Exploring the effects of state highway safety laws and sociocultural characteristics on fatal crashes

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ABSTRACT

Objective: Distinguished from the traditional perspectives in crash analyses, which examined the effects of geometric design features, traffic factors, and other relevant attributes on the crash frequencies of roadway entities, our study focuses on exploring the effects of highway safety laws, as well as sociocultural characteristics, on fatal crashes across states.

Methods: Law and regulation related data were collected from the Insurance Institute for Highway Safety, State Highway Safety Offices, and Governors Highway Safety Association. A variety of sociodemographic characteristics were obtained from the U.S. Census Bureau. In addition, cultural factors and other attributes from a variety of resources are considered and incorporated in the modeling process. These data and fatal crash counts were collected for the 50 U.S. states and the District of Columbia and were analyzed using zero-truncated negative binomial (ZTNB) regression models.

Results: The results show that, in law and regulation-related factors, the use of speed cameras, no handheld cell phone ban, limited handheld cell phone ban, and no text messaging ban are found to have significant effects on fatal crashes. Regarding sociocultural characteristics, married couples with both husband and wife in the labor force are found to be associated with lower crash frequencies, the ratios of workers traveling to work by carpool, those driving alone, workers working outside the county of residence, language other than English and limited English fluency, and the number of licensed drivers are found to be associated with higher crash frequencies.

Conclusions: Through reviewing and modeling existing state highway safety laws and sociocultural characteristics, the results reveal new insights that could influence policy making. In addition, the results would benefit amending existing laws and regulations and provide testimony about highway safety issues before lawmakers consider new legislation.

Introduction

Highway-related crashes are a major concern worldwide, because they result in innumerable fatalities, injuries, property lost, and medical dollars spent. To improve traffic safety, many researchers (Chen et al. 2012; McCartt et al. 2010; Pei et al. 2011) used police-reported data, such as vehicle information, geometric design features, traffic factors, and other relevant attributes, as explanatory variables in crash frequency and injury severity modeling. Nonetheless, there are many cases where macrolevel measures might be important determinants. Regarding the usages of macrolevel data, researchers have examined the effects of sociodemographic characteristics on traffic safety, such as age and gender differences in driving behaviors (Alver et al. 2014; Brusque and Alauzet 2008; Dobson et al. 1999). Recent research extended the explored variables and cultural factors were included to estimate the crash counts. Two published papers (Melinder 2007; Nordfjærn et al. 2012) indicated that sociodemographic characteristics and cultural factors are significantly associated with safety performance and could be used to predict crash counts. In our study, in addition to sociodemographic and cultural factors, state highway safety law-related factors are considered as explanatory variables, because they have potential significant effects on traffic safety.

Compared to studies that use police-reported data, there are limited research efforts to explore state highway safety law-related factors and sociocultural characteristics and seek to extract information from such databases to improve safety practice and develop effective safety policies. Generally, safety law-related factors and sociocultural characteristics can be obtained from 2 resources: Survey data, which can be collected by mail, phone, or in person, and official resources. According to the data used in the studies, we classify the literature into 2 categories: Those mainly using survey data and those mainly using official data. Regarding survey data-based studies, those that account for sociocultural characteristics have been reviewed and incorporated, because their efforts are mostly related to the topic of the current article. Dobson et al. (1999) collected data on demographic characteristics, social and lifestyle factors, and driving experience and behavior through a mailed questionnaire to examine factors affecting crash rates among females in Australia.
The results showed that females born in non-English-speaking countries had a higher risk of being involved in a crash compared to Australian-born females. To investigate the effects of mobile phone use while driving, Brusque and Alauzet (2008) collected interview data from 1,973 French people regarding their driving practices. Logistic regression was used to examine the effects of talking on the phone while driving. The results showed that there are significant differences between males and females. The relationship between sociodemographic characteristics, traffic rule violations, and traffic crashes among young drivers has been investigated using ordered probit models and binary logit models (Alver et al. 2014). The data were collected through questionnaire survey in 4 cities in Turkey. Four types of traffic rule violations, including red light violations, seat belt violations, speeding, and driving under the influence of alcohol, were examined. The results showed that road type and age are significant factors for seat belt use by young drivers. The research results also indicated that the presence of older passenger decreased the odds of speeding violations; impressing friends, peer pressure, an adrenaline rush, and a desire to show off were identified as significant factors for speeding. Based on their findings, the authors suggested that road safety should be studied in areas and populations with similar characteristics and the policies should be determined regionally.

