Original Research Paper

Investigating temporal trends in the explanatory variables related to the severity of drivers' injuries in single-vehicle collisions

Essam Dabbour

Abu Dhabi University, College of Engineering, P.O. Box 59911, Abu Dhabi, United Arab Emirates

Abstract

This study identifies and quantifies the effects of different explanatory variables that increase the severity of drivers' injuries related to single-vehicle collisions involving light-duty vehicles. The research is based on utilizing logistic regression to analyze records of all traffic collisions that occurred in North Carolina for the years from 2007 to 2013. The study also investigates temporal stability of the identified explanatory variables throughout the analysis period. The identified explanatory variables include those related to the roadway, vehicle, driver, and environmental conditions. The explanatory variables related to the roadway include whether the roadway is divided or undivided, and whether it is in an urban or rural area. The explanatory variables related to the vehicle include vehicle's age, travel speed, and the type of the light-duty vehicle. The explanatory variables related to the driver include driver's age, gender, influence by alcohol or illicit drugs, and the use of seatbelt. The explanatory variables related to the environmental conditions include weather, lighting, and road surface conditions. Three of the investigated explanatory variables were found to be temporally unstable with significantly varying effects on the severity of drivers' injuries. Those temporally unstable variables include the travel speed, the type of the light-duty vehicle, and the age of the driver. All other investigated variables were found to be consistently significant throughout the analysis period. The findings of this research have the potential to help decision makers develop policies and countermeasures that reduce the severity of drivers' injuries by focusing on explanatory variables that consistently exhibit significant effects on the severity of drivers' injuries. The findings of this research also provide quantitative measures that may be used to determine the feasibility of implementing those countermeasures in reducing the severity of drivers' injuries related to single-vehicle collisions. Recommendations for future research are also provided.

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* Corresponding author. Tel.: +971 2 5015634; fax: +971 2 5860182.
E-mail address: essam.dabbour@adu.ac.ae.
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1. Introduction

Single-vehicle collisions result in a significant number of fatalities and severe injuries each year, and therefore they are a major concern related to traffic safety. According to statistical data obtained from the National Highway Traffic Safety Administration (2016a), more than 46% of fatal traffic collisions in the United States are related to single vehicles.

Several research studies investigated different explanatory variables that may increase injury severity resulting from a single-vehicle collision given that such a collision has already occurred. Behnood and Mannering (2015) used mixed-logit modeling to explore the temporal stability of factors affecting the severity of drivers’ injuries in single-vehicle crashes by using data from Chicago, Illinois for the years from 2004 to 2012. Several explanatory variables were tested, including variables related to drivers, roadways, vehicles, and environmental conditions. It was found that the effects of most explanatory variables were generally temporally unstable, which may be due to different factors related to temporal changes in vehicle-safety features, drivers response to those improved safety features, and drivers response to changes in microeconomic conditions, among other factors.

Islam et al. (2014) used random-parameter logit models to analyze the severity of injuries resulting from large truck at-fault collisions in Alabama for the years from 2010 to 2012. Four separate models were provided to model the severity of injuries resulted from single-vehicle and multi-vehicle collisions in rural and urban locations. Several characteristics were found to increase the severity of injuries resulted from those types of collisions. The characteristics identified include those related to driver, vehicle, roadway, land use, and time of the day.

Martensen and Dupont (2013) used logistic regression to identify explanatory variables that differentiate between single-vehicle and multi-vehicle crashes based on data from six European countries (France, Finland, Germany, Italy, Netherlands, and the United Kingdom), and they found that multi-vehicle crashes usually occurred on busy roads and junctions, while single-vehicle crashes usually occurred on empty road-sections between junctions. They also found that roads with physically divided opposite traffic lanes usually had higher proportion of single-vehicle crashes than on other road types. Furthermore, they also found that heavy vehicles and motorcycles were less likely to be involved in single-vehicle crashes than passenger cars.

