Journal of Safety Research 80 (2022) 311–319

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

The influence of inferred traffic safety culture on traffic safety performance in U.S. States (1994–2014)

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ARTICLE INFO

Article history:
Received 13 December 2020
Received in revised form 24 May 2021
Accepted 14 December 2021
Available online 24 December 2021

Keywords:
Traffic safety culture
Traffic safety
Modeling

ABSTRACT

Introduction: Traffic safety performance (crash fatalities per billion vehicle miles traveled) is influenced by many factors related to the physical and social environment. The traffic safety culture in the local environment can influence behaviors that influence the risk of a fatal crash. However, if traffic safety culture is defined as "shared beliefs," it is not possible to directly observe the effect of culture on traffic safety performance. *Method:* This study replicated the method proposed by Page (2001) to infer the effect of traffic safety culture on traffic safety performance for U.S. states between 1994 and 2014. This method infers the influence of traffic safety culture from the error between actual and predicted performance based on observable variables that measure the physical and social environment as well as behavioral hazards. *Results:* The results suggest that a positive traffic safety culture can have a protective effect by producing a lower-than-expected fatality rate. Conversely, a negative traffic safety culture can have an exacerbating effect by producing a larger-than-expected fatality rate. *Conclusion:* The derived metric for estimating traffic safety culture had strong concurrent validity by correlating with the ranking of states based only on total crash fatality rate. *Practical Implications:* Consistent with Page (2001), the analysis also identified common risk factors across states including per capita alcohol consumption and unemployment rate.

1. Introduction

Traffic crashes were among the top 10 leading causes of death in the world in 2016 (WHO, 2018). In the United States, traffic crashes ranked in the top three causes of death and disability as early as 2003 (NHTSA, 2006). The health issue created by roadway performance is multifaceted with positive and negative influences from both physical and legal systems, road user behavior, and traffic safety culture. Given the associated social and economic costs, the performance of our roadway system should be a primary public health issue. To improve traffic safety performance, we first need to understand the nature of safety hazards within the roadway system. For example, Eiksund (2009) proposed the road safety hazard model shown in Fig. 1.

In this model, there are two sources of hazard relevant to traffic safety performance. The physical environment creates "system hazards" in the form of adverse weather, natural obstacles, and constraints to safe roadway system design. These hazards increase both crash risk (e.g., icy roads) and crash severity (e.g., natural roadside obstacles). The physical environment also influences the development of certain social environments. The social environment can be characterized by resident demographics, viable industries, governance methods, educational institutions, social services, economic systems, and so forth. In turn, the social environment fosters a local culture, which can influence the behavior of road users and traffic safety stakeholders sharing that culture. Aspects of local culture that influence deliberate stakeholder actions (e.g., setting and enforcing speeding laws) and road user behaviors (e.g., violating those laws by speeding) can be termed traffic safety culture, which we define as "the shared belief system of a group of people, which influences road user behaviors and stakeholder actions that impact traffic safety" (Ward, Otto, & Finley, 2019). Page (2001) notes, the safety performance of the transportation system depends on the interplay between stakeholder actions and road user behaviors, which is demonstrated by "the ability of a road safety policy to be effective and the ability of a population to accept and respect this policy" (p. 372).

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https://doi.org/10.1016/j.jsr.2021.12.014
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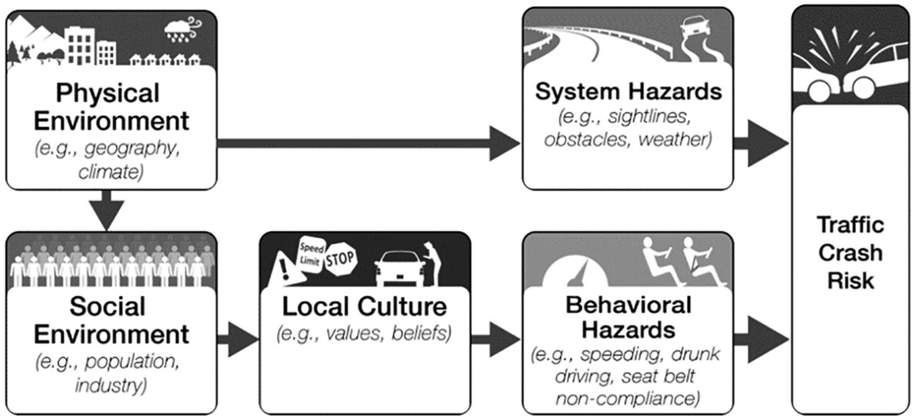

Fig. 1. Road safety hazard model based on physical and social environments (adapted from Eiksund, 2009).

Both the physical and social environments as well as their systems and behavioral hazards are directly observable. Similarly, crash risk is calculated from observed and reported vehicle crashes. For example, for each reported fatal crash, the Fatal Analysis Reporting System (FARS) identifies the associated system hazards (e.g., weather conditions, road surface conditions, presence of roadside obstacle) and behavioral hazards (e.g., speeding, no seatbelt, presence of alcohol). In contrast, local culture as a component of this model and defined as "the shared values and beliefs" cannot be directly observed because these mental representations are internalized. Thus, traffic safety culture must be measured indirectly as a mediating variable in this model.