Regarding the use of official data, Narayanamoorthy et al. (2013) analyzed the frequencies of pedestrian and bicycle injuries using a spatial multivariate count model. Data related to land use, sociodemographics, and network information were obtained from the census tract of Manhattan, New York. The results showed that census tracts with a high population density, minority population groups, low education levels, and high built-up density are vulnerable to nonmotorized injuries. Li et al. (2013) examined the relationship between fatal crashes and traffic patterns, road network attributes, and sociodemographic characteristics using county-level data collected from 58 counties in California. Results showed that the percentage of freeway mileage in a county, road density, median household income, traffic density, and percentage of urban traffic were negatively associated with the fatal crashes; daily vehicle miles traveled, population density, and percentage of drivers under 18 were positively related to the risk of fatal crashes.

From the literature review, it can be concluded that most sociocultural characteristics have been used to address highway safety issues and have revealed some insights. Nonetheless, sociocultural data-based research has some weaknesses. First is sample selection and how to determine the appropriate sample size and population to prevent estimation bias. Second is inaccuracies due to the use of self-reported data and the risk of underreported illegal behaviors. Regarding studies based on highway safety law data, most aimed to verify advanced statistical methods, which address complex issues of methodologies with little practical meaning. The intent of this article is to focus on integrating secondary data sources in a novel way to examine the factors that have significant effects on fatal crash counts. Various data and fatal crash counts were collected from multiple resources for the 50 U.S. states and the District of Columbia and were analyzed using zero-truncated negative binomial (ZTNB) regression models. The results provide useful information about highway safety issues before lawmakers consider new legislation.

**Methods**

**Data source**

A 3-year data set, from 2010 to 2012, was collected for the 50 U.S. states and the District of Columbia. The data set includes fatal crash counts as a dependent variable and characteristics of regulation and law, culture, and sociodemographics as the independent variables for each individual state and the District of Columbia. All data were collected from the authoritative agencies in the United States for consistency and reliability. Fatal crash counts aggregated by state level were obtained from the Fatality Analysis Reporting System, which is a nationwide census providing NHTSA, Congress, and the American public yearly data. Fatal crashes are defined as a crash in which the most severe injury resulted in death within 30 days of the motor vehicle crash. Fatal crash counts per year in the 50 states and the District of Columbia ranges from 15 in the District of Columbia in 2012 to as high as 3,398 in Texas in 2012, with a mean of 647.31 and a standard deviation of 648.38.

Regulation and law-related factors were collected from the Insurance Institute for Highway Safety, State Highway Safety Offices, and Governors Highway Safety Association. Eleven key highway safety laws, including automated enforcement laws, aggressive driving laws, sobriety checkpoint laws, seat belt laws, highest speed limit regulations, alcohol-impaired driving laws, graduated driver licensing laws, distracted driving laws, mature driver laws, work zone traffic laws, and helmet laws were considered.

In addition to regulation and law-related factors mentioned above, our data set includes a variety of sociocultural characteristics. The cultural characteristics obtained from the Population Reference Bureau include church attendance rate, whether the state contains dry counties, whether the state is in the Bible Belt, and total population whose first language is other than English and speak English less than “very well.” Other attributes including total licensed drivers, average daily traffic per lane on principal arterials, registered vehicles, total motor fuel use, tax rates on gasoline, annual vehicle miles traveled, and seat belt use rates were obtained from the Federal Highway Administration for the 50 states and the District of Columbia. These variables are considered because they have potential significant effects on fatal crash counts.