Other research studies related to single-vehicle crashes include a study by Chang and Yeh (2006) who identified and quantified different explanatory variables that increased the odds of fatalities in single-vehicle crashes related to motorcycles and other light-duty vehicles by using logistic regression to analyze all fatal crashes that occurred in Taiwan in year 2000. Islam and Mannering (2006) investigated the effect of driver ageing on the injury severity resulting from single-vehicle collisions related to passenger cars based on police report data from the state of Indiana in the year 1999. Yau (2004) used logistic regression to identify risk factors that increased injury severity related to single-vehicle traffic collisions based on data from Hong Kong for the years 1999 and 2000. Separate models were developed for passenger cars, trucks, and motorcycles. Several factors were found to increase injury severity for passenger cars, including driver’s age and gender, vehicle age, time of the collision, lighting conditions, and the geographical location of the collision. Renski et al. (1999) investigated the effect of speed limit increase on the severity of single-vehicle crashes on North Carolina interstate highways by comparing the severity of crashes one year before increasing the speed limit with the severity of crashes one year after increasing the speed limit. Ostrom and Eriksson (1993) investigated the effect of alcohol consumption on the severity of single-vehicle crashes in northern Sweden by comparing data related to multi-vehicle crashes with data related to single-vehicle crashes for the years 1980–1989.

Logistic regression was also used in several other recent studies related to road safety analysis. Ye et al. (2015) used logistic regression to investigate different factors affecting lower-limb injuries in traffic collisions. Wang et al. (2016) used logistic regression to investigate factors that increased injury severity of trespassers at railway crossings in the United States for the years from 2004 to 2013. Peng et al. (2016) used logistic regression to investigate risk factors associated with fatal bus accidents and their impact on different types of bus drivers in the United States.

The purpose of this study is twofold. The first purpose is to identify and quantify different explanatory variables that affect the severity of drivers’ injuries resulting from single-vehicle collisions related to light-duty vehicles. The research is based on analyzing records of all traffic collisions that occurred in North Carolina for the years from 2007 to 2013. The second purpose of this research is to evaluate whether the effects of those identified explanatory variables are temporally stable throughout the analysis period that extends for seven years from 2007 to 2013. The findings of this analysis have the potential to assist decision makers identifying the more significant factors that increase the severity of drivers’ injuries so that different resources may be allocated to reduce the impacts of those contributing factors. The findings of this research also provide quantitative measures that may be used to determine the feasibility of implementing those countermeasures in reducing the severity of drivers’ injuries related to single-vehicle collisions.

2. Methodology and data collection

With no other vehicles involved, driver behavior or human factors that contribute to the severity of single-vehicle collisions may be explored more effectively (Chang and Yeh, 2006). Therefore, analyzing single-vehicle collisions has the potential to provide valuable insights regarding the behavior of the specific driver involved in the collision, and when aggregated, may provide more details about the effects of different explanatory variables related to different driver groups.

This research utilizes logistic regression to analyze severity level of drivers’ injuries resulting from single-vehicle collisions in North Carolina during the period from 2007 to 2013.
Using crash records that extend for seven years provides the benefits of capturing year-to-year temporal changes over that period. Due to the substantial differences between the characteristics of light-duty vehicles and those of other vehicles (including heavy vehicles and two-wheel vehicles), this analysis focuses only on single-vehicle collisions related to light-duty vehicles. Those light-duty vehicles include passenger cars and light-duty trucks. The light-duty trucks include pickup trucks, panel trucks, mini-vans, vans, and sports-utility vehicles.

Logistic regression is a generalized linear model that predicts the probability of occurrence of an event by fitting data to a logit function in the form of Eq. (1) (McCullagh and Nelder, 1989)

\[
f(z) = \frac{e^z}{1 + e^z}
\]

where \( z \) is the logit function, which is a measure of the total contribution of all the explanatory variables used in the model, \( f(z) \) is a dichotomous variable that is assumed to follow Bernoulli distribution. It represents the probability that driver's injury being fatal or incapacitating, given that a collision has already occurred and has already resulted in an injury to the driver. Based on that, the variable \( f(z) \) takes the value of “1” if the driver's injury is fatal or incapacitating, or “0” if the driver's injury is minor. For the purpose of this research, minor injuries include Class B (non-incapacitating) and Class C (possible injuries) (Council et al., 2006; Huang et al., 2001). The logit function has the following form

\[
z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k
\]

where \( \beta_0 \) is the intercept, \( \beta_1, \beta_2, \ldots, \beta_k \) are the regression coefficients of explanatory variables of \( x_1, x_2, \ldots, x_k \), respectively.