2. Measuring traffic safety culture

Several methods may be used to indirectly measure traffic safety culture. First, we can use observable elements of the social environment as *surrogates* for local culture. For example, Melinder (2007) showed that census indicators of socioeconomic factors such as religious affiliation and economic wealth can correlate with traffic safety. Second, we can create surveys that capture self-reported values and beliefs. For example, Gaygisiz (2010) used self-report measures of perceived governance quality across 51 different countries, which correlated with traffic fatality rates (traffic safety). Third, we can infer culture based on statistical methods that predict the number of traffic fatalities based on observable variables (Page, 2001). The logic of this method assumes that the unobserved effect of culture is contained within the residual error of the prediction model that uses relevant observed variables; that is, traffic safety culture accounts for part of the discrepancy between the number of traffic fatalities predicted by directly observable hazards (Fig. 1) compared to the actual number of traffic fatalities.

This study explores the inferential method to estimate state-level traffic safety culture based on the model Page (2001) developed for a set of European countries. Page (2001) used regression modeling (time-series, cross-sectional) to predict the number of traffic fatalities in 21 countries between two time periods that spanned approximately a decade (1980–1982 and 1992–1994). The original set of predictor variables are observable variables known to correlate with fatal crashes, shown in Table 1. Several of these observable variables reliably predicted traffic fatalities within these countries. For example, a 10% increase per capita alcohol consumption was associated with a nearly 4% increase in the number of traffic fatalities.

Table 1
Observable variables predicting changes in traffic fatalities (Page, 2001).

A 10% increase in these	leads to this change	
*Population	+9.6%	
Percentage of youngsters (15–24 years)	+8.3%	
Percentage of urban population	−4.1%	
*Percentage of population employed	+3.9%	
Vehicle fleet per capita	+2.8%	
Percentage of motorized fleet that are buses or coaches	−1.6%	
*Alcohol consumption per capita	+3.9%	in traffic fatalities

Note: * Variables were also predictors in analysis reported in this paper.

Based on the final regression model, Page (2001) asserted the residual error included the unobserved effect of *traffic safety culture.*[1] Using this residual error, Page (2001) computed a metric that can be interpreted as an estimation of the prevailing traffic safety culture. Fig. 2 illustrates this metric for each country at both time periods. According to Page (2001), this metric is an alternative measure of safety performance that accounts for "exogenous variables" that are characteristics of different countries. Countries (for a given year) that had a <u>lower</u> than predicted number of traffic fatalities were assumed to have a stronger (protective) traffic safety culture. In these cases, some aspect of the local culture was assumed to have offset the number of traffic fatalities that was expected based only on the observable hazards. Conversely, countries having a <u>higher</u> than predicted number of traffic fatalities were assumed to have a weaker traffic safety culture – one which exacerbates the observable hazards. In these cases, local culture was assumed to have increased traffic fatalities beyond what was expected based only on the observable hazards. Within a country, the change in the value of this metric between time periods shows the direction of change in estimated culture.

From this analysis, it is interesting to note that the estimated traffic safety culture of the United States was low compared to most other countries. Indeed, it's apparent that U.S. growth in traffic safety culture over this time period was one of the smallest. What is it about the culture of the U.S. that resulted in a weak traffic safety culture that had minimal growth over time? Given that the U.S. is one of the largest countries in the world and comprised of many independent states, the answer to these questions may best be understood by examining the different local cultures within these states. The study reported here adapted Page's

[1] Page actually refers to this as "system performance' but given the consistency of his use with traffic safety culture, we are using the latter term.

