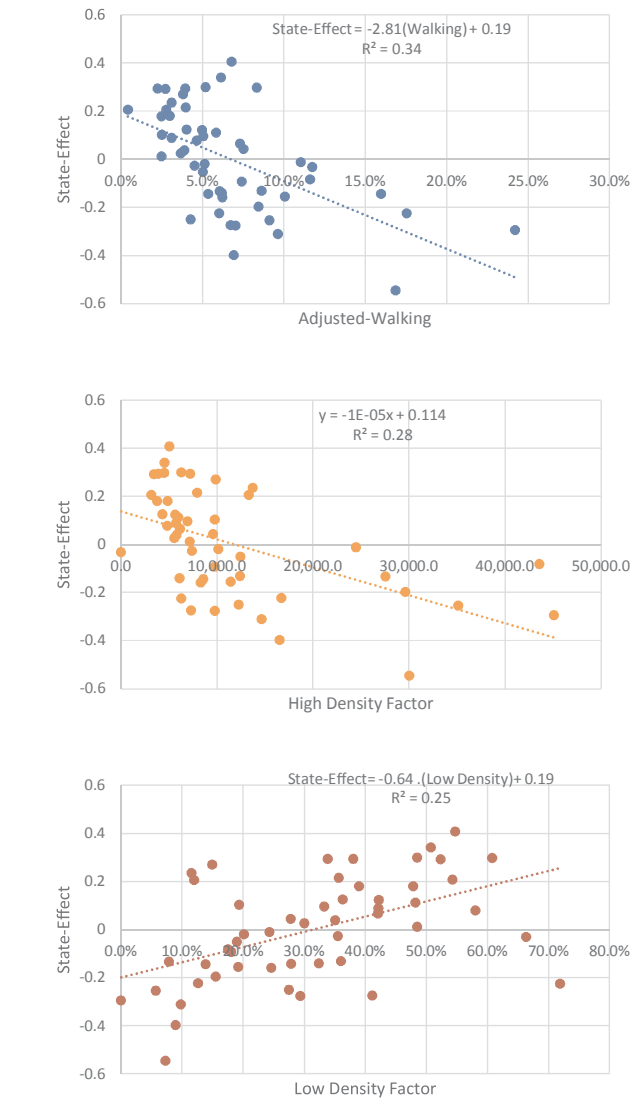


Fig. 4. Estimated State-Effect Coefficient vs Walking, Low Density, and High Density Factors.

estimated model is as follow:

$$\text{State-effect} = 0.004 + 0.492 * \text{Low Density} - 2.367 * \text{Walk share}$$

The t-value shows that both variables are highly statistically significant in this model. The R^2 value is 0.48, which indicates that these two variables explain about 50% of the variations embedded in the

state effect coefficient. This analysis suggests the importance of infrastructure and urban form in affecting the differences in traffic fatality between different states.

5. Discussion and conclusions

In this paper, we present an empirical study to quantify the impact of a wide range of variables on traffic fatality rates (defined as deaths per 100,000 population) for the fifty states and Washington DC using annual data from 1997 to 2013. We use panel models to evaluate both spatial and temporal variations in safety patterns with the overarching objective of understanding what factors explain variations in traffic fatalities between states. We then go on to consider the effect of two important factors—density and mode share (as a proxy for infrastructure conditions) to consider the potential impact of these factors that we were not able to include in our panel model.

The starting point for our empirical approach is a conceptual framework that we developed which builds on a schema from the World Health Organization (WHO). This conceptual framework is designed in order to capture a more complete set of factors that could potentially explain traffic fatalities. The categories of variables considered in this analysis include standard metrics to represent socio-economic characteristics such as GDP per capita, gas prices, unemployment and demographic structure; exposure variables measured by vehicles per capita; and mitigating factors such as the quality of the health care system. Additional variables considered in this analysis include the adoption of state-wide regulations on seat belts and graduated driver’s licensing (GDL), as well as behavioral variables such as the percentage of seat belt usage, the percentage of fatalities caused by speeding, and the percentage of fatalities caused by drivers deemed to be under the influence of alcohol.

Variables that we were not able to include in our panel model are urban form and mode share (as a proxy for infrastructure). These are important to consider because of their well-documented impacts on traffic fatalities (Ahangari et al., 2014). Accordingly, we analyze the state effects generated by the panel models alongside proxies for some of the omitted variables to understand what role they may play in transportation safety.

We found that without including the state effect the panel model explained 79% of the variation in traffic fatality rates between states of the 16 variables initially included in the model we eventually eliminated four variables which were found to not be statistical significant in the model. In order to understand the explanatory power of each variable we compared the elasticity values for each of the variables in the final model. We found that the variables listed in order of their contribution to the differences in traffic fatality rates between states is as follows (the elasticity value are given in brackets): Vehicle per population (+0.862), VMT per vehicle (+0.840), Infant Mortality (a

proxy for the quality of health care in the state) (+0.315), Unemployment (−0.220), Percent of Fatality Caused by Under Influence Drivers (+0.186), Seat belt Usage (−0.170), Gasoline Price (−0.110), and GDP per Capita (−0.105). In other words, Vehicle per population and VMT per vehicle are the two factors that contribute the most to the variation in traffic fatality between states. The 0.862 elasticity value for Vehicles per population can be interpreted to mean that a 10% increase in vehicle ownership is associated with an 8.62% in traffic fatality rate. It is interesting to note that the elasticity found for gas price at −0.110 is smaller but in the range found by Grabowski (−0.340) and in an earlier study of countries by Ahangari (−0.220).

We also found that the state effect contributes to a 17-percentage point increase in the explanatory power of the model. This state effect is given in terms of the state effect coefficient. As discussed previously, the state effect coefficient is one way of representing variables that we were unable to include directly in the panel model. These variables include percentage of people walking to work (which is a proxy for transportation infrastructure supportive of multimodal travel) and measure of urban form (a high-density factor and a low-density factor). We found that all these variables were significantly related to the state effect coefficient. States with more people working were found to have lower traffic fatality after correcting for all the other factors considered in this study. States with high-density factors also had lower traffic fatality rates after correcting for all other factors.

Taken as a whole, our findings suggest that if additional progress is to be made in reducing traffic fatalities, emphasis needs to move beyond simply focusing on policies such as GDL and seat belt laws, which have already been adopted by almost all jurisdictions across the United States. We need to also consider factors that focus on the type of urban form that we are creating to ensure that we are fostering environments that encourage multi-modal transportation such as walking.

A body of literature does exist looking at the linkage between road design, infrastructure, and built environment, on the one hand, and road fatality, on the other. However, none of these studies has looked at how these factors affect road fatality in comparing differences between states. Our study is one of the first to demonstrate a correlation between urban form and traffic fatality at the statewide scale. Thus our results suggest an urgent need to more fully characterize the underlying nature of this relationship.

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