Relevant collision data records for the years 2007–2013 were obtained from the Highway Safety Information System, which is managed by the University of North Carolina Highway Safety Research Center under contract with Federal Highway Administration (2016). Different explanatory variables are provided in the dataset, and the explanatory variables that are selected for this analysis include:

(1) Roadway-related variables: the presence of a physical median and whether the roadway is in an urban or a rural area.
(2) Vehicle-related variables: vehicle's age, travel speed, and the type of the light-duty vehicle.
(3) Driver-related variables: age, gender, the use of alcohol or illicit drugs, and the use of seatbelt.
(4) Lighting condition variable: whether the collision occurred under lighting conditions (i.e., daylight or roadway illumination) or under darkness conditions.
(5) Environmental-related variables: weather and road surface conditions.

After excluding incomplete and irrelevant records (that represent less than 0.61% of the dataset), the number of collisions that caused injuries to drivers is shown in Table 1. A Wald test is used to test the statistical significance of each of the estimated coefficients (\( \beta_1, \beta_2, \ldots, \beta_k \)). The Wald statistic of asymptotic chi-square distribution is the squared value of the Z statistic and is computed as

\[
\text{Wald} = \frac{\hat{\beta}_i}{\text{SE}(\hat{\beta}_i)}^2
\]

where \( \hat{\beta}_i \) is the \( i \)th estimated coefficient, \( \text{SE}(\hat{\beta}_i) \) is the standard error of that coefficient.

In this study, the odds ratio (OR) is used to interpret the significance of different explanatory variables where an estimate of the odds ratio of a certain explanatory variable is \( \exp(\hat{\beta}_i) \) while holding all other explanatory variables unchanged. Finally, the 95% confidence interval (CI) is also used in this study to describe the upper and lower limits of the odds ratio with 95% confidence level and is given by \( [\hat{\beta}_i \pm Z_{0.95} \cdot \text{SE}(\hat{\beta}_i)] \).

### 3. Results and discussion

Table 1 shows the frequencies and percentages of different levels of drivers' injuries that resulted from single-vehicle collisions during the period from 2007 to 2013. As shown in the table, the overall number of all driver injuries seems to be temporally stable over the analysis period with a mean value of approximately 11,790 injuries, and a standard deviation of approximately 463 injuries. The number and
The Table 2 shows the percentages of drivers’ serious injuries associated with the dichotomous explanatory variables investigated in this research. In the table, favorable environmental conditions exist when the road surface is dry and the weather is either clear or cloudy. As shown in the table, undivided and rural roads are overrepresented in serious collisions. Light-duty vehicles that are not passenger cars are also overrepresented in serious collisions. Those overrepresented light-duty vehicles include pickup trucks, panel trucks, mini-vans, vans, and sports-utility vehicles. Driver groups that are overrepresented in serious collisions include older drivers (65 years or older), male drivers, and drivers who are under the influence of alcohol or illicit drugs, or fail to use seatbelts, or have been driving above the speed limit.

An interesting finding in Table 2 is that collisions occurred in poor lighting conditions, where the roadway is not illuminated, are found to result in more serious injuries than collisions occurred during daylight or during nighttime on illuminated roads. This finding actually contradicts the findings of previous studies on drivers’ injuries resulting from single-vehicle collisions in Hong Kong (Yau, 2004) where it was found that poor lighting conditions have a lower risk of severe injury as compared to daylight or good lighting conditions. Another study by Krull et al. (2000), which was based on analyzing three-year crash data from Michigan and Illinois, found also that the severity of drivers’ injuries increased in daylight. However, a more-recent study (Kim et al., 2013) on all crashes that occurred in California in 2003–2004 concluded that darkness conditions significantly increased the severity of drivers’ injuries. Abdel-Aty (2003) also found that darkness conditions contributed to higher probability of severe injuries on roadway sections. A possible explanation for the increased severity of drivers’ injuries in dark conditions could be the increased reaction times of drivers when driving at low luminance levels (Plainsis and Murray, 2002), and therefore those drivers would have less time to take any evasive measures to reduce the severity of collisions.