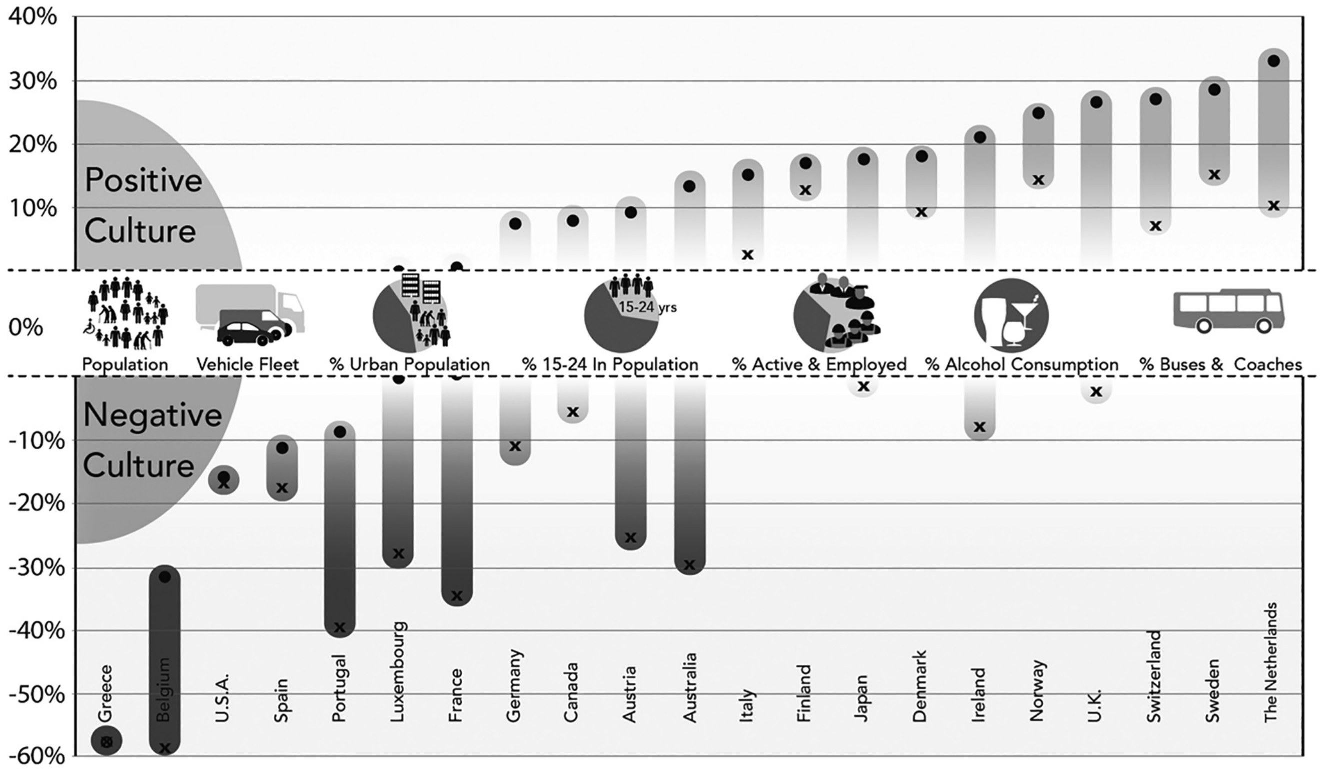

Fig. 2. Estimated traffic safety culture by country between controlling for selected observable variables for 1980–1982 and 1992–1994 (adapted from Page, 2001).

(2001) method to measure the estimated traffic safety culture of individual U.S. states in the decades between 1994 and 2014. At the time this project was conducted, this data set (1994–2014) was the most recent and available for all the states, encompassing the physical and social elements of the road safety hazard model outlined above. Like Page (2001), our time span let us estimate culture at two points in time to assess the amount of change over time. Our study used the traffic safety model in Fig. 1 as a framework to select relevant predictor variables within this time span to estimate safety culture.

Methodology

Our interest is in understanding estimates of traffic safety culture and the impact of that culture on traffic safety performance. Adapting Page's (2001) work, we used the error term in a model of traffic safety performance to estimate traffic safety culture. The development of our model required multiple steps. The process began with collection of data from a wide variety of sources. Given the variability of sources, in many cases the data was incomplete. Therefore, the second step was the imputation of missing data. This complete data set was then utilized to develop individual regression models for each state.

2.1. Data set

Our model criterion for traffic safety performance was defined as the annual number of traffic fatalities per billion vehicle miles travelled for each state (1994–2014) based on the Fatal Accident Reporting System (FARS). Thus, we did not account for population size as a characteristic of the social environment as Page (2001) did in his model but instead included this as an exposure term for our criterion.

The proposed model, shown in Fig. 1, of the physical environment and social environment as well as system and behavioral hazards was used as a framework to select relevant predictor variables. These data were obtained from a variety of public datasets. Our purpose was not to provide an exhaustive test to validate all the predicted relationships in this model. Instead, we focused on a subset of the most meaningful relationships for which reliable data were available across our time span.

A total of 46 different predictor variables were identified as listed in Appendix I. As an example, the following is an abbreviated list of variables used to measure each component of the hazard model (see Fig. 1):

- *Physical environment* including items such as annual temperature and precipitation
- *System hazards* such as total road length and registered motorcycles
- *Social environment* such as number of community hospitals, unemployment rate, and total percentage of male drivers
- *Behavioral hazards* including alcohol consumption rates and the percentage of fatal crashes related to distraction

2.2. Missing data

Given the large number of data elements and the 21-year timeline, the data used in the model for all variables in all states at all times was not complete. Evaluating the missing-ness of the data, other than a pattern of some fields not being available in early years, it appeared that the data was missing completely at random. Details of the missing data related to the variables are summarized in Table 2.

To account for this, missing data were imputed using the multiple imputation method provided by the PROC MIANALYZE method using SAS (v.9.4) to create 10 data sets for each year. This process used Rubin's (1987) method for combining the results of separate estimates and standard errors from datasets into a pooled estimate with standard error, confidence intervals, and p-values.

Table 2
Summarized information on the missing data for each state.

Variables	Number of Missing Data	Which year the data is missing
Urban Population	9	1994–97, 2009, 2011–14
Rural Population	9	1994–97, 2009, 2011–14
Number of Hospitals	5	1994–1998
Number of Nurses	3	1994–1996
Number of Emergency Response Team	3	1994–1996
Annual Price of Diesel	3	1994–96 (17 states only)
Number of Beds per 1000 person	3	1995, 1999 & 2014
Number of Physicians per 1000 people	2	1999 & 2014
Percentage of Male Driver	1	1994
Percentage of Male Driver	1	1994
Expenditures of Road Improvement	1	2011

This imputation model was used in some instances of 11 different variables ranging from a single time period for variables such as road improvement spending, to 9 instances of urban population. In total, only 40 data points were imputed from a total of nearly 1,000 collected to develop the model for each state, indicating a minimal risk created by this technique.