A variety of sociodemographic characteristics for each individual state and the District of Columbia are available from the U.S. Census Bureau. In this study, the population, average household size, education level data, divorce rate, marriage rate, employment ratio, means of travel to work, rates of working outside the county of residence, median family income, population without health insurance coverage, population with a disability, and housing units that are mobile homes are considered as the explanatory variables because they have been commonly used in previous studies for state-level crash analyses and have potential to reveal new insights. The investigated categorical and continuous independent variables and their summary descriptive statistics are shown in Tables A1 and A2 (see online supplement), respectively. The dependent variable is the fatal crash counts per year in each state and the District of Columbia and the relevant statistics are shown in Table A2.
Data analyses

Analyses of collected fatal crash counts show that the variance is greater than the mean, which means that the crash data are overdispersed. In cases of overdispersion, a negative binomial (NB) model typically fits better than a Poisson model, because NB regression models allow the variance of the observations to differ from the mean. The analyses of our data also indicate that the dependent variable does not have a value of zero and the mean of the dependent variable is relatively large. In other words, collected fatal crash counts are truncated at zero. For this type of crash count, the standard NB distribution does not provide a satisfactory fit due to truncation, whereas a ZTNB distribution would be appropriate according to goodness-of-fit and overdispersion tests (Lee et al. 2003; O’Neill and Faddy 2003; Sampford 1995). Under such circumstances, ZTNB models are considered in this study. The probability function of the ZTNB distribution used in this article has the following form, which is appropriate for modeling fatal crash counts when the data are both overdispersed and zero-truncated.

\[ P(y_i) = \frac{\Gamma(y_i + \theta)}{\Gamma(\theta) y_i^\theta (1 - u_i)^y_i} \left(1 - \frac{\theta}{u_i}\right)^{y_i} \]

where \( y_i = \theta_i/(\theta_i + \lambda_i) \) and \( \theta = 1/\alpha, \theta \) is the size parameter, and \( \lambda_i \) is the expected mean number of fatal crashes in state \( i \).

\[ \ln(\lambda_i) = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_m x_{mi} + \epsilon_i, \]

where \( EXP(\epsilon_i) \) is a gamma-distributed error term with mean 1 and variance \( \alpha \). The ZTNB model results from NB distribution by dividing its probability function by 1 minus the probability that \( y_i = 0 \). Hence, the log likelihood of the ZTNB distribution is

\[ \log(L) = \log(L_{NB}) - \log(1 - \mu^\theta). \]

The goodness of fit was evaluated by several measures, including the Pearson’s chi-square statistic, Akaike’s information criterion (AIC), AICC (the small sample size–corrected version of AIC), and Schwarz’s Bayesian criterion (also known as the Bayesian information criterion, BIC). The definitions of the employed Pearson’s chi-square statistic, AIC, AICC, and Schwarz’s Bayesian criterion are listed below:

\[ \chi^2 = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{\hat{y}_i} \]

\[ AIC = -2 \ln(L) + 2k \]

\[ AICC = AIC + \frac{2k(k + 1)}{n - k - 1} \]

\[ BIC = -2 \cdot \ln(L) + k \cdot \ln(n), \]

where \( y_i \) is an observed crash count; \( \hat{y}_i \) is a predicted crash count; \( df \) is the degrees of freedom, which is equal to \( n - k \), where \( n \) is the number of observations and \( k \) is the number of estimated parameters; and \( L \) is the maximized value of the likelihood function for the employed model.

The statistical software SAS Version 9.3 was used to estimate the coefficients of the model parameters. Our data set includes a significant number of the investigated variables. To obtain a converged model and improve the goodness of fit, 2 subgroups of explanatory variables were used: law and regulation-related factors and sociocultural characteristics. Two ZTNB models were developed for the individual groups. For each individual model, significant factors were obtained and combined as the third group and were modeled using same methodologies.

Results

### Initial individual model results

Tables 1 and 2 summarize the model parameter estimates and their associated statistics. Only significant factors are presented. The estimated dispersion parameters are greater than zero, which indicates the appropriateness of the ZTNB models over the zero-truncated Poisson models. The results show that the ZTNB model in Table 2, which addresses sociocultural effects, with an AIC statistic of 708.70, AICC statistic of 712.20, and BIC statistic of 754.16, has better goodness of fit compared to the ZTNB model of law and regulation group in Table 1, which has an AIC statistic of 755.00, AICC statistic of 758.50, and BIC statistic of 800.46. The Pearson’s chi-square statistics also confirm this conclusion with a value of 0.979 for the ZTNB model of sociocultural group. The results indicate that if only one type of information is available to estimate fatal crash counts, using sociocultural factors will have superior prediction results.