Another interesting finding in Table 2 is that collisions occurred during favorable environmental conditions (i.e., dry road surface with clear or cloudy weather) resulted in more fatal/severe injuries to drivers. This interesting finding is consistent with the findings of several other studies (Adams, 1985; Behnood and Mannering, 2015; Behnood et al., 2014;
Logistic regression coefficients and standard errors of all explanatory variables tested are shown in Table 3. The odds ratios (OR) associated with different explanatory variables (factors), including the lower and upper 95% confidence intervals (CIs), are shown in Table 4. The parameters for overall model fit for all models are significant at 5% significance level. Furthermore, all the tested explanatory variables shown in the table are also found to be significant at 5% significance level, except for two variables that are found to be insignificant in certain years at 5% significance level. The first variable is the type of the vehicle, which was found to be insignificant in 2009, and the second variable is the driver’s age, which was found to be insignificant in 2012.

As shown in Tables 3 and 4, the most significant explanatory variable that increased the severity of drivers’ injuries related to single-vehicle collisions is failure to properly use seatbelt. The odds ratios for this explanatory variable are consistently high throughout the analysis period. This finding contributes to the greatly increasing evidence supporting the importance of using seatbelts to reduce the severity of collisions.

Travel speed is found to be another significant explanatory variable that greatly increased the severity of drivers’ injuries related to single-vehicle collisions. However, although travel speed is found to be a significant explanatory variable throughout the analysis period, its magnitude shows temporal instability where the odds ratio in year 2013 is 6.21% for every mile-per-hour increase in the travel speed above the speed limit (with lower and upper 95% confidence intervals of 5.58% and 6.84%, respectively). That odds ratio is significantly different from the odds ratio in year 2012, which is 3.85% (with lower and upper 95% confidence intervals of 3.34% and 4.36%, respectively).

Driving under the influence of alcohol or illicit drugs is found to be another significant explanatory variable that increased the severity of drivers’ injuries related to single-vehicle collisions. This finding is consistent with the findings of almost all similar studies (Behnood and Mannering, 2015; Behnood et al., 2014; Kim et al., 2013; Suriyawongpaisal et al., 2002). The obvious explanation for this finding is the fact that an impaired driver (who is under the influence of alcohol or illicit drugs) may not be able to take the appropriate evasive measures (in terms of proper steering and/or braking or accelerating) that may reduce the severity of a collision.

Another significant explanatory variable is the vehicle age at the time of the collision with odds ratios consistently high throughout the analysis period and ranging between 1.19% (for collisions occurred in 2008) and 3.04% (for collisions occurred in 2011) for every year increasing in vehicle age. This finding is consistent with the findings of several other research studies (Behnood and Mannering, 2015; Behnood et al., 2014; Kim et al., 2013; Yau, 2004). This finding may be attributed to the ongoing improvements in the passive safety features and driver assistance systems that are being implemented in modern vehicles to protect drivers, and other occupants, in case of a collision. To test for this hypothesis, all the records related to the entire analysis period are combined into one single database. The vehicle’s manufacturing year is tested in that combined database as a

Table 3 – Logistic regression coefficients (and standard errors).