2.3. Prediction model

The purpose of our analysis was to explore which variables were predictors of safety performance. Stepwise regression was utilized to select and reduce the set of potential predictor variables suggested by the full model in Fig. 1. Initial data analysis separated the data for each state and constructed 50 separate regression models (one for each state). These regression models were utilized to identify significant predictors in any state. This list of likely significant regressors was utilized to begin exploration for the panel data with all 50 states for development of the universal model.

In our model, we are predicting traffic safety performance based on observed variables as shown in Eq. (1) in which $i = 1, 2\ldots$ N represents the cross-sectional component, the individual states, and $t = 1, 2\ldots$ T represents the time index ($t = 21$). Y_{it} is the dependent variable of traffic fatalities for the jurisdiction and time modeled. Traffic safety culture is unobserved but also influences that performance. Traffic safety culture is part of the error term in the prediction of performance.

$$Y_{it} = \beta_0 + \sum \beta_j X_{it} + u_{it} \tag{1}$$

In contrast to Page (2001), who utilized a log function regression model for fatalities, this study utilized simple linear regression modeling with the dependent variable being fatality per billion Vehicle Miles Travelled (VMT). This simple conversion allowed our data to meet the assumptions required for use of regression (i.e., normalcy) without employing a data transformation (such as log or Box) that would move the data out of a readily understandable format.

To obtain the results, an initial screening process of regression models was run with SAS software (v.9.4). A PROC MI statement was utilized to generate 10 multiple imputed datasets, which was determined to be statistically sufficient to generate reliable estimates using the PROC MIANALYZE procedure. In the PROC MIANALYZE statement, Rubin's (1987) rule was used to combine the separate estimates. In addition, PROC REG and PROC PANEL statements were used to obtain the necessary results for the stepwise analysis of VIF, model fit, diagnostics results, estimates, and other parameters. A threshold for variance inflation factor (VIF) of 5 was utilized to avoid issues with multicollinearity. This screening yielded an initial list of 15 suitable variables. By checking both the heteroscedasticity of the error term and the VIF values for multicollinearity, the authors have ensured that the error terms were uncompromised.

Thereafter, a second level screening was accomplished by removing low contributing (p-value >0.05) variables using stepwise regression. When all the variables were found to be significant, the final regression model was attained using PROC MIANALYZE, which uses Rubin's rule of pooled estimation. The final set of parameters was identified for the final regression model (Eq. (2)). The details of the final set of predictor variables for our analysis is summarized in Table 3.

$$\begin{aligned}
&\textbf{\textit{Crash Fatality Rate}}\ (\textbf{\textit{Fatalities per billion VMT}}) \\
&\quad = 11.87 + (-0.19 * Unemployment) + (0.00002 * Length) \\
&\qquad + (0.21 * Temperature) + (2.37 * Alcohol) - (0.51 \\
&\qquad * Seatbelt) + (0.56 * Cellphone) + (2.13 * Inattention) \\
&\qquad + (0.23 * Beds) - (0.00016 * Population) - (0.17 \\
&\qquad * Physicians) - (0.05 * Democratic) - (0.06 * Republican)
\end{aligned} \tag{2}$$

2.4. Traffic safety culture estimation

Based on the average estimates, the overall model fit (R-square) value was 13.81% with a range between 13.69% and 13.96%. While this fit is lower than might be hoped for in a model of human behavior, it is not an unreasonable level of explanation given the complexity of the outcome being modeled (Stevens, 2002) and the expectation that residual error is an indication of traffic safety culture. As Page (2001) stated, this lack of fit "simply means that many unexplained variations are contained in residuals and that intervention variables and additional exogenous variables are powerful in explaining road safety levels and road safety trends" (p. 380).

Using a similar approach to Page (2001), our analysis then focused on the residuals error ($R_{it}^{\wedge}$) produced by this model, where $R_{it}^{\wedge}$ is defined by Eq. (3).

$$\begin{aligned} R_{it}^{\wedge} &= \text{Observed Traffic Fatality Rate} \\ &\quad - \text{Predicted Trafic Fatality Rate} \end{aligned} \tag{3}$$

In Eq. (3), $R_{it}^{\wedge}$, represents the overall estimate of the residual for an individual state in an individual year using the pooled error from the 10 data sets imputed for each year.

Using these residuals, the final of the estimated traffic safety culture (eTSC) is included in the error term given by Eq. (4):

$$I_{it} = 100 - R_{it}^{\wedge}/\text{actual fatality per billion VMT} * 100 \tag{4}$$

Table 3
Pooled estimates for model predicting crash fatality rate.