Examination of the law and regulation factors indicates that 13 parameter estimates are statistically significant at a 95% confidence level. From the perspective of law and regulation effects, automated enforcement laws, sobriety checkpoint laws, alcohol-impaired driving laws, speed limit laws, and distracted driving

| Parameter                          | Estimate | SE  | t Value | P > |t| |
|-----------------------------------|----------|-----|---------|-----|---|
| Intercept                         | 4.22     | 0.57| 7.35    | .<.0001|
| Automated enforcement laws        |          |     |         |     |   |
| Speed camera law_1                | -1.62    | 0.54| -3.01   | .0041|
| Speed camera law_2                | -1.02    | 0.49| -2.08   | .043 |
| Red light camera law_1            | 2.63     | 0.54| 4.85    | <.0001|
| Sobriety checkpoint law           | 0.83     | 0.28| 2.92    | .0051|
| Alcohol-impaired driving laws     |          |     |         |     |   |
| Restore driving privileges         | -0.81    | 0.33| -2.5    | .0158|
| during suspension_2               |          |     |         |     |   |
| Speed limit laws                  |          |     |         |     |   |
| Highest speed limit               | -0.89    | 0.30| -2.93   | .0051|
| Differential speed limit          | 0.70     | 0.29| 2.38    | .0213|
| Distracted driving laws           |          |     |         |     |   |
| Handheld Ban_1                    | 0.68     | 0.24| 2.86    | .0062|
| Handheld Ban_2                    | 1.07     | 0.28| 3.77    | .0004|
| Text messaging Ban_1              | 0.26     | 0.12| 2.16    | .0352|
| Text messaging Ban_2              | 0.46     | 0.14| 3.42    | .0013|
| Helmet laws                       |          |     |         |     |   |
| Motorcycle helmets                | 0.53     | 0.24| 2.27    | .0275|
| Bicycle helmets                   | 0.70     | 0.25| 2.83    | .0067|
| Alpha                             | 0.26     | 0.05| 5.13    | <.0001|
| Goodness of fit                   |          |     |         |     |   |
| Pearson’s chi-square              | 0.960    |     |         |       |
| AIC                               | 755.00   |     |         |       |
| AICC                              | 758.50   |     |         |       |
| BIC                               | 800.46   |     |         |       |

*All at a significance level of 0.05."
laws have significant effects on fatal crash counts. In the automated enforcement law-related factors, no speed camera laws and authorized speed camera laws are found to be associated with lower fatal crash counts compared to prohibited use of speed cameras. No red light camera law is found to be associated with higher fatal crash counts. No restored driving privilege during a suspension is found to be associated with lower fatal crash counts in the alcohol-impaired driving law-related factors. In speed limit law-related factors, highest speed limit regulation is found to be associated with fatal crash count reductions and differential speed limit laws are found to be associated with increasing fatal crash counts. No handheld cell phone ban, secondary handheld cell phone ban, no text messaging ban, and secondary text messaging ban are found to be associated with higher fatal crash counts compared to primary handheld cell phone bans and primary text messaging bans in distracted driving law-related factors. In helmet law-related factors, limited motorcycle helmet law and no bicycle helmet law are found to be associated with higher fatal crash counts.

Regarding the results of the ZTNB model related to the sociocultural characteristics, population; percentage of workers ages 16 and older who traveled to work by car, truck, or van–carpoled; percentage of workers ages 16 and older who traveled to work by car, truck, or van–drove alone; percentage of workers ages 16 and older who worked outside the county of residence; church attendance rates; belonging to the Bible Belt; and the number of licensed drivers have been found positively associated with the fatal crash counts. Average household size, divorce rate per 1,000 men 15 years and older, percentage of married couples with both husband and wife in the labor force, and language other than English and speaking English less than very well are statistical significantly associated with fatal crash reductions.

### Combined model results

The parameter estimates of the ZTNB model related to the combined factors are shown in Table 3. The statistical fit of the combined model that considers all impact factors is quite good as indicated by the Pearson's chi-square statistic of 0.991, AIC of 633.90, AICC of 636.13, and BIC of 670.27. The results indicate that the combined model provides a superior fit over the ZTNB models of subgroups because the goodness-of-fit statistics are by far the lowest of those models. A comparison between Tables 1, 2, and 3 reveals that the coefficients of identified significant factors sometimes change from significant in the individual model to insignificant in the combined model. The result indicates that some variables might have a different effect given the exposure conditions. Though the significant characteristics of effects change for different modeling conditions, the signs of significant coefficients are consistent throughout the models, indicating the robustness of the directions of effects.