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road-related</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Undivided (&gt;1 if yes, “0” if no)</td>
<td>0.4127 (0.0960)</td>
<td>0.4350 (0.1032)</td>
<td>0.3958 (0.1033)</td>
<td>0.2097 (0.1005)</td>
<td>0.4019 (0.1084)</td>
<td>0.5382 (0.1128)</td>
<td>0.4887 (0.1163)</td>
</tr>
<tr>
<td>Rural (&gt;1 if yes, “0” if no)</td>
<td>0.2867 (0.0729)</td>
<td>0.2465 (0.0759)</td>
<td>0.3721 (0.0865)</td>
<td>0.2175 (0.0866)</td>
<td>0.3350 (0.0866)</td>
<td>0.3423 (0.0858)</td>
<td>0.3576 (0.0877)</td>
</tr>
<tr>
<td>Vehicle-related</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years) (#)</td>
<td>0.0298 (0.0051)</td>
<td>0.0118 (0.0042)</td>
<td>0.0148 (0.0065)</td>
<td>0.0212 (0.0065)</td>
<td>0.0300 (0.0057)</td>
<td>0.0194 (0.0042)</td>
<td>0.0201 (0.0047)</td>
</tr>
<tr>
<td>Speed over limit (mph) (#)</td>
<td>0.0498 (0.0025)</td>
<td>0.0513 (0.0028)</td>
<td>0.0503 (0.0026)</td>
<td>0.0449 (0.0025)</td>
<td>0.0455 (0.0025)</td>
<td>0.0378 (0.0025)</td>
<td>0.0602 (0.0030)</td>
</tr>
<tr>
<td>Not a passenger car (&gt;1 if yes, “0” if no)</td>
<td>0.2432 (0.0678)</td>
<td>0.2468 (0.0717)</td>
<td>N.S. (##)</td>
<td>0.2244 (0.0785)</td>
<td>0.3180 (0.0777)</td>
<td>0.3483 (0.0775)</td>
<td>0.2236 (0.0799)</td>
</tr>
<tr>
<td>Driver-related</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>65 years or older (&gt;1 if yes, “0” if no)</td>
<td>0.3509 (0.1452)</td>
<td>0.3817 (0.1369)</td>
<td>0.3342 (0.1500)</td>
<td>0.3218 (0.1486)</td>
<td>0.5786 (0.1371)</td>
<td>N.S. (##)</td>
<td>0.5383 (0.1332)</td>
</tr>
<tr>
<td>Male (&gt;1 if yes, “0” if no)</td>
<td>0.7519 (0.0751)</td>
<td>0.5781 (0.0771)</td>
<td>0.6327 (0.0820)</td>
<td>0.6880 (0.0846)</td>
<td>0.6902 (0.0848)</td>
<td>0.5851 (0.0827)</td>
<td>0.6501 (0.0861)</td>
</tr>
<tr>
<td>Influenced (&gt;1 if yes, “0” if no)</td>
<td>1.0919 (0.0713)</td>
<td>1.0974 (0.0745)</td>
<td>1.1695 (0.0793)</td>
<td>1.1576 (0.0814)</td>
<td>1.1842 (0.0805)</td>
<td>1.2196 (0.0800)</td>
<td>1.0258 (0.0846)</td>
</tr>
<tr>
<td>Seatbelt not used (&gt;1 if yes, “0” if no)</td>
<td>2.1019 (0.0707)</td>
<td>2.1496 (0.0749)</td>
<td>2.0883 (0.0789)</td>
<td>2.1215 (0.0814)</td>
<td>2.1814 (0.0818)</td>
<td>2.0037 (0.0807)</td>
<td>1.9327 (0.0827)</td>
</tr>
<tr>
<td>Lighting-related</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No daylight or lighting (&gt;1 if yes, “0” if no)</td>
<td>0.5459 (0.0678)</td>
<td>0.4747 (0.0717)</td>
<td>0.3987 (0.0760)</td>
<td>0.4183 (0.0785)</td>
<td>0.3868 (0.0777)</td>
<td>0.3929 (0.0775)</td>
<td>0.3821 (0.0796)</td>
</tr>
<tr>
<td>Environmental-related</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Favorable condition (&gt;1 if yes, “0” if no)</td>
<td>0.5019 (0.0956)</td>
<td>0.4045 (0.0864)</td>
<td>0.6602 (0.0921)</td>
<td>0.7544 (0.1035)</td>
<td>0.5375 (0.1058)</td>
<td>0.5246 (0.1032)</td>
<td>0.6437 (0.1001)</td>
</tr>
</tbody>
</table>

Note: (#) means in the year of the accident; (##) means it is as estimated by the investigating police officer based on the evidence available; (##) means the driver is influenced by alcohol or illicit drugs; (###) means the road surface is dry and the weather is either clear or cloudy; (####) means not significant at 5% significance level.

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Kru ll et al., 2000). A possible explanation for this finding is the lower driving speeds and the increased attention paid by drivers in poor environmental conditions. 
Table 4 – Odds ratios (with 95% lower and upper CI).