Variable	Estimate	95th Percent Confidence Interval		Significance
Intercept	11.87	3.00	20.75	<0.009
Physical Environment				
Average annual **temperature** (Fahrenheit)	0.21	0.14	0.27	<0.0001
Social Environment				
Unemployment Rate (percentage of population unemployed)	−0.19	−0.29	−0.08	<0.0005
Presence or absence of **seatbelt** law	−0.51	−0.84	−0.18	<0.003
Presence or absence of **cellphone** law (for novice and teen drivers)	0.56	0.24	0.89	<0.0007
Total number of **beds** in community hospitals (excluding federal, psychiatric and long-term care)	0.23	0.01	0.45	<0.04
State level **population** (thousands)	−0.00016	−0.00026	−0.00006	<0.002
Active (non-federal) **physicians** per 1000 residents	−0.17	−0.31	−0.03	<0.02
Percentage of votes for **Demographic** president candidate.	−0.05	−0.09	−0.01	<0.02
Percentage of votes for **Republican** president candidate.	−0.06	−0.11	−0.02	<0.002
System Hazards				
Length of rural classified roads.	0.000020	0.00000	0.00004	<0.01
Behavioral Hazards				
Proportion of fatal crashes related to "**inattentive** driving and cellphone use while driving"	2.13	0.50	3.75	<0.01
Average annual consumption of **alcohol (gallons)[1]	2.37	1.59	3.16	<0.0001

Note: ** Variable was also significant in analysis by Page (2001) as shown in Table 1.
[1]Aged 14 years and older: https://pubs.niaaa.nih.gov/publications/surveillance104/CONS14.htm.

When the value of $R_{it}^{\wedge}$ was negative, the estimated fatality was higher than the actual value. To explain this, we assume traffic safety culture had added risk to the traffic system (I_{it} is <100). Conversely, when the value of $R_{it}^{\wedge}$ was positive, the estimated fatality was lower than the actual value. To explain this, we assume traffic safety culture had a protective effect across the traffic system (I_{it} is >100). Thus, as this discussion shows, $R_{it}^{\wedge}$ and I_{it} together demonstrate the inferred effect (→) of traffic safety culture on safety performance within the traffic system (see Eq. (5)):

$$\begin{aligned} +R_{it}^{\wedge} &= -I_{it} \rightarrow \text{Risky safety culture} \\ -R_{it}^{\wedge} &= +I_{it} \rightarrow \text{Protective safety culture} \end{aligned} \tag{5}$$

To examine state-level differences in the inferred traffic safety culture, I_{it} for each state was calculated within two time periods (1994–1996 and 2012–2014) by calculating the average $R_{it}^{\wedge}$ across the three years within each time period. The change in estimated traffic safety culture between these periods within each state is depicted in Fig. 2.

Finally, as a simple validation of eTSC, we correlated the number of crash fatalities per million VMT and calculated I_{it} across all states for 2014. This resulted in a large and statistically negative correlation ($r = -0.82$), which suggests that a protective traffic safety culture resulted in a lower crash fatality rate. This level and direction of the correlation appears to further validate the interpretation of our estimate of traffic safety culture using model errors.

3. Discussion

Our physical and social environments determine the local traffic safety culture, which in turn can influence behavioral hazards affecting such outcomes as traffic safety (Fig. 1). In this study, traffic safety culture was assumed to be an *unobserved* variable that predicts the crash fatality rate. Adopting the method used by Page (2001), we assumed traffic safety culture could be estimated from the residual error of a regression model to predict crash fatality rate based on *observed* variables to measure the physical and social environment, as well as system and behavioral hazards (Fig. 1). From this logic, we were able to provide estimates of traffic safety culture for all states for 1994–1996 and 2012–1014. A review of these results indicated that most states had protective traffic safety cultures at the end of this time period, in that their actual crash fatality rate was lower than the predicted rate. This suggests that the (unobserved) traffic safety culture offsets some of the inherent risk imposed by the observed factors in the traffic safety system. For example, Minnesota showed a large increase in traffic safety culture between these time periods, which may be related to the early adoption of a vision for zero traffic fatalities as an effort that sought to improve local traffic safety culture (Fig. 3).

Reviewing the significant predictor variables in the model states (Table 3), some of the estimated effects are intuitive and consistent with published research:

- Higher unemployment resulted in a lower predicted crash fatality rate, presumably because unemployment reduces driving exposure and greater perceived risk of a crash due to higher subjective costs (Reinfurt et al., 1991).
- The more rural the driving environment (e.g., rural road classification, lower state population) the higher the crash fatality rate given that such environments have more hazards (Brown, Khanna, & Hunt, 2000; Henning-Smith & Kozhimannil, 2018).
- An increase in distraction and drunk driving resulted in higher crash fatality rates, consistent with evidence that these are both significant behavioral risk factors in fatal crashes (Shyhalla, 2014). Indeed, these behavioral risk factors had the largest effect on predicted crash fatality rate, which is consistent with evidence that driver behavior is the most common "critical reason" for fatal crashes (Singh, 2018).
- The presence of seatbelt laws reduced the crash fatality rate, consistent with evidence that wearing a seatbelt reduces the severity of crash outcomes (Steptoe et al., 2002).
- Finally, the more (non-federal) physicians available also reduced the crash fatality rate, presumably because available (quicker) care from physicians after a crash can also reduce the severity of crash outcomes (Brodsky, 1993).