The results show that 4 law and regulation-related factors and 6 sociocultural factors have significant effects on fatal crash counts. In law and regulation-related factors, the use of speed camera, no handheld cell phone ban, limited handheld cell phone ban, and no text messaging ban are found to have significant effects on fatal crash counts. Regarding sociocultural characteristics, married couples with both husband and wife in the labor force are found to be associated with lower fatal crash counts; the rest of the significant variables, including the ratios of workers traveling to work by carpool, driving alone, the ratio of workers worked outside the county of residence, language other than English and limited English fluency, and the number of

### Table 2. Parameter estimates of the ZTNB model associated with sociocultural characteristics

| Parameter                                           | Estimate | SE     | t Value | P > |t |
|-----------------------------------------------------|----------|--------|---------|-----|---|
| Intercept                                           | 4.07     | 0.80   | 5.1     | <.0001 |   |
| Population (million)                                | 0.09     | 0.01   | 7.88    | <.0001 |   |
| Average household size                              | −2.67    | 0.66   | −4.04   | <.0002 |   |
| Divorce rate per 1,000 men 15 years and older       | −0.14    | 0.06   | −2.54   | .014  |   |
| Married couples with both husband and wife in the labor force (%) | −0.09    | 0.04   | −2.37   | .0216 |   |
| Workers traveled to work by car, truck, or van–carpoled (%) | 0.30     | 0.08   | 3.89    | .003  |   |
| Workers traveled to work by car, truck, or van–drove alone (%) | 0.16     | 0.03   | 4.63    | <.0001 |   |
| Workers worked outside county of residence (%)      | 0.03     | 0.01   | 3.19    | .0024 |   |
| Church attendance rates                             | 1.89     | 0.54   | 3.54    | .0005 |   |
| Bible Belt                                          | 0.31     | 0.10   | 3.04    | .0027 |   |
| Language other than English and limited English proficiency | −0.06    | 0.01   | −7.47   | <.0001 |   |
| Licensed drivers (millions)                         | 0.39     | 0.09   | 4.21    | <.0001 |   |
| Alpha                                               | 0.10     | 0.02   | 4.81    | <.0001 |   |
| Goodness of fit                                     |          |        |         |      |   |
| Pearson's chi-square                                | 0.979    |        |         |      |   |
| AIC                                                 | 708.70   |        |         |      |   |
| AICC                                                | 792.20   |        |         |      |   |
| BIC                                                 | 754.16   |        |         |      |   |

*a All at a significance level of 0.05.

### Table 3. Parameter estimates of the ZTNB model associated with the combined factors

| Parameter                                           | Estimate | SE     | t Value | P > |t |
|-----------------------------------------------------|----------|--------|---------|-----|---|
| Intercept                                           | −4.59    | 1.23   | −3.74   | .0005 |   |
| Speed camera law_1                                  | −0.33    | 0.06   | −5.41   | <.0001 |   |
| Handheld ban_1                                      | 0.22     | 0.09   | 2.39    | .0206 |   |
| Handheld ban_2                                      | 0.23     | 0.06   | 3.87    | .0003 |   |
| Text messaging ban_2                                | 0.28     | 0.07   | 4.18    | .0001 |   |
| Married couples with both husband and wife in the labor force (%) | −0.02    | 0.01   | −3.8    | .0004 |   |
| Workers traveled to work by car, truck, or van–carpoled (%) | 0.16     | 0.03   | 6.1     | <.0001 |   |
| Workers traveled to work by car, truck, or van–drove alone (%) | 0.11     | 0.01   | 9.89    | <.0001 |   |
| Workers worked outside county of residence (%)      | 0.01     | 0.00   | 3.15    | .0027 |   |
| Language other than English and limited English proficiency | 0.05     | 0.01   | 7.51    | <.0001 |   |
| Licensed drivers (millions)                         | 0.26     | 0.02   | 16.49   | <.0001 |   |
| Alpha                                               | 0.06     | 0.01   | 8.02    | <.0001 |   |
| Goodness of fit                                     |          |        |         |      |   |
| Pearson's chi-square                                | 0.991    |        |         |      |   |
| AIC                                                 | 633.90   |        |         |      |   |
| AICC                                                | 636.13   |        |         |      |   |
| BIC                                                 | 670.27   |        |         |      |   |