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Undivided roads</td>
<td>1.5110 (1.2517–1.8239)</td>
<td>1.5450 (1.2622–1.8912)</td>
<td>1.4855 (1.2133–1.8188)</td>
<td>1.2333 (1.0128–1.5017)</td>
<td>1.4946 (1.2084–1.8485)</td>
<td>1.7130 (1.3734–2.1366)</td>
<td>1.6303 (1.2978–2.0478)</td>
</tr>
<tr>
<td>Rural roads</td>
<td>1.3321 (1.1547–1.5367)</td>
<td>1.2795 (1.1026–1.4848)</td>
<td>1.4508 (1.2246–1.7187)</td>
<td>1.2430 (1.0490–1.4728)</td>
<td>1.3979 (1.1797–1.6566)</td>
<td>1.4082 (1.1903–1.6661)</td>
<td>1.4299 (1.2041–1.6981)</td>
</tr>
<tr>
<td>Vehicle age (years)</td>
<td>1.0302 (1.0199–1.0406)</td>
<td>1.0119 (1.0037–1.0201)</td>
<td>1.0149 (1.0021–1.0280)</td>
<td>1.0214 (1.0085–1.0345)</td>
<td>1.0304 (1.0189–1.0421)</td>
<td>1.0196 (1.0112–1.0282)</td>
<td>1.0203 (1.0109–1.0299)</td>
</tr>
<tr>
<td>Speed over limit</td>
<td>1.0510 (1.0459–1.0562)</td>
<td>1.0526 (1.0470–1.0583)</td>
<td>1.0516 (1.0461–1.0570)</td>
<td>1.0459 (1.0408–1.0510)</td>
<td>1.0465 (1.0414–1.0517)</td>
<td>1.0385 (1.0334–1.0436)</td>
<td>1.0621 (1.0558–1.0684)</td>
</tr>
<tr>
<td>Not a passenger</td>
<td>1.2753 (1.1165–1.4566)</td>
<td>1.2799 (1.1120–1.4732)</td>
<td>N.S. (^{(a)})</td>
<td>1.2516 (1.0730–1.4599)</td>
<td>1.3744 (1.1802–1.6004)</td>
<td>1.4166 (1.2170–1.6489)</td>
<td>1.2506 (1.0693–1.4627)</td>
</tr>
<tr>
<td>65 years or older</td>
<td>1.4204 (1.0685–1.8881)</td>
<td>1.4648 (1.1202–1.9154)</td>
<td>1.3969 (1.0411–1.8743)</td>
<td>1.3796 (1.0311–1.8459)</td>
<td>1.7836 (1.3632–2.3335)</td>
<td>N.S. (^{(a)})</td>
<td>1.7131 (1.3194–2.2242)</td>
</tr>
<tr>
<td>Male driver</td>
<td>2.1211 (1.8308–2.4574)</td>
<td>1.7826 (1.5325–2.0734)</td>
<td>1.8827 (1.6032–2.2109)</td>
<td>1.9897 (1.6857–2.3484)</td>
<td>1.9941 (1.6887–2.3546)</td>
<td>1.7952 (1.5265–2.1111)</td>
<td>1.9157 (1.6182–2.2678)</td>
</tr>
<tr>
<td>No daylight or</td>
<td>1.7262 (1.5113–1.9716)</td>
<td>1.6076 (1.3969–1.8500)</td>
<td>1.4898 (1.2838–1.7290)</td>
<td>1.5194 (1.3029–1.7719)</td>
<td>1.4722 (1.2642–1.7145)</td>
<td>1.4813 (1.2726–1.7242)</td>
<td>1.4653 (1.2537–1.7127)</td>
</tr>
<tr>
<td>Lighting</td>
<td>1.6519 (1.3696–1.9923)</td>
<td>1.4986 (1.2651–1.7753)</td>
<td>1.9351 (1.6156–2.3177)</td>
<td>2.1263 (1.7360–2.6042)</td>
<td>1.7116 (1.3910–2.1062)</td>
<td>1.6898 (1.3803–2.0687)</td>
<td>1.9034 (1.5642–2.3162)</td>
</tr>
</tbody>
</table>

Note: \(^{(a)}\) means it is not significant at 5% significance level.
The severity of drivers’ injuries related to single-vehicle collisions when controlling for all other factors, a newer vehicle will reduce the odds of driver’s injury to be serious by approximately 4.47% as compared to the odds associated with a vehicle manufactured a year earlier, given that a single-vehicle collision has already occurred and resulted in an injury for the driver.