The potential causal mechanism of other significant predictors was less intuitive:

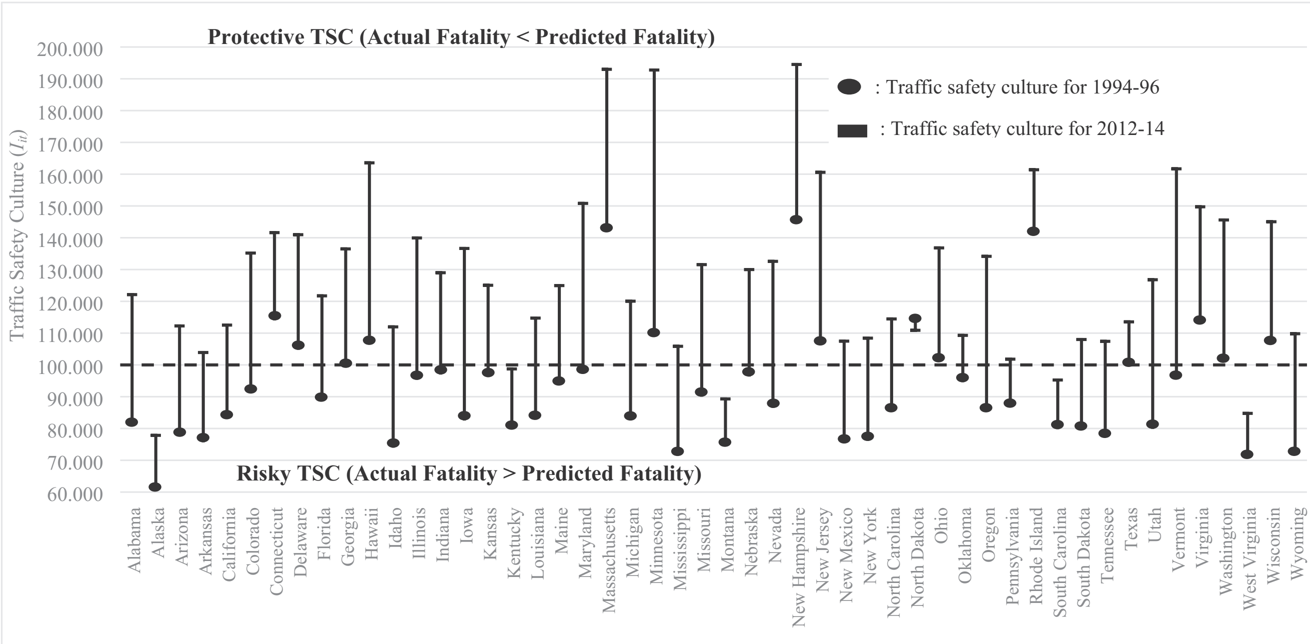

Fig. 3. Estimated traffic safety culture (eTSC) for each state in 1994–96 and 2012–14.

- It is difficult to explain why a larger resident population may reduce the crash fatality rate unless we assume this represents the relationship between lower speeds in higher populated (urban) areas (Zaidel et al., 1992) and reduced severity of crash outcomes (Aarts & van Schagen, 2006). Regardless, the effect size of this predictor variable was negligible and may also reflect a statistical aberration.
- The reason the percentage of votes for both democratic and republican presidential candidates had negative effect on the crash fatality rate is not obvious unless we interpret voting as a prosocial behavior. Voting is often perceived as a civic duty and used as a surrogate measure for "social capital" (Farr, 2004). Social capital within a community has been related to reducing crash fatality rates because of greater awareness and effort to make decisions that support community health (Nagler, 2013a, 2013b).

Admittedly, the relationship of some significant predictors to fatal crash risk was unexpected:

- It is not clear why cellphone laws for novice and teen drivers would increase the crash fatality rate unless we assume these laws are most prevalent in areas with high populations of novice and teen drivers that are prone to have a higher fatal crash risk (Curry et al., 2017) – although it's important to note that the variable representing the population of young drivers was not itself a significant predictor. This outcome may also reflect that these laws are newer and were adopted in response to a known problem. If that is the case, the result may simply reflect a known problem (high fatality rate) where the solution is not yet showing a significant effect.
- And finally, it is not clear why a large number of community hospital beds would relate to an increase in crash fatality rate unless we assume that community hospitals are more prevalent within the rural areas already associated with a higher incidence of fatal crashes.

This discussion suggests that the identification of relevant risks and protective factors from these predictive models may help traffic safety stakeholders prioritize and develop targeted strategies to reduce the crash fatality risk. In so doing, these stakeholders would have another source of data to justify and support their development of a vision for zero traffic fatalities and serious injuries. Indeed, by using a predictive model to estimate traffic safety culture as part of the residual error (I_{it}), stakeholders could routinely use this metric as another performance measure for their efforts in addition to the traditional measures of fatality and serious injury frequency. However, all these suggestions are predicated on the accuracy of the predictive model. Rather than use the form of predictive model derived in this study based on all states, it may be more relevant for states to derive models specific to their own physical and social environments.