*a All at a significance level of 0.05.
Discussion

Most of our findings are expected and consistent with numerous previous studies (Alver et al. 2014; Li et al. 2013; Narayananmorrthy et al. 2013) in terms of the effects of sociocultural characteristics, such as workers working outside the county of residence and the number of licensed drivers, on the occurrence of fatal crashes. Nonetheless, some results reveal new insights and should be highlighted. Compared to those who use public transportation or drive alone, the percentage who travel to work by carpool is found to be associated with higher fatal crash counts. The possible explanation is that the carpooling drivers are more likely to be distracted due to engaging in one or more of the following activities while driving a vehicle: talking to others in the car, talking on a cell phone (hands-free or not), texting, drinking coffee, and eating (Huisingle et al. 2015). In addition, we believe that, unlike drivers driving alone and public transportation drivers, who drive the same routes every weekday, carpoolers usually take turns as the driver, which increases the risk of crash occurrences because alternating driving responsibilities on a daily, weekly, or monthly basis would potentially cause a lack of driving experience and lead to unsafe driving conditions. Though carpools can reduce traffic congestions and save money, our study shows that there is a higher risk of fatal crash occurrences compared to driving alone and traveling by public transportation.

The results related to married couples with both husband and wife in the labor force show that increases in the value of the factor are associated with a reduction in fatal crash counts. The results reveal that good marriage commitment and stable employment are beneficial in reducing fatal crash counts. In other words, we believe that, unlike drivers driving alone and public transportation drivers, who drive the same routes every weekday, carpoolers usually take turns as the driver, which increases the risk of crash occurrences because alternating driving responsibilities on a daily, weekly, or monthly basis would potentially cause a lack of driving experience and lead to unsafe driving conditions. Though carpools can reduce traffic congestions and save money, our study shows that there is a higher risk of fatal crash occurrences compared to driving alone and traveling by public transportation.

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Speeding is one of the most prevalent factors contributing to traffic crashes and deaths in the United States. In 2012, of all traffic crash fatalities (33,561), 31% (10,219 fatalities) are caused by speeding (NHTSA 2014). Because speed cameras can lower overall traffic speeds and are effective at reducing the number of speeders driving more than 15 mph over the posted speed limits (Retting et al. 2008), speed cameras are permitted in 10 states and the District of Columbia and aim to decrease the number and severity of crashes. Our finding shows that, compared to states that prohibit the use of speed cameras, states that have laws authorizing speed camera enforcement are associated with lower fatal crashes (28% less) while holding other variables constant. This finding is consistent with previous studies (Mountain et al. 2005; Retting et al. 2008; Shin et al. 2009), which show that speed cameras can reduce crashes substantially. Though studies in North America, Australia, and Europe (Delaney et al. 2005; Mountain et al. 2004; Tay 2010) have found speed cameras to be effective in reducing speeds and crashes and public opinion surveys around the world have indicated that speed cameras are supported by the majority of drivers, speed camera use in the United States is still controversial. Delaney et al. (2005) declared that, based on the experience worldwide, revenue from fines, fairness, speeding not being perceived as a safety problem, reliability, and privacy are recurring controversies that generally arise whenever speed cameras are used. To generate support from the public, a shift in public attitudes on speeding and its consequences is needed. As pointed out by Mountain et al. (2004), speeding should be considered, like smoking in public places or drinking and driving, to endanger the quality of life of both the individual and others and is socially unacceptable. We hope the above information can promote state laws on the implementation of speed camera enforcement.

Though handheld cell phone use has been proven to increase crash risk by impairing driver performance, such as increasing tension, delaying reaction time, and decreasing awareness in laboratory setting, the long-term effects of distracted driving laws on driving behavior and crash frequencies are still controversial and there is a need to develop convincing arguments in support of or against legislation. Our results show that, compared to the primary handheld cell phone law, the secondary (or limited) handheld cell phone law and no handheld cell phone enforcement increase the likelihood of fatal crash occurrences by 25 and 26%, respectively. These results are consistent with previous studies (Cowles et al. 2010; McCartt et al. 2010; Nikolaev et al. 2010) that showed that handheld cell phone bans have positive effects on traffic safety. Though numerous studies showed that handheld cell phone laws have reduced handheld cell phone use and are effective in reducing crash counts, a majority of states (32 states) do not restrict drivers from using a handheld cell phone while driving. In a recent study (Goodwin et al. 2012), the results showed that North Carolina’s cell phone restriction has had no long-term effect on the behavior of teenage drivers after 2 years. The result merits further discussion and investigation.