The type of the light-duty vehicle is found to be a significant factor that increased injury severity throughout the analysis period, with the exception of year 2009. It is found that the severity of drivers’ injuries related to single-vehicle collisions increase when the light-duty vehicle is not a passenger car. Those vehicles that are found to increase injury severity include pickup trucks, panel trucks, mini-vans, vans, and sports-utility vehicles. All of those vehicle types typically have higher locations of their center of gravity and also higher height-to-width ratios than typical passenger cars. Previous research found that due to the differences, those types of vehicles were usually more likely to be involved in severe or fatal single-vehicle collisions such as rollover (Dabbour, 2012; Friedman and Grzebieta, 2009; McLean et al., 2005). The temporal instability in the effect of the type of light-duty vehicles may be attributed to the rapid progress related to the improvements of passive safety features in all vehicle types, so that several light-duty trucks now have the same safety rating of passenger cars as demonstrated in the vehicle-safety rating database provided by the National Highway Traffic Safety Administration (2016b).

Driver’s gender is found to be another significant explanatory variable where male drivers are found to be more likely involved in severe single-vehicle collisions. This finding is consistent with the findings of most similar research studies (Abdel-Aty, 2003; Kim et al., 2013; Morgan and Mannering, 2011; Ulfarsson and Mannering, 2004; Yau, 2004). One of those previous studies (Ulfarsson and Mannering, 2004) attributed this gender difference to the behavioral and physiological differences between male and female drivers.

To test for the effect of driver’s age, a new variable is created that takes the value of “1” if the driver’s age was 65 years or older, and “0” otherwise. That variable is found to be a significant explanatory variable for all years except for year 2012. This temporal instability in the effect of driver’s age may be attributed to the small percentage of older drivers (with age 65 years or older) as compared to the overall population of drivers involved in single-vehicle collisions that resulted in injuries to drivers. That percentage ranges from 4.34% (in 2007) to 6.49% (in 2013). In addition to testing the effect of older age drivers, the effect of young age drivers are also tested for significance at different age thresholds (18, 19, 20, and 21 years). None of those younger-age groups was found to have significant effect on the severity of drivers’ injuries related to single-vehicle collisions when controlling for the effects of all other factors.

Lighting conditions are found to be a significant explanatory variable where the severity of drivers’ injuries related to single-vehicle collisions significantly increased in poor lighting conditions. As explained earlier, this finding is consistent with the findings of other previous research studies (Abdel-Aty, 2003; Kim et al., 2013; Plainis and Murray, 2002). This effect shows temporal stability with magnitudes range between 72.62% (for collisions occurred in 2007) and 46.53% (for collisions occurred in 2013). The lack of daylight or roadway illumination is the only explanatory variable that has odds ratios that exhibit consistent decrease over the analysis period from 2007 to 2013, but that decrease is not statistically significant at 5% significance level.

Favorable environmental conditions are found to increase the severity of drivers’ injuries related to single-vehicle collisions. As explained earlier in this paper, this interesting finding is consistent with the findings of other research studies (Adams, 1985; Behnood and Mannering, 2015; Behnoood et al., 2014; Krull et al., 2000). The possible explanation is that adverse environmental conditions may result in lower driving speeds and increased attention paid by drivers; and therefore, the severity of a collision, should it occur, would be decreased.