This study does have a number of limitations that affect the interpretation of its results and conclusions. First, the selection of (observable) predictor variables was guided by our choice of model to represent the traffic safety system (Fig. 1) but was limited by the availability of associated datasets. During development phase of the dataset, the authors realized the importance of race/ethnicity as a cultural factor and its potential impact on traffic safety culture. However, the needed data were not reliably available for the early years of the study time span and therefore were excluded. Similar challenges were faced obtaining data on vehicle safety features, their application, and the vehicle population associated with such safety features. It is important to note that economic indicators from the later time period include the timeline of the great recession. While the recession impacted all areas of the United States, it is possible that some hidden difference in its impact on states is unaccounted for here and is impacting differences between states. It is possible that alternative system models and alternative datasets could produce more comprehensive sets of predictors. Given that this method infers traffic safety culture from the residual error term – which also includes many other forms of unmeasured variables – the more measured variables that future research can include in these models, the less uncertain such inferences may become.

In addition, the use of imputed measures for missing data has the potential to add bias to the results. We believe the multiple imputation methods based on Rubin (1987) employed here have greatly reduced this risk, but future studies where all data are available may find some evidence of bias.

Finally, we acknowledge that the analysis methods used here simply show correlation between the predictors, the indirect measure of traffic safety culture, and traffic fatalities. While we are interested in causation of this important measure, achieving a measure of cause is not possible employing these methods with the available data. Additionally, employing a multi-level hierarchical modelling approach to the data set might have identified more striking differences in state level models, which might present an alternative analysis path to understand differences in traffic safety culture between the states.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

Predicted Variable	Definition	Comments
Fatalities per Billion VMT	Number of fatalities from motor vehicle crashes involving vehicle occupants and non-occupants per Annual Billion Annual Motor Vehicle Miles travelled	The predicted value was deduced from dividing number of fatalities by Billion VMT
Fatalities	Number of fatalities from motor vehicle crashes involving vehicle occupants and non-occupants	https://www-fars.nhtsa.dot.gov/Main/index.aspx (Accessed at September 2016)
Billion VMT	Annual travel by motor vehicles in billion miles	https://www.nhtsa.gov/ (Accessed at September 2016)

Physical Environment and System Hazards		
Temp	Annual temperature in degree Fahrenheit	https://www.ncdc.noaa.gov/ (Accessed at October 2016)
Preci	Annual rainfall or precipitation in inches	
RoadLength	Total road length in miles	https://www.nhtsa.gov/ (Accessed at September 2016)
RuralRoad	Total road length in miles in rural areas	

Social Environment		
Hospitals	Total number of community hospitals in states (federal hospitals, psychiatric hospitals, long term care hospitals are excluded)	https://www.cdc.gov/nchs/hus/previous.htm (Accessed at September 2016)
Beds	Beds per 1000 person in community hospitals in states (Beds in federal hospitals, psychiatric hospitals, long term care hospitals are excluded)	
Physicians	Active non-federal physicians per 10,000 civilians	http://kff.org/ (Accessed at September 2016)
Labor	Total number of civilian labor force	https://www.bls.gov/ (Accessed at September 2016)
Employed	People employed within the labor force	
Unemp	People unemployed with the labor force	
UnempRate	Percentage of unemployed people	
GDP	Average income per person in dollars	https://www.bea.gov/ (Accessed at September 2016)
RoadExp	Total Statewide improvement capital outlay/expenditures for interstate, arterial and collector systems	https://www.nhtsa.gov/ (Accessed at September 2016)
Population	Total state level population in thousands	
UrbanPop	State level population in thousands in urban areas	
RuralPop	State level population in thousands in rural areas	
DiesPrice	Annual average diesel price per gallon	https://www.eia.gov/ (Accessed at September 2016)
GasPrice	Annual average gasoline price per gallon	
MotorVehicles	Total registered motor vehicles	
MotorCycles	Number of motorcycles owned privately & commercially	
HeavyTrucks	Total number of truck tractors registered	
RoadUsers	Total registered and licensed drivers	
YoungUsers	Registered and	

(*continued on next page*)

	licensed driver from age 15 to 20	
MD	Percentage of male driver of the total road users	
Fdriver	Percentage of female driver of the total road users	
Nurses	Total number of registered and licensed nurses	https://www.bls.gov/ (Accessed at September 2016)
ERTeam	Total number of people of emergency medic team and police, fire and ambulance dispatchers	
SBLaw	Primary enforcement of seatbelt law (presence/absence)	http://www.iihs.org/iihs/ratings (Accessed at November 2016)
CRLaw	Primary enforcement of child restraint law (presence/absence)	
HelLaw	Primary enforcement of helmet law (presence/absence)	Chase (2014)
TextingLaw	Texting on the cellphone or smartphone while driving law (presence/absence)	
BACLaw	Blood alcohol concentration (≤0.08) while driving level law (presence/absence)	https://www.rita.dot.gov/ (Accessed at November 2016)
HandheldLaw	Primary enforcement of handheld devices while driving law (presence/absence)	
CellLaw	Cellphone use while driving for novice and teen drivers' law (presence/absence)	McCartt, Kidd, and Teoh (2014)
DemOrRep	Candidate representing which party during presidential election (Dem = 1, Rep = 0)	http://uselectionatlas.org/ (Accessed at February 2017)
Dem	Vote percentage obtained by Democratic party candidate in presidential election	
Rep	Vote percentage obtained by Republican party candidate in presidential election	
VotePer	Percentage of vote cast from voter population	
AlCons	Per capita consumption of all beverages (wine, beer and spirits) in gallons	https://www.niaaa.nih.gov/ (Accessed at October 2016)