Because text messaging requires visual, manual, and cognitive attention, it is considered the most alarming distraction. However, only a few studies (Atchley et al. 2011; Ehsani et al. 2014; Hallett et al. 2012; Harrison 2011) have examined text messaging behavior and the effects of text messaging on driving performance and safety in the past decade. One possible reason is that there are not sufficient data to conduct research, because the first texting ban was enacted in the District of Columbia in 2007. Though drivers perceive replying or reading texts as very risky and riskier than talking on a cell phone while driving, several studies (Atchley et al. 2011; Hallett et al. 2012; Harrison 2011) revealed that perception of risk was a very weak predictor of behavior or had no effect on texting. In other words, although drivers are aware of the high risk involved in texting while driving, they continue to engage in this behavior. Moreover, age was found to be an important indicator of estimating text messaging behavior while driving, and younger drivers are found more likely to engage in this behavior (Hallett et al. 2012). Our results show that no text messaging law enforcement is associated with 32% higher fatal crash counts compared to the primary text messaging law. This result is consistent with the results of Ehsani et al. (2014), which found significant decreases in crashes after a text messaging law was implemented in Michigan.
Because specific highway safety laws and regulations vary greatly from state to state, in addition to sociocultural characteristics, there is a need to investigate the relationship between fatal crash counts and the above-mentioned factors to assess the performance and efficiency of the implemented laws and regulations. Statewide indicators considered in this study are variables related to highway safety laws and regulations, cultural factors, and sociodemographic characteristics. ZTNB models were employed due to the statistical characteristics of the investigated variables. The results of the combined model show that 4 law and regulation-related factors and 6 sociocultural factors have significant effects on fatal crash counts. Other than the findings that are expected and consistent with numerous previous studies, our analyses provide new insights that have not been revealed before, which are summarized below.

The increase in carpooling is found to be associated with higher likelihood of fatal crash occurrences compared to driving alone and traveling by public transportation. Our finding shows that, compared to states that prohibit the use of speed cameras, states that have laws authorizing speed camera enforcement are associated with lower fatal crashes while holding other variables constant. Compared to the primary handheld cell phone law, the secondary (or limited) handheld cell phone law and no handheld cell phone enforcement increase the likelihood of a fatal crash. No text messaging law enforcement is associated with lower fatal crashes while holding other variables that, compared to states that prohibit the use of speed cameras, are expected and consistent with numerous previous studies, our findings show higher likelihood of fatal crash occurrences compared to driving alone and traveling by public transportation. Our findings show that, compared to states that prohibit the use of speed cameras, states that have laws authorizing speed camera enforcement are associated with lower fatal crashes while holding other variables constant. Compared to the primary handheld cell phone law, the secondary (or limited) handheld cell phone law and no handheld cell phone enforcement increase the likelihood of a fatal crash. No text messaging law enforcement is associated with higher fatal crash counts compared to the primary text messaging law.

Limitations

Child passenger safety laws are excluded from the study, because they do not modify the behaviors of vehicle operators and are therefore less directly related to fatal crash counts. In addition, all 50 states and the District of Columbia have the same laws for child passengers, which require child passenger restraints based on age, weight, and height. The data set we used covered 3 years, which limits model performance in terms of less variables found to be significant. Though using several years of data can achieve better modeling results, the main concern is that the variables for specific state laws might stay the same and would be considered as independent variables, which would lead to significant estimation bias. In further study, we would like to include more samples and develop more sophisticated models. In addition, one specific highway safety law might have significant effects on one type of crashes and would be insignificant for other types of crashes. We are interested to analyze the effects of state highway safety laws on crash severities. Thus, multivariate regression models are needed, because crash counts are interdependent. Modeling the counts of specific types of crashes (as opposed to total crashes) can reveal new insights that benefit policy making. We hope to include these in future studies. Furthermore, we are interested in using random-parameter regression models, because they can address the heterogeneity issue among states, which might reveal new insights.

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