Three of the explanatory variables identified and shown in Tables 3 and 4 are found to be temporally unstable. Those explanatory variables are the travel speed, the type of the light-duty vehicle, and the age of the driver. This finding is consistent with the findings of a previous research study (Behnoood and Mannering, 2015) where it is found that the same three explanatory variables are also temporally insignificant. However, there are six other explanatory variables that are temporarily stable in this research while they were found to be temporally unstable in that previous research study (Behnoood and Mannering, 2015). Those variables include vehicle age, the presence of a physical median, lighting and environmental conditions, driver’s gender, and whether the driver is influenced by alcohol or illicit drugs. Those inconsistencies may be attributed to the differences between the two studies in terms of model structure and its empirical settings. In this current study, the level of the severity of drivers’ injuries is coded as a single dichotomous variable that takes the value of “1” if the driver’s injury is fatal or incapacitating, or “0” if the driver’s injury is minor. This is different from that previous study (Behnoood and Mannering, 2015) where three different models were developed to represent each of the three severity levels of drivers’ injuries (no injury, minor injury, or severe injury). Another possible explanation for the discrepancies regarding vehicle age and lighting and environmental conditions is the differences in the methods used to code those variables into their respective models. For example, vehicles age is modeled in this research study as a continuous variable while the same variable is modeled in that previous research study (Behnoood and Mannering, 2015) as a dichotomous variables that takes the value of “1” if the vehicle is more than ten years old.

Furthermore, the models developed in that previous research study (Behnoood and Mannering, 2015) are exclusively based on urban data collected from the city of Chicago, while the models developed in this current study are based on both urban and rural data collected from the entire state of North Carolina.
4. Conclusions

In this study, logistic regression is utilized to identify and quantify the effects of different explanatory variables that increase the severity of drivers’ injuries resulting from single-vehicle collisions related to light-duty vehicles. The research is based on analyzing records of all traffic collisions that occurred in North Carolina for the years from 2007 to 2013. The seven-year analysis period allows for testing the temporal stability of the factors associated with identified explanatory variables. Some of the identified explanatory variables are related to the roadway (the presence of a physical median, and whether the road is in an urban or rural area). Other identified explanatory variables are related to the vehicle (vehicle’s age, travel speed, and the type of the light-duty vehicle), driver (age, gender, being influenced by alcohol or illicit drugs, and failure to properly use seatbelt), or environment (lighting, road surface, and weather conditions).

Three of the tested explanatory variables are found to be temporally unstable. They include the travel speed (mph), the type of the light-duty vehicle, and the age of the driver. For the travel speed, although it has significant effects on the severity of drivers’ injuries throughout the analysis period, the magnitude of those effects exhibited temporal instability. The type of the light-duty vehicle is found to be another explanatory variable that is temporally unstable where it is insignificant in 2009 and significant in the other six years. The third variable that exhibited temporal instability is the driver’s age where it is found that 65 years or older drivers are associated with increased injury severity, related to single-vehicle collisions, for the years from 2007 through 2011, in addition to year 2013. However, the same variable is found to have insignificant effect in year 2012.

All other explanatory variables identified are found to be temporally stable with significant effects throughout the analysis period. Those variables include undivided roads, rural roads, vehicle’s age at the time of the collision, vehicle’s manufacturing year, male drivers, being influenced by alcohol or illicit drugs, failure to use seatbelt, lack of daylight or roadway illumination, and favorable environmental conditions. Due to the possible correlation between vehicle’s age (at the time of the collision) and vehicle’s manufacturing year, the two variables were tested separately and it is found that the vehicle manufacturing year has more significant effect than the vehicle’s age at the time of the collision.

The findings of this research may help decision makers to develop policies and countermeasures to reduce the severity of drivers’ injuries by focusing on factors that exhibit significant effects with temporally stability, such as the lack of a physical median or the lack of roadway illumination. Further research is recommended to develop models that predict the temporal changes in the factors that exhibit temporal instability such as speeding, the age of the driver, or the type of the vehicle. Those models will be necessary in future before-and-after studies that measure possible safety improvements associated with implementing countermeasures related to those temporally unstable factors. Without developing those prediction models, it will not be possible to determine if any safety improvements are actually resulting from the implemented countermeasures or simply due to the temporal instability related to those factors.

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Dr. Essam Dabbour is an associate professor and the Director of the Center of Transportation & Traffic Safety Studies at Abu Dhabi University. He obtained PhD in Civil Engineering from Ryerson University, Canada. Dr. Dabbour has published more than 35 research papers in international journals and refereed conference proceedings in areas related to highway design, intelligent transportation systems, traffic management, and road safety.