Behavioral Hazards		
Speeding	Percentage of 'driving too fast for conditions or more than posted maximum' of all the errors & violations by drivers that led to fatal crashes	https://www-fars.nhtsa.dot.gov/Main/index.aspx (Accessed at September 2016)
DisDriving	Percentage of 'Inattentive driving and cellphone use while driving' of all the errors and violations by drivers that led to fatal crashes	
DrDriving	Percentage of 'under the influence of drugs, alcohol or medication while driving' of all the errors & violations by drivers that led to fatal crashes	

References

Aarts, L., & van Schagen, I. (2006). Driving speed and the risk of road crashes: A review. *Accid Anal Prev., 38*(2), 215–224.

Brodsky, H. (1993). The call for help after an injury road accident. *Accident Analysis & Prevention, 25*(2), 123–130.

Brown, L. H., Khanna, A., & Hunt, R. C. (2000). Rural vs urban motor vehicle crash death rates: 20 years of FARS data. Prehospital Emergency Care. 4(1):7–13.

Curry, A. E., Metzger, K. B., Williams, A. F., & Tefft, B. C. (2017). Comparison of older and younger novice driver crash rates: Informing the need for extended Graduated Driver Licensing restrictions. *Accident Analysis and Prevention, 108*, 66–73.

Eiksund, S. (2009). A geographical perspective on driving attitudes and behaviors among young adults in urban and rural Norway. *Safety Science, 47*, 529–536.

Farr, J. (2004). Social capital: A conceptual history. *Political Theory., 32*(1), 6–33.

Gaygisiz, E. (2010). Cultural values and governance quality as correlates of road traffic fatalities: A national level analysis. *Accident Analysis and Prevention, 42*, 1894–1901.

Henning-Smith, C., & Kozhimannil, K. B. (2018). Rural-urban differences in risk factors for motor vehicle fatalities. *Health Equity, 2*(1), 260–263.

McCartt, A. T., Kidd, D. G., & Teoh, E. R. (2014). Driver cellphone and texting bans in the United States: Evidence of effectiveness. *Annals of Advances in Automotive Medicine, 58*, 99–114.

Melinder, K. (2007). Socio-cultural characteristics of high versos low risk societies regarding road traffic safety. *Safety Science, 45*, 397–414.

Nagler, M. G. (2013a). Does social capital promote safety on the roads? *Economic Inquiry, 51*, 1218–1231.

Nagler, M. G. (2013b). Playing well with others: The role of social capital in traffic accident prevention. *Eastern Economic Journal, 39*(2), 172–200.

NHTSA. (2006). Motor vehicle traffic crashes as a leading cause of death in the United States, 2003. NHTSA Traffic Safety Facts (DOT HS 810 568).

Page, Y. (2001). A statistical model to compare road mortality in OECD countries. *Accident Analysis and Prevention, 33*, 371–385.

Reinfurt, D. W., Stewart, J. R., & Weaver, N. L. (1991). The economy as a factor in motor vehicle fatalities, suicides, and homicides. *Accident Analysis & Prevention, 23*(5), 453–462.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. New York: John Wiley & Sons Inc..

Shyhalla, K. (2014). Alcohol involvement and other risky driver behaviors: Effects on crash initiation and crash severity. *Traffic Injury Prevention, 15*(4), 325–334.

Singh, S. (2018, March). Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey. (Traffic Safety Facts Crash Stats. Report No. DOT HS 812 506). Washington, DC: National Highway Traffic Safety Administration.

Steptoe, A., Wardle, J., Fuller, R., Davidsdottir, S., Davou, B., & Justo, J. (2002). Seatbelt use, attitudes, and changes in legislation: An international study. *American Journal of Preventive Medicine, 23*(4), 254–259.
Stevens, J. P. (2002). *Applied multivariate statistics for the social sciences* (4th Edition). Mahwah, NJ: Lawrence Erlbaum Associates.
Ward, N. J., Otto, J., & Finley, K. (2019). *Traffic safety culture primer*. Helena, MT: Montana Department of Transportation. Retrieved from: https://www.mdt.mt.gov/other/webdata/external/research/docs/research_proj/tsc/TSC_PRIMER/PRIMER.pdf.
World Health Organization. (2018). The top 10 leading causes of death. Retrieved from: https://www.who.int/en/news-room/fact-sheets/detail/the-top-10-causes-of-death.
Zaidel, D., Hakkert, A. S., & Pistiner, A. H. (1992). The use of road humps for moderating speeds on urban streets. *Accident Analysis and Prevention, 24*(1), 45–56.

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